Preventive Technologies: Evidence from a Choice Experiment with Dairy Farmers

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Abstract

This paper studies how risk preferences influence farm management when farmers have limited control over individual production units. We focus on health-related risks in dairy farming to elicit farmers' risk preferences and their willingness to pay for information, using a novel choice experiment in Colombia. Our findings reveal that cows managed by risk-averse farmers have a lower prevalence of ketosis, a metabolic disorder that reduces productivity. This result is primarily observed in lower-income farms and is consistent with a self-protection strategy, where farmers use preventive technologies to mitigate their risk exposure. We find that farm management practices mediate the relationship between risk aversion and ketosis, particularly those practices that improve cows' health by reducing disease likelihood but also lower revenue. Additionally, we observe a positive association between risk aversion and farmers' willingness to pay for information about cows' health status, an experimental measure comparable to investments in diagnostic equipment.

JEL codes: C93, D81, O33, Q12, Q16.

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1 Introduction

Many of the world's low-income farmers are vulnerable to uncertain productive conditions and have limited risk management options (Dercon, 2002; Lesk et al., 2016). Biological and environmental threats significantly impact crop yield variability (Heino et al., 2023; Vogel et al., 2019), with pests and diseases alone accounting for 20% to 40% of global crop losses (FAO, 2020). These risks are particularly relevant in low-income economies, where farmers often lack information and resources needed to mitigate such events (Carter et al., 2007). Moreover, resource-constrained farmers have limited control over individual production units, creating uncertainty between actions and outcomes that often prevents farmers from adjusting their management practices in response to risk events (Cole et al., 2013; Falco and Veronesi, 2013).

This paper examines how risk preferences farm management decisions under uncertainty. Farmers' attitudes toward risk significantly shape their responses to production risks, which can explain why some farmers under-invest in potentially profitable technologies. Farmers may not adopt improved inputs or modern practices if the perceived risk associated with these investments is too high (Magruder, 2018; Foster and Rosenzweig, 2010). Thus, risk aversion is often found to negatively impact technology adoption, especially in the presence of insurance, credit, and information constraints (Liu, 2013; Dercon and Christiaensen, 2011; Barrett et al., 2004).

In contrast to technologies aimed at increasing yield potential but perceived as too risky for adoption, preventive or risk-reducing technologies can help mitigate exposure to events that lower farm yields. A frequently cited example is the application of pesticides (Sexton, 2007; Horowitz and Lichtenberg, 1994). However, not all individuals would benefit from these investments. Risk-averse farmers, in particular, have incentives to minimize risks such as those from crop pests, livestock diseases, or seasonal droughts and floods (Koundouri et al., 2006). These incentives should drive demand for risk-reducing technologies that either mitigate losses as a form of self-insurance or reduce the occurrence of risk events as a form of self-protection (Horowitz and Lichtenberg, 1994).

We focus on risk events in pasture-based dairy farming in Colombia. Specifically, we examine the relationship between risk aversion and the prevalence of ketosis—a metabolic disease that reduces milk production, reproductive performance, and overall health in dairy cows (Ospina et al., 2010; Chapinal et al., 2011; McArt et al., 2012). We collected blood samples from early-lactation cows and tested them for concentrations of BHB, an organic compound produced by the liver. This metabolite provides an objective measure of ketosis prevalence, determined by the ratio of positive cases (whole blood BHB $\geq$ 1.2 mmol/L) to the total number of tests conducted."

Dairies in developing countries exhibit lower yields and higher production costs compared to those in industrialized countries (Knips, 2005). To bridge this gap and improve yields per animal, it is crucial to improve farmers' decisions regarding feed quality and frequency, as well as the diagnosis and treatment of cattle diseases.[1] However, monitoring and controlling forage intake and overall feed quality is particularly challenging in pasture-based dairies. This often leads to lower yields per cow, reduced profits, and potentially higher risks of nutritional deficiencies (Gillespie and Nehring, 2014; Hanrahan et al., 2018). Notably, Colombia's dairy industry is predominantly pasture-based and faces difficulties in improving quality and yields to compete in increasingly globalized dairy markets (Carulla and Ortega, 2016; Villa-Arcila et al., 2017).

As in other settings, determining the extent to which risk affects behavior is challenging without an experimental design. To address this, we conducted a lab-in-the-field experiment to elicit the risk preferences of farmers. Using lotteries, the experiment involved a trade-off between the cost of improved feeding practices and the risk of disease. The choices made by participants reflect scenarios where farm management requires upfront costs while benefits remain uncertain. We varied lottery probabilities to capture different levels of risk associated

[1]For instance, effective early-lactation management should ensure a better transition from non-productive to productive periods, minimizing metabolic disorders and other health issues, thereby enhancing dairy farm productivity (Yepes et al., 2020; Ospina et al., 2013; Chapinal et al., 2011).

with changes in disease prevalence. Additionally, we included a treatment condition to assess whether farmers are willing to pay for information about their cows' health status. This information simulates the use of a keto-meter, a device used to diagnose ketosis. This experimental design allows us to identify farmers' risk profiles using context-specific framing, relating animal feeding practices to the likelihood of metabolic disorders.

The main results show that risk aversion is negatively associated with the prevalence of ketosis. We compare the likelihood of ketosis across different risk profiles, controlling for a comprehensive set of farming practices, cow-level characteristics, and region-specific fixed effects. Consistent with the Expected Utility model, cows managed by risk-averse individuals exhibit a lower prevalence of the disease. This difference is primarily driven by farms with lower income and larger herd sizes, where risk aversion tends to be higher. Additionally, Our results indicate that risk-reducing feeding practices during periods of high energy demand are significantly associated with ketosis. For instance, gradually reducing milking before the next lactation period decreases the likelihood of the disease, though it may reduce yields in the short term. Moreover, veterinary visits increase production costs but also reduce ketosis prevalence.

A possible explanation for these results is that risk-averse dairy farmers adopt practices that prevent metabolic diseases affecting milk production. This is consistent with the idea that preventive health practices serve as risk management tools, particularly since animal diseases are significant barriers to higher dairy yields in developing countries (Hernández-Castellano et al., 2019). To empirically test this explanation, we focus on feeding practices, as nutritional mismanagement directly impacts cows' metabolic conditions

Using observational survey data, we find no significant mean differences in most farm practices between risk-averse and non-risk-averse farmers. However, a third of ketosis cases in our sample occur on farms that do not use feed concentrates during the fresh period –the few weeks after calving when milking drastically increases cows' energy demand. In contrast, risk-averse farms tend to use higher shares of feed concentrates in their cows' diets. Additionally, experimental results show a positive correlation between risk aversion and farmers' willingness to pay (WTP) for information about their cows' health status. This WTP serves as a proxy for the demand for testing devices or similar diagnostic services.

This paper is closely related to the literature on agricultural technology adoption, particularly in low-income countries. Notably, Emerick et al. (2016) shows that farm practices that reduce downside risks promotes investment in modern technologies. Recent studies have emphasized the demand for risk-reducing technologies among risk-averse agricultural producers. For example, risk-averse farmers are more likely to adopt pesticides (Liu and Huang, 2013), moisture control devices for rice crops (Shimamoto et al., 2017), and improved seeds (Asravor, 2018). Additionally, Crentsil et al. (2020) finds that risk-averse farmers were early adopters of fishing innovations designed to enhance disease and contamination resistance.

Our results expand this literature by showing that risk aversion is associated with a lower prevalence of the disease. We provide evidence that preventive care practices, such as regular veterinary visits and reducing milking frequency before dry-off, play a crucial role in helping farmers manage animal disease risks. Additionally, we show that risk-averse use higher shares of commercial feed concentrates, an input that remains underutilized in pasture-based dairies in low-income countries (FAO et al., 2014; Duncan et al., 2013).

Additionally, this paper contributes to the experimental economics literature on risk preferences. It is closely related to methodological approaches that use experimental methods to study individual preferences, including tests of theoretical predictions about social, other-regarding, time, and risk preferences (Fehr and Leibbrandt, 2011; Carpenter and Seki, 2011; Pace and Daidone, 2024). We combine lab-in-the-field experiments, biological indicators, and survey instruments to understand how risk preferences affect economic outcomes when direct observation and randomized evaluations are not feasible. Specifically, we show that experimental measures of risk and willingness to pay (WTP) can explain differences in the management of preventable events affecting agricultural production. Furthermore, our experiment integrates designs from Eckel and Grossman (2002) and Holt and Laury (2002), two well-established methods for risk elicitation, to account for changes in risk probabilities. This approach offers a framework for classifying risk profiles with precise calibration of relative risk aversion parameters.

The rest of the paper is organized as follows. The second section presents a theoretical model explaining self-protection and self-insurance as risk-reducing strategies. Section 3 summarizes the experimental design used to elicit dairy farmers' risk preferences. Section 4 describes the data and empirical strategy for estimating the relationship between risk aversion and the prevalence of ketosis. Sections 5 and 6 reports the main results and robustness checks. The final section discusses the main results and their broader implications.

2 Risk-reducing incentives

We build a model based on the endogenous risk literature to characterize farmers' behavior when confronting risk events affecting yields (Horowitz and Lichtenberg, 1994; Sexton, 2007; Archer and Shogren, 1996; Ehrlich and Becker, 1972). Specifically, we follow a framework developed to rationalize pest and disease control in agriculture (Sexton, 2007). Productivity risk in dairy farming can arise from several sources. For example, metabolic diseases impact dairy farms by reducing milk yield and increasing production costs due to treatment. While farmers can address sick cows individually, most inputs and practices in pasture-based dairy systems are determined at the herd level. This means that investments to mitigate disease risk must be applied across the entire herd.

The model describes the behavior of farmers that maximize the expected utility given inputs and practices that reduce the likelihood and impact of animal disease (see equation 1). Farmers choose a level of inputs, X, and pre-event actions, s, to maximize the expected utility of consumption, $EU(c)$. It is assumed that $EU(c)$ depends on farm profits, such that $c = \Pi(f(X, s; \omega), p)$. The technology f, in value terms, is assumed to be increasing and convex with respect to X and s. Per-unit input costs are denoted as p_x, and the cost of preventive actions is denoted as p_s.

$$\max_{X,s} E\left[U\big(f(X,s;\omega) - p_s s - p_x X\big)\right] \tag{1}$$

The production technology is given by $f(X,s;\omega) = h(X,\omega)\,(1-d(s))$, with partial derivatives $f_X > 0$ and $f_s > 0$. The function $h(X,\omega)$ is potential output that depends on inputs X, where $h_X \geq 0$, and a random parameter ω that affects disease damage independently of X. This parameter is indexed by states of nature, such that a higher realization of ω corresponds to higher disease damage and, consequently, lower output. The term $d(s) \in [0,1]$ captures the probability of risk event occurrence as the fraction of damaged output, which would be equivalent to the percentage of sick cows out of the total herd. This probability is a function of pre-event action, which reduces the likelihood of damage such that $d_s(s) < 0$.

2.1 Self-protection and self-insurance

Farmers can self-insure by reducing the severity of a risk event and self-protect by decreasing its likelihood (Archer and Shogren, 1996; Ehrlich and Becker, 1972). Self-insurance involves investing in risk-reducing inputs that mitigate losses when risk events occur. For example, farmers might adopt improved forage varieties or feed supplements with better nutritional content to increase the yield potential of sick cows and reduce the impact of disease on output.

An input is considered risk-reducing if the second derivative $f_{X,\omega}(X,s;\omega) < 0$, which indicates that inputs contribute less to production when disease damage is high (Horowitz and Lichtenberg, 1994).[2] This implies that an input X is risk-reducing if $f_{X,\omega} = h_{X,\omega}(X,\omega)(1-d(s))$. Since $(1-d(s))$ is non-negative, $f_{X,\omega}$ will be negative when the marginal product of inputs decreases in less favorable states of nature, such that $h_{X,\omega} < 0$.

[2] Horowitz and Lichtenberg (1994) modelpest control with additional sources of uncertainty, where yield potential is affected by random factors independent of X and s. In such cases, determining whether an input is risk-reducing requires additional assumptions about the correlation between these random factors and ω to establish the sign of $f_{X,\omega}$.

Alternatively, farmers self-protect by influencing the conditions under which risk events occur to reduce their likelihood. These actions may include consulting veterinary services to formulate adequate diets and diagnose health-related problems, which can help minimize the share of sick cows. Preventive actions always reduce risk since $f_{s,\omega} = -h_\omega(X,\omega)d_s(s) < 0$ for any non-zero values of s, X, and ω. In other words, preventive actions reduce risk by decreasing the share of output affected by disease, especially in states of nature where damage is high.

The main difference between X and s is that, while some inputs X are used in production regardless of the damage level, pre-event actions s are specifically implemented to reduce the likelihood of damage. Furthermore, not all inputs are risk-reducing, as $f_{X,\omega}$ may be zero or positive depending on the type of input (Horowitz and Lichtenberg, 1994).

Self-insurance and self-protection practices act as alternatives to commercial insurance for covering potential losses from harmful productivity shocks. These strategies are especially important when insurance markets are incomplete. In low-income countries, farm insurance is notably limited, and available policies rarely cover production animals. Additionally, information about underlying risks is often lacking or unverifiable, preventing insurance providers from offering competitive risk reduction solutions. In such situations, risk-reducing technologies become essential, if not the only alternative, for farmers to mitigate downside risks.

2.2 Risk aversion

A risk-reducing practice can also be defined as an input X or action s that a risk-averse producer will utilize more than a risk-neutral producer (Leathers and Quiggin, 1991). To illustrate this, consider the first-order condition of (1) with respect to X, given by $\frac{\delta EU(c)}{\delta X} = E\big[U'(c)\big(f_X - p_x\big)\big] = 0$. The second partial derivative of this condition with respect to ω is

$$\frac{\delta EU(c)}{\delta X \delta\omega} = E\left[U''(c)\big(f_X - p_x\big)f_\omega\right] + E\left[U'(c)f_{X,\omega}\right] \tag{2}$$

where $f_w < 0$, $U' > 0$, $f_X \geq p_X$, and $f_{X,\omega} < 0$ for risk-reducing inputs. The first term in (2) represents the expected income effect, which does not impact risk-neutral individuals since $U'' = 0$, but it does affect risk-averse individuals where $U'' < 0$. The second term captures the pure marginal productivity effect, influencing all individuals regardless of their risk preferences. Consequently, changes in the use of risk-reducing inputs lead to higher expected utility for the risk-averse, especially in less favorable states of nature.

The model suggests that risk-averse individuals have stronger incentives to make risk-reducing investments. As long as these investments are cost-effective at reducing risk, meaning they satisfy the first-order conditions, risk-averse farmers benefit from these actions. In contrast, risk-neutral and risk-seeking individuals may experience lower or even negative expected utility from the same investments.

2.3 Expected effects

Based on this framework, we formulate two sets of expected effects for dairy farmers facing the risk of events such as metabolic diseases. First, the model suggests that risk-averse farmers are more likely to invest in risk-reducing strategies than their non-risk-averse counterparts. Therefore, we should observe differences in practices that mitigate disease across risk profiles, either through self-protection or self-insurance. In particular, diagnostic information about cows' health status enables farmers to adjust their management to less uncertain conditions. As a result, the willingness to pay for this information is expected to be higher among risk-averse farmers.

Second, the prevalence of the disease should be lower on farms managed by risk-averse individuals. Self-protection practices are expected to decrease the likelihood of ketosis, conditional on all other factors affecting disease prevalence that are independent of management. As risk-averse farmers are more incentivized to invest in self-protection, the likelihood of risk events such as ketosis should be lower among these farmers. In contrast, some actions may mitigate downside costs without affecting the likelihood of occurrence. Therefore, self-insurance strategies should have no effect on the prevalence of the disease.

Note that the risk-reducing practices described here are correlated with production scale. The cost of inputs increases with herd size, while the cost of preventive actions may remain independent of production scale. Additionally, risk aversion tends to decrease with increases in endowments such as income, land, and, in the context of dairy farming, herd size (Pratt, 1964; Arrow, 1971; Guiso and Paiella, 2008). Together, these ideas suggest that herd size plays a significant role in farmers' risk management strategies, as the relative benefits of risk-reducing inputs may diminish for those managing larger farms. Consequently, we expect to observe a stronger relationship between risk aversion and the prevalence of the disease among smaller-scale farmers.

3 Experimental design

Our risk-elicitation experiment is based on the design proposed by Eckel and Grossman (2002, EG henceforth), which we have adapted to capture behavioral effects related to changes in risk probabilities. In the EG design, participants choose one lottery from a set of binary lotteries, each with a probability of $p = 0.5$ for both outcomes, but differing in expected payoffs. This design identifies preferences using the constant relative risk aversion (CRRA) parameter r as a metric. Individuals are classified as risk-averse if the CRRA parameter implied from their choices is $r > 0$, risk-neutral if $r = 0$, and risk-seeking if $r < 0$. As described by Dave et al. (2010), comparing choices across different lotteries allows us to derive r cutoff points that capture not only risk aversion but also risk-neutral and risk-seeking behavior.

We framed lotteries to mirror the risk associated with farmers' feeding decisions. This design simulates the economic trade-offs between investing in higher-quality feed to reduce the likelihood of metabolic diseases. We present lotteries as feed quality menus, where feed quality refers to combinations of quantity and frequency of various food types (forage, feed concentrates, or supplements). Participants choose among three feed quality options (high, medium, and low), which correspond to different ranges for CRRA parameter. This setup reflects the idea that higher-quality feeds reduce monetary losses from disease, though at a higher production cost. In contrast, lower-quality feeds decrease costs but may lead to reduced overall profits if the disease occurs.

An important challenge is that the classification of risk profiles in the EG design depends on the specific risk probability p used. Changes in the likelihood of outcomes can lead to different profile assignments, particularly for ranges of the CRRA parameter r that include indifference points between lotteries. For example, it may be difficult to differentiate between risk-neutral and risk-seeking behaviors when the CRRA parameter falls within a range where $r \leq 0$. To address this, we follow the logic behind the price list design (Holt and Laury, 2002), varying the probabilities p to calculate the implied CRRA cutoff points for three different sets of feed quality menus.

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In our experiment, we established three risk conditions to simplify the design and due to the lack of prior information about the prevalence of ketosis in the study regions. The low-risk condition corresponds to 20% of the herd being at risk of developing the disease, the medium-risk condition corresponds to 50%, and the high-risk condition corresponds to 80%. Although these risk levels may exceed the actual prevalence of metabolic diseases in our context, they are used to illustrate relative differences in disease prevalence in a way that makes it easier to distinguish between the available options. [3]

Table 1 reports the payoffs and probabilities of the lotteries presented to the farmers. For each risk condition, participants choose from three feed quality options. The table also includes additional statistics such as expected values, standard deviations, and CRRA cutoff points, which were not shown to the participants but are utilized in the EG procedure to identify risk preferences. For instance, when the probability is $p = 0.2$, a risk-averse individual would prefer the high-quality option due to its lower standard deviation, despite its lower expected value. In contrast, a risk-neutral individual would select the option with the highest expected value, which could be either the medium or low-quality feed. If an individual chooses the low-quality feed when a medium-quality feed offers the same expected payoff with a lower standard deviation, this indicates risk-seeking behavior. However, this classification logic does not apply to all three risk conditions. As the risk level increases, the classification procedure requires incorporating multiple CRRA cutoff points to accurately identify risk preferences.

Table 1: Payoff tables by risk condition

Feed quality option	Payoff if cow is healthy	Pr(healthy)	Payoff if cow is sick	Pr(sick)	E[x]	S.D.	CRRA parameter cutoff points
			20% risk				
high	17	0.8	14	0.2	16.4	7.6	$6.26 \leq r$
medium	25	0.8	12	0.2	22.4	12.4	$0 \leq r \leq 6.26$
low	27	0.8	4	0.2	22.4	14.7	$r \leq 0$
			50% risk				
high	17	0.5	14	0.5	15.5	1.1	$3.02 \leq r$
medium	25	0.5	12	0.5	18.5	4.6	$-1.18 \leq r \leq$3 .02
low	27	0.5	4	0.5	15.5	8.1	$r \leq -1.18$
			80% risk				
high	17	0.2	14	0.8	14.6	5.5	$0 \leq r$
medium	25	0.2	12	0.8	14.6	3.2	$-2.47 \leq r \leq 0$
low	27	0.2	4	0.8	8.6	1.6	$r \leq -2.47$

Notes: Payoffs in USD. Letter r denotes the constant relative risk aversion (CRRA) parameter.

[3]As shown by Dave et al. (2010), simpler risk elicitation tasks are more suitable for contexts with low numeracy, which is often the case in rural communities in low-income countries.

We then combine ranges of the CRRA parameter to construct profiles that account for the change in the risk levels. Using the procedure presented in figure 1, we classify subjects into three profiles.[4] The basic case is when individuals choose the same option in all three risk conditions. If the high-quality option is always selected, the farmer is inferred to be risk averse. In this case, the decision in the lowest prevalence condition provides enough information to determine the risk profiles. On the other hand, risk neutrality (seeking) requires that the medium (low) quality option is always chosen. In this case, the classification procedure yields the same profiles as if subjects were classified using the regular EG design (Eckel and Grossman, 2002).

We then combine ranges of the CRRA parameter to construct profiles that account for changes in risk levels. Using the procedure outlined in Figure 1, we classify subjects into three profiles. [5] The basic scenario occurs when individuals choose the same option across all three risk conditions. If the high-quality option is consistently selected, the farmer is classified as risk-averse. In this case, the decision made in the lowest prevalence condition provides sufficient information to determine the risk profile. Conversely, consistent selection of the medium (risk-neutral) or low-quality (risk-seeking) option yields profiles consistent with those from the standard EG design (Eckel and Grossman, 2002).

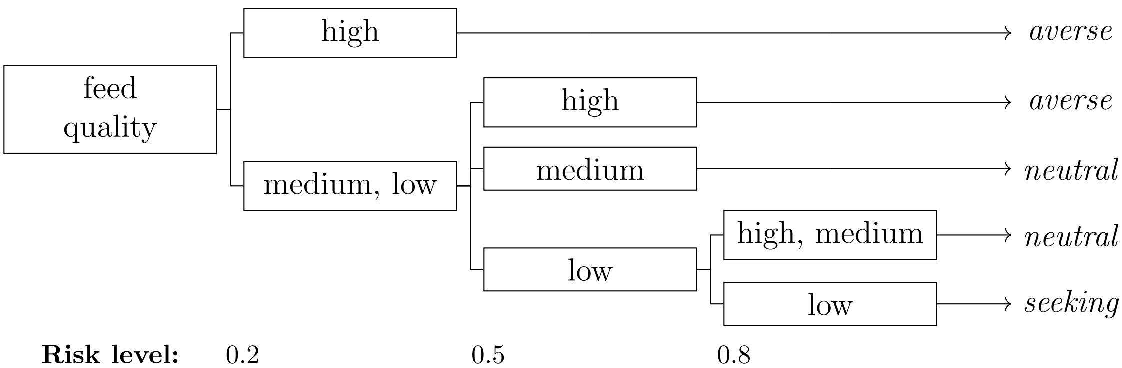
Different combinations of choices provide more detailed information about individuals' risk preferences. For example, a risk-averse individual would choose the medium-quality option when $p = 0.2$ and select the high-quality option for both $p = 0.5$ and $p = 0.8$. This pattern implies a CRRA parameter within the range $3.02 \leq r \leq 6.26$. Figure 1 illustrates the classification procedure, which begins from the left with the lowest risk level. However, the resulting profiles are independent of the sequence in which decisions are made. Note

[4]Technically, up to five profiles can be derived using this classification process, including two degrees of risk-averse/seeking behaviors. These profiles come from each of the five CRRA cutoff points, as presented in table 1. For instance, a higher degree of risk aversion derives from choices that yield $r \geq 6.26$ than for those that imply $3.02 \geq r \geq 6.26$.

[5]Technically, up to five profiles can be derived using this classification process, which includes two degrees of risk aversion or risk-seeking behaviors. These profiles are based on the five CRRA cutoff points presented in Table 1. For example, a higher degree of risk aversion corresponds to choices yielding $r \geq 6.26$, compared to choices that imply $3.02 \geq r \geq 6.26$.

that if an individual's behavior cannot be classified into any profile, it indicates a deviation from Expected Utility Theory. This situation is analogous to selecting a higher-risk gamble after previously choosing a safer option in the Holt and Laury design (2002).

Figure 1: Risk profile classification based on lottery choices



Notes: This figure describes, from left to right, the risk profile classification procedure. This classification is based on feed quality choices made in the base game of the risk elicitation experiment. Each subsequent node after feed quality correspond to risk levels, framed as the likelihood of the disease. The resulting risk profiles describe behaviors as averse, neutral and seeking.

Finally, we included a treatment to determine if there is a positive willingness to pay (WTP) for information about the health status of cows. In this treatment, individuals can pay a fixed amount, c, to learn whether the cow is sick or healthy before choosing between feed quality lotteries. Using the same basic experimental setup as before, individuals reveal a positive WTP whenever they pay c for this information. Once the cow's health status is known, there is no uncertainty about the prevalence of the disease, but feed quality payoffs are lower than in the baseline scenario.

The net benefit of this decision is determined by comparing the expected payoff of paying for information about a cow's health status versus playing the game under the baseline conditions explained earlier. Once farmers know their cows' health status, they can select a higher payoff in each case, either \$27 or \$14. For each probability p, using values from table 1, the expected payoff of paying for information is then $\mathrm{E}[x|c] = p(27 - c) + (1 - p)(14 - c)$. Each term represents the utility of the maximum payoff if the cow is healthy (sick), multiplied by the probability of a healthy (sick) cow. The price of information was defined as $c = \$2$

USD.

Note that this treatment does not alter the game's payoff structure. Since the risk probabilities remain the same, the only change is the amount of information available to farmers. With this information farmers can make more appropriate feeding decisions once the cows' health status is revealed. However, paying for information does not change the expected payoffs, as there is no difference between choosing the medium-quality option and opting not to pay c before knowing the lottery's outcome. As shown in Table 2, the values of E$[x|c]$ match the expected payoffs and standard deviations of the medium feed quality option in each lottery set (see table 1).

Table 2: Expected payoffs net of payment for information

Risk condition	High payoff: $27-c$	Pr(healthy)	Low payoff: $14-c$	Pr(sick)	E$[x\|c]$	S.D.
1: 20%	25	0.8	12	0.2	22.4	12.4
2: 50%	25	0.5	12	0.5	18.5	4.6
3: 80%	25	0.2	12	0.8	14.6	3.2

Notes: Payoffs in USD.

3.1 Field protocol

The study was conducted in three of Colombia's main dairy farming regions (Cundinamarca, Antioquia, and Caldas).[6] In collaboration with a team of local veterinary scientists, we collected information on three levels of analysis: cows, farms, and farmers.

Farms were sampled to participate through the extension programs of two local universities using convenience sampling. From the pool of farms serviced by the universities, those willing to participate and meeting two criteria were invited to join the study. The criteria were that the farm must have records of production, management practices, and basic cattle health status, and the farm's herd size must be large enough to ensure the availability of

[6] The protocols for this study were approved by the Institutional Review Board for Human Participants (protocol 1805007984), and the Animal Care and Use Committee (protocol 2018-0012) at Cornell University.

early lactation cows for testing. In Section 3, we discuss how farms in our sample compare to other dairies in Colombia.

A group of veterinary students visited a total of 56 farms, collected blood samples from over 900 dairy cows, and tested these samples to determine the cow-level prevalence of ketosis. They used a portable ketone meter to measure the β-hydroxybutyrate (BHB) blood concentration in dairy cows between 1 and 42 days after calving. A BHB blood concentration ≥ 1.2 indicates that a cow has ketosis. This threshold is standard in most research on ketosis prevalence in dairy cows (Ospina et al., 2010; Chapinal et al., 2011; Oetzel, 2004).

However, cows with ketosis may not always show clinical signs of the disease. Instead, ketosis can lead to a drop in milk production and increase the risk of developing other diseases and reproductive problems. As a result, the prevalence of ketosis directly impacts farm management through reduced productivity and higher cattle health-related costs. Therefore, in addition to the blood tests, we collected information on the cow's last calving and a body condition score (BCS), which indicates the general nutritional status of each cow using a standardized five-point scale (Edmonson et al., 1989).

After the animal sampling, a survey and a risk-elicitation choice experiment were conducted with farmers. The survey gathered information on farm characteristics and management practices, focusing on practices before and after calving. Additionally, farm managers—those responsible for making feeding decisions—participated in the choice experiment. Each farmer received a show-up fee of $5 USD before the experiment began. Instructions were read to each farmer in private, and a native Spanish-speaking enumerator conducted each session face-to-face with all farmers.[7]

Farmers made a total of six decisions. The first set of three decisions was used to establish the risk profiles of the farmers. The second set was used for a willingness-to-pay treatment for information on the health status of cows. The instructions clarified that rounds were independent, meaning that decisions made in a given round did not affect the game dynamics

[7] An English version of the experiment's instructions is available as supplemental materials at the end of this document. The Spanish version of the instructions is available upon request.

or payoffs of any other round. Within each set of rounds, the distribution of risk levels was randomized to minimize ordering effects.

In each of the first three rounds, participants were asked to choose one of three feed quality options for their farm. As presented in Table 1, each option had two payoffs, a higher payoff if the cow was healthy and a lower payoff if the disease was present. Participants were not given information on the cow's health status (healthy or sick) before making their decision. Instead, a lottery determined the health status at the end of the game, based on the probabilities of each risk condition. For example, in the low-risk condition, the probabilities were framed as "two out of ten cows on your farm are currently at risk of developing the disease." Participants were also informed that only one of the six decisions would be randomly selected to determine the final payoffs.

In rounds 4 to 6, farmers were asked if they were willing to pay a fixed amount of $2 USD to conduct the lottery before making their feed quality decisions. The rounds were conducted as before, with the main difference being a reduction in each lottery's payoff if the farmer chose to pay for information about the cow's health status. A new version of Table 1 was presented, showing the payoffs of each outcome after subtracting $2. If farmers agreed to pay this amount, a lottery was run to determine the cow's health status at the end of each round. After learning the cow's health status, farmers made their feed quality decision based on the same three quality options explained earlier.

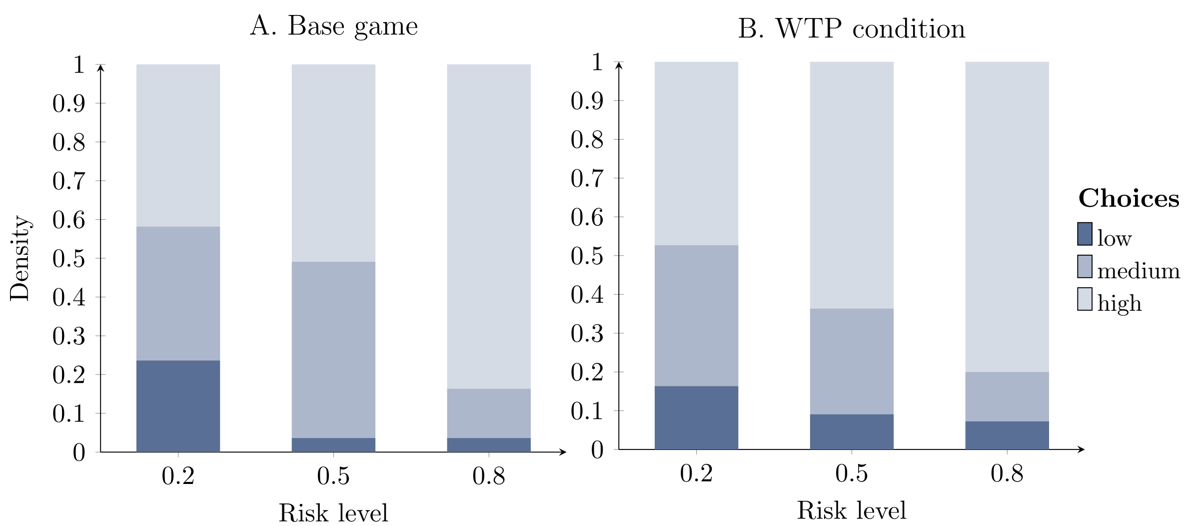
Once all decisions were made, bags filled with plastic balls were used to determine the final payoffs of the game. In the first bag, six balls numbered 1 to 6 were used to select the round to be paid. The second bag contained ten balls, divided between white balls representing a healthy cow and red balls indicating a sick cow. The risk condition determined the proportion of each color. For example, under a risk condition of 0.5, half of the ten balls were white and the other half were red. Each participant first randomly selected a ball from the first bag to determine the round for which they would be paid, and then drew a ball from the second bag to ascertain the cow's health status. After the lotteries, a short survey on the socioeconomic information of farmers and their households was conducted. Finally, payments in cash were made according to the experiment's payoffs.

4 Data and Empirical Strategy

4.1 Experimental data

Figure 2 reports the distribution of choices in the risk experiment. The distribution shows how farmers' choices change with the risk level. In the low-risk condition ($p = 0.2$), about 25 percent of the farmers chose the low feed quality option. The share of low-quality feed choices decreases as the risk of the disease increases. The high-quality option is selected more frequently, ranging from 40 to 80 percent across all risk levels. In the moderate-risk condition ($p = 0.5$), there is an almost even split between the high and medium options. The share of the medium-quality option is higher when $p = 0.5$, but decreases significantly when the risk level increases to $p = 0.8$. These patterns are similar between the base game and the willingness to pay treatment.

Figure 2: Distribution of choices by risk level



Notes: This figure reports the distribution of choices during the risk-elicitation experiment. Panel A reports choices for the base fame (rounds 1-3). Panel B reports choices for the willingness to pay (WTP) condition (rounds 4-6).

Based on this data, the procedure explained in Section 2 classifies 65% of the farmers as risk-averse, 26% as risk-neutral, and 9% as risk-seeking.[8] This distribution is comparable to other studies using a single probability.[9] In the treatment rounds, we find that 37% of farmers decided to pay for information in the 0.2 risk condition, 64% in the 0.5 risk condition, and 45% in the 0.8 risk condition.

Additionally, farmers chose to pay for cows' health information approximately 51% of the time. This percentage was highest in the moderate-risk condition at 60%, though there were no statistically significant differences compared to the low- and high-risk conditions, where the percentages were 45% and 49%, respectively.

The distribution shown in Figure 2 highlights the potential for misclassification if only one probability condition is used to determine risk profiles. For example, the high proportion of farmers choosing the low-quality feed in the moderate-risk condition compared to the low-risk condition could have led to an incorrect classification of more farmers as risk-seeking. These results validate the importance of including multiple risk levels in our classification procedure for determining risk profiles.

4.2 Survey data and prevalence estimates

Table 3 presents summary statistics of the variables used in our analysis. The top panel provides information at the animal level, showing that 4.3% of the cows in the sample were diagnosed with some level of ketosis based on BHB concentration estimates. The highest prevalence of ketosis was observed in Cundinamarca (9.4%), followed by Caldas (4.4%) and Antioquia (2.1%). Differences across regions were statistically significant between Cundinamarca and Antioquia (Pearson's χ^2: 19.4, p-value: 0.00) and between Cundinamarca

[8] It was not possible to determine the risk profile of one farmer whose decisions were inconsistent with the classification procedure. For this reason, information for this farm is not included in the data set used for estimation.

[9] For instance, Eckel and Grossman (2002) find in their no-loss treatment that Averse: 57%, Neutral: 17%, Seeking: 25% from a sample of college students.

and Caldas (Pearson's χ^2: 3.38, p-value: 0.07).[10]

Table 3: Summary statistics

	mean	S.D.	min	max
Panel A. Animal level, n=891				
Ketosis prevalence (%)	4.26	20.22	0.00	100.00
BHB (mml/L)	0.60	0.34	0.00	4.40
Weeks since calving	3.25	1.90	0.14	8.86
Body conditioning score (1-5)	2.77	0.35	2.00	4.00
Parity (number of pregnancies)	3.11	1.99	1.00	12.00
Last calf sex (male = 1)	0.49	0.50	0.00	1.00
Last calf sex (yes = 1)	0.04	0.19	0.00	1.00
Holstein (yes=1)	0.96	0.19	0.00	1.00
Panel B. Farm level, n=55				
Mean production (kg/cow/day)	20.47	4.04	11.00	36.00
Fat in milk (%)	3.54	0.26	3.02	4.06
Concentrate share (%)	19.50	19.51	0.00	80.00
Feeding frequency (times/day)	3.90	1.06	2.00	6.00
Veterinary visits (times/day)	85.45	35.58	0.00	100.00
Farm size (ha)	2.13	3.89	0.13	14
Herd size (hundred cows)	3.34	3.18	0.41	12.21
On-site milking (yes=1)	0.15	0.36	0.00	1.00
Fresh-cows separation (yes = 1)	0.29	0.45	0.00	1.00
Milking reduction (yes = 1)	0.32	0.47	0.00	1.00
Panel C. Farmer level, n=55				
Risk averse (yes=1)	0.65	0.47	0.00	1.00
Age (years)	39.41	13.30	20.00	80.00
Male (yes = 1)	0.82	0.39	0.00	1.00
Manager only (yes = 1)	0.79	0.40	0.00	1.00
Education (years)	12.54	4.48	5.00	18.00
Credit access (yes = 1)	0.51	0.50	0.00	1.00
Income (million COP)	10.21	11.56	0.80	40.00

The veterinary medicine literature on early lactation diseases identifies several risk factors that contribute to ketosis, including high parity, elevated body condition score (BCS), Holstein breed, male calves, and conditions related to the last calving.[11] On average, our sample primarily consists of Holstein cows that are more than 21 days post-calving, with

[10] It is important to note that previous epidemiological studies of ketosis in Colombia reported higher prevalence levels of subclinical ketosis, with estimates ranging from 8.3% to 26% during the first six weeks of lactation (Villa-Arcila et al., 2017; Brunner et al., 2018; Garzón-Audor and Oliver-Espinosa, 2019).

[11] See Garzón-Audor and Oliver-Espinosa (2018) for a review.

approximately three previous pregnancies, and a mean BCS of 2.8 out of 5.0.

The second panel of Table 3 presents information at the farm level. Farms in our sample are characterized by a pasture-based production system with an average daily production of about 20.4 kg per cow, 3.5% milk fat, and an estimated stocking density of approximately three cows per hectare. For conventional dairy farms in Colombia, the corresponding values are 12 to 14 kg/day, 3.5%, and 1 to 2 cows/ha on average (Carulla and Ortega, 2016), which are slightly different from those in our sample. These differences may be attributed to the exclusion of relatively smaller and less professionally managed farms from our study. Our sample was intentionally designed to include farms with a sufficient number of cows and good management practices to properly identify cows to be tested for ketosis.

Other farm-level variables include the percentage of concentrate in cows' diets during the fresh period (the first weeks after calving), feeding frequency (including both pasture and grain concentrates), whether milking is gradually reduced before the next lactation (milk reduction before dry-off), whether lactating cows are managed separately from the rest of the herd (fresh-cows separation), the number of animals, farm size, and whether cows are milked in the fields rather than traveling to a milking parlor.

Lastly, the bottom panel of Table 3 provides information on the farmers in the sample. The majority are middle-aged males with an average level of high school education. The table also reports farm income, a binary indicator for cases where the farmer is the manager but not the owner of the farm, and another binary variable identifying farmers with access to credit.[12]

4.3 Reduce form estimation

We first examine the relationship between risk aversion and the prevalence of ketosis. The estimating model is presented in equation (3). This model relates the likelihood of ketosis, Pr(Ketosis=1), for cow i in farm j to an indicator variable $Averse_j$, which equals one if the

[12] These credit sources include credit cards, commercial bank loans, and credit from input suppliers.

farm manager is risk-averse and zero otherwise. Additional explanatory variables include farm-level production practices, represented by vector X_j, a set of animal-level characteristics Z_{ij}, and differences in the productive and environmental conditions of farm location, captured by the region fixed effects indicator D_j. The error term ϵ_{ij} captures any additional unobserved variability in prevalence levels.

$$\Pr(\text{Ketosis=1})_{ij} = \alpha + \beta Risk\ Averse_j + \gamma X_j + \eta Z_{ij} + D_j + \epsilon_{ij} \tag{3}$$

Our objective is to test whether there is a negative and significant association between risk aversion and the prevalence of ketosis. In this model, we focus on β as the key parameter to identify the extensive margin effect of risk aversion, distinct from other risk factors influencing ketosis. The main hypothesis is that $\hat{\beta} < 0$. A similar effect should be observed in the BHB estimates, as higher BHB concentrations increase the likelihood of a ketosis diagnosis. This is the case because the ketosis indicator is directly linked to BHB blood concentration. Consequently, we also estimate the model in equation 3, substituting BHB blood concentration as the dependent variable.

We then examine the relationship between risk aversion and willingness to pay (WTP) for information. To do this, we estimate a linear probability model that relates farmers' decisions during the treatment rounds to their risk profiles, as specified in equation 4. For each risk level, the dependent variable is a binary variable WTP_j, which equals one if farmer j chooses to pay for information about their cows' health status. The model also includes indicator variable $Risk\ Averse_j = 1$, identifying whether a farmer is risk-averse. Additionally, we control for socioeconomic characteristics C that the literature on risk elicitation identifies as important in explaining behavior under risk, including income, age, gender, education, and access to formal credit.

$$\Pr(\text{WTP} = 1)_j = \theta_0 + \theta_1 Risk\ Averse_j + \theta_2 C_j + \epsilon_j \tag{4}$$

4.4 Descriptive and mediation analysis

To explore farm management practices, we compare differences between risk-averse and non-risk-averse farmers. First, we test for mean differences in practices that could affect cows' health status, specifically focusing on risk factors associated with the prevalence of ketosis. Additionally, we examine the distribution of feeding practices and inputs, with particular attention to practices related to the risk elicitation method used, as risk profiles are based on the farmers' feeding choices.

We also conduct a mediation analysis using the model specification described in (3). In this analysis, we asses the sensitivity of the coefficient β to model selection when management practices are included in the estimation. While this coefficient captures the correlation between risk aversion and the likelihood of ketosis, any potential direct effect of risk aversion is expected to be mediated by management practices. In other words, farmers influence cows' health status through the adoption of certain practices that either contribute to or prevent ketosis. If the inclusion of management practices results in an estimated coefficient that is not statistically different from zero, this would indicate that the effect of risk aversion is fully mediated by management. Moreover, practices that mediate this effect are also expected to have a significant association with ketosis.

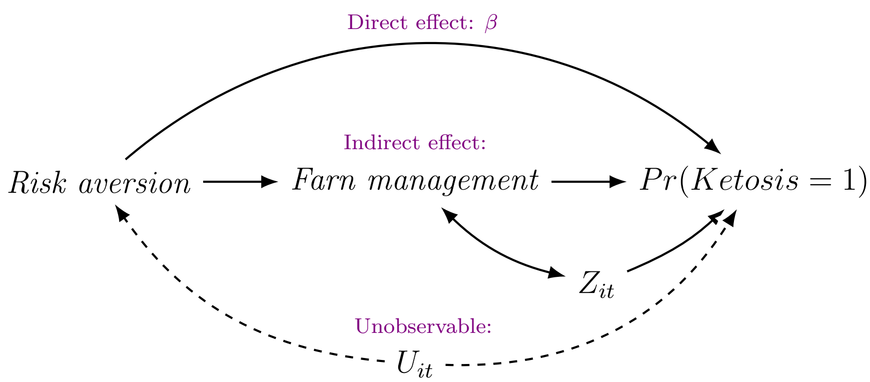
To test for mediation, we estimate several model specifications with and without farm-level controls. We include practices and characteristics known to influence cow health in general and the likelihood of ketosis in particular. These variables are reported in Panel B of Table 3. For instance, farmers might use specific pasture varieties with higher nutritional content (Kolver, 2003; Compton et al., 2015; Garro et al., 2013; Daros et al., 2017; Wilkinson et al., 2019).[13] Additionally, farmers might reduce milking frequency before dry-off or increase feeding frequency to lower the cows' energy demands (González et al., 2008; Sahar et al., 2020; Yepes et al., 2020).

[13] In our sample, Kikuyu (*Pennisetum clandestinum*) was the predominant variety, present on 86% of farms. It is not clear a priori whether this pasture variety provides better or worse nutritional content compared to others.

4.5 Identification and limitations

A key challenge in our estimation is properly controlling for both observable and unobservable confounders. As shown in Figure 3, we cannot guarantee that the estimated coefficients represent true causal effects because of potential biases caused by omitted and unobserved variables. The main issue is our inability to control for farm fixed effects, which would account for unobserved variability in management, as risk preferences are identified at the same level of analysis. Nevertheless, we aim to provide the most accurate and unbiased estimates possible by conditioning on observable characteristics. Additionally, we assess the potential bias caused by selection on observables using the procedure proposed by Oster (2017).

Figure 3: Modeled causal relationships



Notes: This Directed Acyclic Graph (DAG) describe the direct and indirect causal paths between risk aversion and the prevalence of ketosis. The graph includes farm management practices X_j and cow level characteristics Z_{ij}. The dashed lines identifies the open paths caused by omitted and unobservable variables U_{ij}, which, if not accounted for, can lead to biased estimates and non-causal associations.

To address potential confounding factors, our econometric estimation controls for a comprehensive set of farm- and cow-level covariates, selected based on evidence from veterinary science regarding the determinants of ketosis. Additionally, we designed our field protocol to include only specific cow breeds and farm types, thereby limiting variability across these characteristics. We also used a biological indicator as an objective measure to determine the prevalence of the disease. Nevertheless, the estimated coefficients are sensitive to model selection, which is why we compare across different specifications using mediation analysis.

Another relevant concern is the relatively low prevalence of ketosis. A significant percentage of cows test negative for ketosis at the pre-specified cut-off of 1.2 mmol/L BHB, leading to a relatively small number of positive cases in the dependent variable. Given the sample size, this makes positive cases of ketosis rare in a statistical sense. To address this issue, in section 6, we consider alternative estimation methods for equation (3) to evaluate potential finite sample bias associated with rare events. Specifically, we estimate the standard probability models, and the Penalized Maximum Likelihood Estimation proposed by Firth (1993). Additionally, we also conduct a sensitivity analysis using alternative BHB thresholds as a robustness check.

5 Results

In the results section, we examine the relationship between risk aversion and disease prevalence, with a particular focus on how this relationship varies with farm management practices and herd size. We analyze the estimated coefficients for risk aversion across various reduced-form regression models and evaluate the impact of farm management practices on the likelihood of ketosis. Additionally, we investigate how risk aversion interacts with farm income to determine if its effects vary across farms of different production scales. Finally, we report results on the willingness to pay for information about cows' health status.

5.1 Disease prevalence

Table 4 reports the estimated coefficients of risk aversion on the prevalence of ketosis based on the model (3). The coefficient for the risk aversion indicator variable is negative across all specifications. Specifically, Column (1) of Table 4, which includes no control variables or region fixed effects, indicates that cows managed by risk-averse farmers are 3.3 percentage points less likely to experience ketosis compared to those managed by farmers with other risk profiles. This reduction corresponds to approximately three-quarters of the 4.3% average ketosis prevalence, or half of the 6.6% mean prevalence among non-risk-averse farmers. Additional results using BHB blood concentrations as the dependent variable reveal a similar pattern of negative coefficients for risk aversion (see Table A2 in the appendix).

The estimated coefficient for risk aversion ranges from 1 to 4 percentage points across different specifications (see Columns 2 to 5 in Table 4). The statistical significance of these coefficients varies depending on farm management practices. Consistent with full mediation, the coefficient decreases to approximately -2 percentage points and becomes insignificant when farm practices are included, as shown in Columns 2 and 4. For comparison, in column 3, when only cow-level characteristics are included in the model, the coefficient for risk aversion remains relatively unchanged compared to the model without controls.[14]

Previous research suggests that factors such as stocking density, daily travel distance to the milking parlor (Scott et al., 2014; Neave et al., 2021), as well as cow age and reproductive history (Seifi et al., 2011; McArt et al., 2013; Benedet et al., 2019; Pralle et al., 2020), contribute to the incidence of metabolic diseases. Moreover, extensive evidence indicates that feed concentrates and individualized feeding can improve energy balance in pasture-based dairy cattle, thereby mitigating disease risks (Wales et al., 2009; Hills et al., 2015; Auldist et al., 2016; Merino et al., 2021).

In our sample, only a few management practices predict the prevalence of ketosis, some of which are consistent with the veterinary medicine literature. In the fully controlled model specification presented in Column 5, the number of veterinary visits and the reduction in milking frequency before dry-off are associated with a lower likelihood of ketosis. The coefficient for milking reduction is -5.7 percentagestockstocking points, making it the strongest individual association. These practices appear to improve cow health, though they come at

[14]These findings are further supported by results from a model that includes all interactions between farm practices and risk aversion. As shown in Table A1 in the appendix, when accounting for all potential correlations with management, the association between risk aversion and ketosis becomes insignificant.

Table 4: Regression results of risk aversion on ketosis

Covariates	Ketosis prevalence (1)	(2)	(3)	(4)	(5)
Risk averse	-0.033*	-0.019	-0.036*	-0.022	-0.014
	(0.019)	(0.017)	(0.020)	(0.018)	(0.015)
Concentrate share		-0.008		-0.011	-0.028
		(0.038)		(0.041)	(0.026)
Feeding frequency		0.025***		0.023***	-0.010
		(0.007)		(0.007)	(0.010)
Veterinary visits		-0.001*		-0.001**	-0.001**
		(0.000)		(0.000)	(0.000)
Farm size		-0.006		-0.007	-0.003
		(0.004)		(0.005)	(0.004)
Heard size		0.005		0.007	0.007
		(0.005)		(0.006)	(0.005)
On-site milking		0.007		0.010	0.024
		(0.019)		(0.020)	(0.021)
Fresh-cows separation		-0.029		-0.029	-0.020
		(0.020)		(0.021)	(0.020)
Milking reduction		-0.025		-0.024	-0.056***
		(0.016)		(0.017)	(0.018)
Weeks since calving			-0.002	-0.001	0.000
			(0.003)	(0.003)	(0.003)
BCS			0.019	0.015	0.023
			(0.024)	(0.025)	(0.026)
Parity			0.007**	0.007**	0.009**
			(0.004)	(0.004)	(0.004)
Last calf sex			0.006	0.005	0.006
			(0.013)	(0.012)	(0.012)
Last calf stillborn			-0.001	-0.001	-0.004
			(0.032)	(0.032)	(0.035)
Constant	0.066***	-0.023	-0.003	-0.081	0.004
	(0.017)	(0.032)	(0.073)	(0.073)	(0.082)
Dependent variable mean	0.043	0.043	0.043	0.043	0.043
Observations	891	891	891	891	891
Region fixed effects	no	no	no	no	yes

Notes: Coefficients estimated using linear regression models with Pr(ketosis=1) as the dependent variable. Clustered-Robust standard errors at the farm level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

cost of higher expenses and lower milk production. Conversely, the results indicate that a higher parity significantly increases ketosis prevalence. These results are consistent with the self-protection strategy described in the theoretical framework.

Other practices may play a role in mitigating the negative effects of ketosis without necessarily affecting its likelihood. For instance, feed concentrate in cows' diets does not show a significant association with the prevalence of the disease. Notably, Columns 2 and 4 suggest that higher feeding frequency is associated to a higher likelihood of ketosis, though this coefficient becomes negative and insignificant when controlling for region-specific fixed effects in Column 5. Additionally, we find no significant coefficients for herd size and farm size (both of which which capture stocking density), or on-site milking (where cows do not travel to a milking parlor).

As discussed in the theoretical framework, there may be heterogeneous effects of production scale on the relationship between risk aversion and the prevalence of ketosis. These effects are influenced by the distribution of endowments, particularly income. A higher percentage of farmers are classified as risk-averse among those managing farms below the median farm income (72%) compared to those above (56%), although this difference is not statistically significant ($t = 1.17$, $p = 0.24$). To further explore these income effects, we estimate a regression model similar to the model in equation (3), including interaction terms between the risk aversion variable with two dummy variables that identify farms below and above the median farm income, respectively.

Table 5 presents the estimated coefficients for the interaction terms between risk aversion and farm income. The results indicate that the results on risk aversion are driven by farms with smaller herds. While the coefficients remain negative across all specifications, they are statistically significant only for farms with below the median farm income. The magnitude of the coefficients for lower income farms is larger and remains statistically significant even when farm management practices are included, as shown in columns 2, 4, and 5. In contrast, no significant association is found for farms above the median herd size, regardless of the specification.

The findings on income effects suggest two key implications. First, partial mediation implies that for farmers with lower income farms, the management practices included in the model do not fully capture how risk-averse farmers manage ketosis. Second, consistent with the theoretical framework, risk aversion may be less relevant for predicting the prevalence of ketosis among higher income farms, where risk aversion is lower. [15]

Table 5: Regression results of risl aversion on ketosis by farm income

	Ketosis prevalence				
Covariates	(1)	(2)	(3)	(4)	(5)
Risk averse					
× Below median farm income	-0.043**	-0.034**	-0.047**	-0.041**	-0.028*
	(0.018)	(0.017)	(0.020)	(0.019)	(0.015)
Risk averse					
× Above median farm income	-0.014	0.021	-0.013	0.025	0.013
	(0.029)	(0.028)	(0.029)	(0.028)	(0.026)
Dependent variable mean	0.043	0.043	0.043	0.043	0.043
Observations	891	891	891	891	891
Farm-level controls	no	yes	no	yes	yes
Cow-level controls	no	no	yes	yes	yes
Region fixed effects	no	no	no	no	yes

Notes: Coefficients estimated using linear regression models with Pr(ketosis=1) as the dependent variable. Clustered-Robust standard errors at the farm level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

5.2 Farm management

As reported in Table 6, our analysis shows no systematic differences in farm practices between risk-averse and non-risk-averse farms when using simple mean difference tests. However, due to small sample size issues, detecting true differences in management practices is challenging. For instance, although risk-averse farmers in the sample operate farms more

[15] As a robustness check reported in section 6, we replicate these results using herd size as dependent variable instead of income.

than twice the size of those managed by non-risk-averse farmers, this difference is not statistically significant. For this reason we also compare the distribution of farm practices using the Kolmogorov–Smirnov test for equality of distributions. This analysis shows that many relevant practices have different distribution risk-averse and non-risk-averse farmers.

Table 6: Differences in farm practices between risk profiles

Practices	Mean Other	Mean Risk-averse	Mean diff. p-value	KS test p-value	Group with larger values
Concentrates share	19.15	19.69	0.92	0.00	risk averse
Feeding frequency	3.94	3.88	0.84	0.00	other
Veterinary visits	14.15	12.47	0.73	0.28	none
Farm size	0.55	1.27	0.18	0.00	risk averse
Heard size	1.74	2.23	0.29	0.00	risk averse
On-site milking	0.31	0.14	0.12	0.00	other
Fresh cow separation	0.21	0.33	0.35	0.00	other
Milking reduction	0.42	0.28	0.29	0.20	none

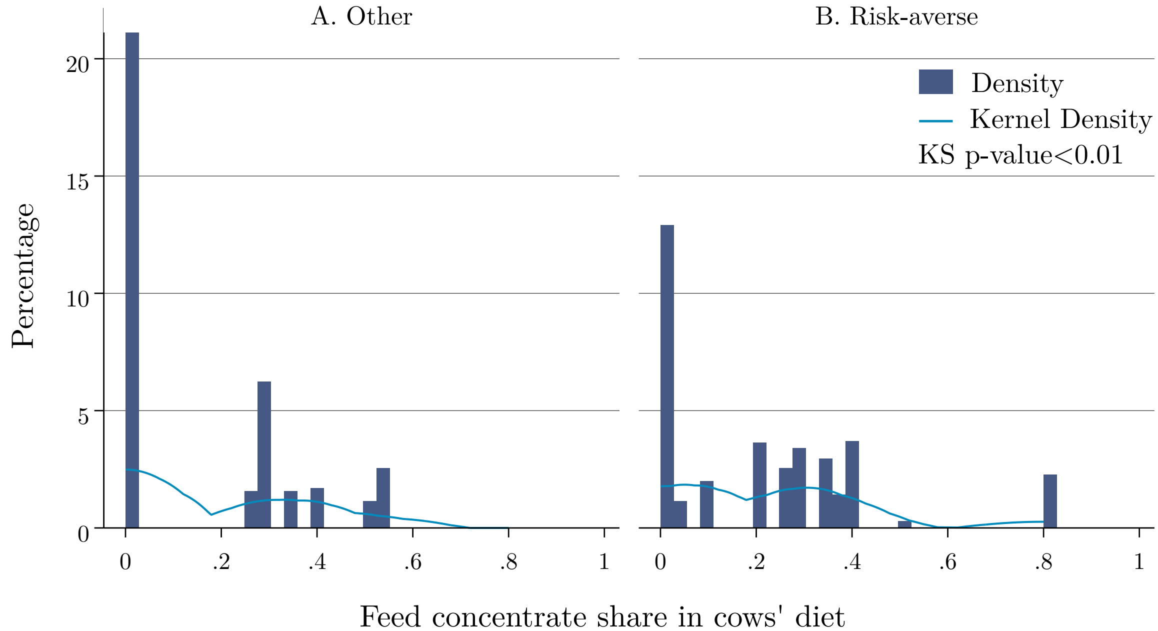
Notes: P-values in the fourth column are calculated using two-tail differences in means tests. The last column reports p-values for the combined Kolmogorov–Smirnov (KS) test that the distribution of each variable is different between risk profiles.

To illustrate the importance of the distribution of farm practices, consider the case of feed concentrates in cows' diets. We find no mean differences in concentrate use between risk profiles (p-value = 0.92), and regression results show a negative but not statistically significant coefficient for concentrate shares. However, it is important to note that more than a third of ketosis cases were detected on farms with no concentrates in cows' diets. This finding is significant, especially given that risk-averse farmers tend to use higher concentrate shares, a pattern confirmed by the Kolmogorov-Smirnov test (p-value = 0.00).

Figure 4 shows that the distribution of feed concentrate shares is more concentrated around zero and lower values in non-risk-averse farms. In contrast, the distribution for risk-averse farmers is less concentrated around zero, with the right-hand tail extending to maximum values 30 percentage points higher than those in non-risk-averse farms.

Although these results are not conclusive, as we cannot entirely rule out alternative explanations, they suggest that risk aversion plays a mediating role in how farm practices affect ketosis. However, it is puzzling that we find no differences in means or overall distribution for practices significantly associated with the prevalence of ketosis. Specifically, we expected to see differences in milking reduction and veterinary visits as evidence of self-protection.

Figure 4: Distribution of concentrate shares



Notes: Histogram of the share of concentrates in cows' diet during the fresh period (after calving) for risk averse farmers (panel A) and non-risk averse farmers (panel B). Black lines indicates the kernel density calculated using a kernel's half-width of 0.08. P-value for the Kolmogorov-Smirnov equality of distribution test reported.

Besides the significant issues related to low statistical power in our case, a possible explanation is that these and other practices are risk-reducing but not necessarily of the self-protection type. Instead, they may serve as self-insurance for farmers against potential losses caused by ketosis, which we cannot estimate due to the lack of animal-level production data on most farms. This limitation is significant, considering that most pasture-based farmers in developing countries do not track productivity at such a granular level.

Another possibility is that the risks farmers face do not elicit a managerial response that matches any specific set of risk preferences. According to our framework, this suggests that the expected effects are too small relative to much larger income effects affecting all profiles equally, which makes differences in management between risk-averse farmers and others negligible. This could be due to low-probability events (e.g., low ketosis prevalence) and farmers' inability to accurately determine the level of risk (e.g., diagnostic failures).

5.3 Willingness to pay for information

The willingness to pay (WTP) for information about cows' health status in our study is comparable to the investments farmers might make in diagnostic technologies, such as the keto-meter we used to test for ketosis. These devices provide data on the metabolic condition of cows, enabling farmers to take timely preventive actions. Our results indicate a positive relationship between risk aversion and the experimental measure of willingness to pay (WTP) for information about cows' health. Risk-averse farmers choose to pay for this information 60% of the time, compared to 40% for non-risk-averse farmers –a significant difference of 19 percentage points (t=-2.33, p=0.02).

Table 7 presents coefficients from the linear probability model of risk aversion on WTP, as described in equation (2). Column 1 shows results for a pooled model, while columns 2 to 4 report results for each risk condition individually. The results consistently show a positive coefficient for the risk aversion indicator across all specifications, which is robust even after including farmer-level controls (as described in panel C of Table 3). This suggests that risk-averse farmers are more likely to demand this type of information than their non-risk-averse counterparts. However, the estimated coefficients in columns 2 to 5 reveal that the risk aversion coefficient is statistically significant only for the lowest risk level. In this condition, where there is a 20% probability that cows are sick, the likelihood that risk-averse farmers will pay for cows' health status information is about 32 percentage points higher.

Additionally, we find that the willingness to pay for information increases with the risk level. WTP is lowest in the low-risk condition, at around 40%, and significantly higher, at 65%, in the moderate-risk condition, where the likelihood of the disease is ambiguous (50/50). In the high-risk condition, WTP is 53%, which is not statistically significantly different from that in the moderate-risk condition. Table 7 confirms these findings, showing a significant coefficient for the 50% risk dummy variable but not for the 80% risk.

Table 7: Regression results of risk aversion and willingness to pay for information

Covariates	Pooled *WTP* (1)	Risk=20% *WTP* (2)	Risk=50% *WTP* (3)	Risk=80% *WTP* (4)
Risk averse	0.211**	0.331**	0.061	0.243
	(0.095)	(0.163)	(0.187)	(0.163)
Risk 50%	0.254***			
	(0.092)			
Risk 80%	0.127			
	(0.091)			
Constant	0.593**	0.033	1.339***	0.764**
	(0.248)	(0.448)	(0.414)	(0.341)
Dependent variable mean	0.53	0.40	0.65	0.53
Individual-level controls	yes	yes	yes	yes
Observations	165	55	55	55
R^2	0.13	0.14	0.14	0.28

Notes: this table reports coefficients from a linear probability model with Pr(WTP=1) as the dependent variable. Individual-level controls include age, gender, education level, and access to formal credit, and income. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

A possible explanation for these findings is that there is an upper limit of risk beyond which additional information on cows' health status offers little value for risk-averse farmers. In situations where the likelihood of cows being sick is high, farmers might view a high disease prevalence as a strong signal, making diagnostic information less relevant for managing risk. For example, if farmers expect a high number of sick cows in a herd or if they find the signal ambiguous, as in the moderate-risk condition, they may prioritize treatment over preventive actions. This interpretation aligns with other literature suggesting that readiness against vector-transmitted diseases diminishes when the probability of disease introduction is lower, the spread is larger, and when post-event strategies are more effective compared to pre-event actions (Elbakidze and McCarl, 2006).

Although we lack the data to directly test this explanation, we investigate it through behavior observed in the choice experiment. Table 8 shows the percentage of farmers who changed their behavior during the WTP treatment after receiving additional information about cows' health status via the outcome of the lottery. A farmer is considered to have "switched" if they chose a different feed quality option compared to their choice at the baseline risk level. We compare the fraction of switchers by risk condition to understand when farmers find the cows' health status informative to change their behavior.

Table 8: Responses to information treatment

Risk condition	Pr(Sick)	Obs.	WTP	Switch	Switch if	
					WTP=0	WTP=1
Overall		165	0.51	0.29	0.19	0.39
Low	20%	55	0.45	0.31	0.23	0.40
Moderate	50%	55	0.60	0.20	0.14	0.64
High	80%	55	0.49	0.16	0.18	0.15

Notes: Define switchers, risk conditions and outcomes.

The results in Table 8 indicate that 29% of farmers changed their behavior, or switched, after receiving additional information. This switching rate is lower than the proportion of farmers who decided to pay for information, and it decreases as the risk level increases. Consistent with the results in Table 7, farmers are most likely to switch after learning about cows' health status during the moderate-risk condition, where the potential risk associated with the disease remains ambiguous. Moreover, most farmers switched their feed quality choices when they also paid to reveal the cows' health status, except in the high-risk condition. In this case, the difference in switching rates between those who paid for information and those who did not is not statistically significant (t=0.29, p=0.76).[16] This implies that even after choosing to pay for this information, farmers do not adjust their decisions when

[16] Note that there would be no reason for a farmer to switch if they did not pay for this information. Table 8 averages across all rounds, and in any given round, farmers may decide whether or not to pay, which explains the non-zero percentages when WTP=0. Restricting the sample to the first round of the WTP condition, the percentage of switchers when WTP=0 is 4%, which is considerably lower than the values reported in the table.

risk is high.

6 Robustness checks

6.1 Selection and omitted variable bias

One major concern is the magnitude of the omitted variable bias and whether it would drastically change our results. We follow Oster (2017) procedure to asses the potential bias caused by selection on observables. We assume an empirical value for R_{max} of 1.3 times the R^2 of the model with controls and compare models in columns (1) and (5) from table 4. The results indicate a value of $\hat{\delta} = 3.03$, which suggests that unobservables would need to be three times more important than our controls to yield a coefficient for the risk aversion variable that is statistically not different from zero. The estimated coefficient for the risk aversion indicator variable, when equally importance is assumed ($\delta = 1$), is $\hat{\beta}_{Oster} = -0.011$ percentage points, which is slightly lower but very close to the value reported in column 5 of table 4. In conclusion, these results suggest that the magnitude of the potential bias from unobservables is likely to be negligible in practical terms.

6.2 Rare events

We also conducted additional robustness checks for the prevalence of ketosis model. We use different methods to estimate the main model specification with to correct for potential bias caused by the low prevalence of ketosis in our sample (appendix table A3 in the appendix). We do not observe significant differences in the indicator variable of risk aversion due to the estimation method. Results show marginal effects ranging between -1.1 and -1.4 percentage points, including 1.3 p.p. for the penalized maximum likelihood model. We conclude that the main results are robust to the estimation method, even when corrected for bias caused by the sample's relatively rare cases of ketosis.

6.3 BHB Threshold

In addition, we conduct a sensitivity analysis using different BHB thresholds. For our main results, we use the standard threshold of BHB ≥ 1.2 to diagnose cows with sub-clinical ketosis, resulting in a prevalence rate of 4.3%. The standard threshold has been determined primarily using data from dairy farms in developed countries, and while well established in the literature, may not reflect the agronomic and environmental conditions of cows in Colombia. Moreover, the diagnostic device used to test blood samples has a margin of error, which can lead to incorrect diagnosis. To address this, in Table A4 we report results with and without controls using additional thresholds of BHB ≥ 1.1 and BHB ≥ 1.3, which yield prevalence rates of 7.5% prevalence and 2.3% respectively. We conclude that our results are not sensitive to the specific threshold used, given these new coefficients are qualitatively the same, including their statistical significance, to those reported in table 4.

6.4 Production scale

The literature suggests that risk aversion tends to decrease with income, wealth, and similar type of endowments. This relationship does not necessarily extend to farm inputs, though herd size does play an important role in farm management under uncertainty. To explore this further, we replicated the results from Table 5, this time comparing farms based on herd size rather than income. We observed a similar pattern of negative coefficients for risk aversion among farms below the median herd size, consistent with the findings on farm income. The new coefficients are still larger and more significant than those in Table 4, but they continue to suggest only partial mediation. Given that reported farm income data may be less precise, the results based on herd size are more conservative and may also be more reliable.

7 Discussion

The main economic trade-off we study in this paper is between the downside risks versus the cost of safer production management. The balance of costs and benefits of risk reduction has been central economic research (Ehrlich and Becker, 1972; Just and Pope, 1979), and documented in other studies examining the relationship between risk management and agricultural productivity (Koundouri et al., 2006). The main challenge to study this trade-off is that risk preferences are essential but mostly unobservable economic primitives, which highlights the importance of using experimental and behavioral economics methods to study problems when no direct observation is available or when randomization cannot be feasibly implemented in the field.

This paper studies the relationship between risk preferences and management in dairy farming, with a focus on health-related risks. Risk aversion can significantly influences farmers' management practices, especially in environments where they have limited control over individual production units, such as pasture-based dairy farming. Our results show that cows managed by risk-averse farmers have a lower prevalence of ketosis, a finding mainly observed in low-income farms. Additionally, we document that some farm practices reduce the likelihood of ketosis and improve cow health, though they may also decrease revenue. Consistent with the expected utility model, these results suggest that risk-averse farmers adopt self-protection strategies by making risk-reducing investments to limit their exposure to health risks. This demand for risk-reducing practices and inputs compares to cases documenting an otherwise negative effect of risk aversion on technology adoption.

To explain these results, we investigate whether the relationship between risk aversion and ketosis is mediated by farm management. Due to the small sample size of farmers, we are unable to detect significant differences in management practices across different risk profiles. However, when comparing the distribution of management practices, we find that risk-averse farmers tend to use higher shares of concentrate feeds in cows' diets, among other practices. Experimental evidence also shows that risk-averse farmers are more willing to pay for diagnostic information. The demand for such information decreases as the likelihood of disease increases, suggesting that there is an upper limit to the perceived value of additional information. These experimental results further support, although do not directly confirm, the idea that risk farmers prioritize preventive measures over other practices. An avenue for future research could focus on testis alternative explanations.

Our findings are particularly relevant to dairy farming. In low-income countries, the risk versus productivity trade-off is often resolved in favor of management strategies that sacrifice cows' health and, as a result, dairy farms productivity. Sources of uncertainty in this sector include price and yield volatility (Neyhard et al., 2013; Schaper et al., 2010), production risks (Flaten et al., 2005; Meuwissen et al., 2001), and climate-related threats (Amamou et al., 2018). Several studies have examined farmers' attitudes toward these risks, revealing differences in farming practices based on the risk profiles of farm managers. For instance, varying degrees of risk aversion influence the use of disease control practices (such as vaccination, prevention, and hygiene), concentrate use, veterinarian consulting, and participation in public programs (Bishu et al., 2016; Bardhan et al., 2006; Tauer, 1986). However, the impact of these differences in reducing risk is unclear, and these effects may be compounded if most dairy farmers are risk-averse, as the evidence suggests (Belhenniche et al., 2009; Tauer, 1986).

In Colombia, as in other developing countries, government programs for dairy and livestock farming invest in vaccines, testing, and animal control to prevent the spread of viruses like foot-and-mouth disease. Given the substantial potential losses from viral diseases, which are common in dairy and livestock production, understanding the range of farmers' risk preferences and how these preferences affect their technology choices is essential for improving the outreach and effectiveness of such policies.

Identifying farmers' risk profiles is crucial for effective policy targeting and the promotion of agricultural innovations. The observed differences in management practices between risk-averse and non-risk-averse farmers suggest that interventions could be more effective if they take farmers' risk profiles into account. Programs could focus on farmers who are more willing to pay for information about their cows' health status, which, in our experiment, is comparable to veterinary consultations or the use of disease diagnostic tools like the keto-meter. Training programs that emphasize the benefits of preventative health measures may be particularly appealing to risk-averse farmers.

While our findings offer valuable insights into how risk preferences influence farmers' technology choices, this study is limited by nature of the problem and the available data. We are not trying to identify the risk factors for ketosis, which would require epidemiological research beyond the scope of this paper. Instead, our focus is on understanding how risk aversion might impact the prevalence of ketosis through management practices. However, the data controls may not capture all variations in outcomes, and unobservable characteristics correlated with risk aversion could influence the occurrence of ketosis, potentially leading to omitted variable bias. Further research is needed to better address these limitations and properly identify the causal effects of farmers' preferences on farm-level outcomes.

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Appendix

Table A1: Regression results of fully interacted model

	Ketosis prevalence		
Covariates	(1)	(2)	(3)
Risk averse	-0.014	-0.030	0.119
	(0.015)	(0.095)	(0.232)
Dependent variable mean	0.043	0.043	0.043
Observations	891	891	891
Farm-level interactions	no	yes	yes
Farm-level interactions	no	no	yes
Farm and cow controls	yes	yes	yes
Region fixed effects	yes	yes	yes

Notes: Coefficients estimated using linear regression models with Pr(ketosis=1) as the dependent variable. Clustered-Robust standard errors at the farm level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table A2: Regression results of risk aversion on BHB blood concentrations

Covariates	(1) ketosis	(2) ketosis	(3) ketosis	(4) ketosis	(5) ketosis
Risk averse	-0.055	-0.021	-0.063	-0.033	-0.020
	(0.049)	(0.048)	(0.051)	(0.051)	(0.046)
Concentrate share		-0.115		-0.119	-0.154**
		(0.099)		(0.103)	(0.076)
Feeding frequency		0.045**		0.043**	-0.023
		(0.020)		(0.021)	(0.029)
Veterinary visits		-0.003***		-0.004***	-0.004***
		(0.001)		(0.001)	(0.001)
Farm size		-0.014		-0.016	-0.008
		(0.013)		(0.014)	(0.014)
Heard size		0.015		0.018	0.016
		(0.015)		(0.016)	(0.016)
On-site milking		0.018		0.030	0.067
		(0.052)		(0.058)	(0.058)
Fresh-cows separation		-0.058		-0.059	-0.044
		(0.057)		(0.059)	(0.060)
Milking reduction		-0.026		-0.024	-0.087*
		(0.045)		(0.047)	(0.050)
Weeks since calving			-0.003	0.001	0.003
			(0.008)	(0.007)	(0.007)
BCS			0.082	0.081	0.093*
			(0.055)	(0.053)	(0.053)
Parity			0.021**	0.023***	0.027***
			(0.008)	(0.008)	(0.008)
Last calf sex			-0.020	-0.021	-0.017
			(0.024)	(0.023)	(0.023)
Last calf stillborn			-0.008	-0.019	-0.025
			(0.040)	(0.038)	(0.043)
Constant	0.636***	0.500***	0.371**	0.226	0.391**
	(0.043)	(0.092)	(0.154)	(0.175)	(0.194)
Observations	891	891	891	891	891
Region Fixed Effects	no	no	no	no	yes

Notes: Coefficients estimated using Tobit regression models with BHB blood concentrations as the dependent variable censored at lower bound of zero (BHB=0). Clustered-Robust standard errors at the farm level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table A3: Model selection and rare-events correction bias

Covariates	(1) ketosis	(2) ketosis	(3) ketosis	(4) ketosis
Risk averse	-0.011	-0.014	-0.012	-0.013
	(0.013)	(0.015)	(0.014)	(0.020)
Concentrates share	-0.042	-0.028	-0.039	-0.045
	(0.038)	(0.026)	(0.034)	(0.047)
Feeding frequency	-0.008	-0.010	-0.006	-0.010
	(0.009)	(0.010)	(0.009)	(0.013)
Veterinary visits	-0.000	-0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Farm size	-0.005	-0.003	-0.005	-0.005
	(0.003)	(0.004)	(0.003)	(0.006)
Herd size	0.008*	0.007	0.007*	0.008
	(0.004)	(0.005)	(0.004)	(0.007)
Fresh cows separation	-0.013	-0.020	-0.014	-0.013
	(0.016)	(0.020)	(0.017)	(0.020)
On-site milking	0.016	0.024	0.016	0.019
	(0.024)	(0.021)	(0.022)	(0.030)
Milking reduction	-0.047***	-0.056***	-0.046***	-0.052**
	(0.015)	(0.018)	(0.016)	(0.021)
Weeks since calving	0.002	0.000	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.004)
BCS	0.022	0.023	0.019	0.026
	(0.022)	(0.026)	(0.022)	(0.022)
Parity	0.008***	0.009**	0.008***	0.010***
	(0.003)	(0.004)	(0.003)	(0.004)
Last calf sex	0.004	-0.004	0.011	0.019
	(0.045)	(0.035)	(0.041)	(0.041)
Last calf stillborn	0.000	-0.007	0.008	0.015
	(0.045)	(0.036)	(0.042)	(0.041)
Observations	891	891	891	891
Region Fixed Effects	yes	yes	yes	yes

Notes: (1) Logit model, (2) OLS, (3) Probit model, (4) Penalized Maximum Likelihood Estimation proposed by Firth (1993). Clustered-Robust standard errors at the farm level in parentheses for models 1 to 3. The dependent variable is Pr(ketosis=1). Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Sensitivity analysis of BHB concentration thresholds

	Ketosis prevalence					
	BHB $\geq$ 1.1		BHB $\geq$ 1.2		BHB $\geq$ 1.3	
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Risk averse	-0.042*	-0.025	-0.033*	-0.014	-0.032*	-0.016
	(0.022)	(0.021)	(0.019)	(0.015)	(0.019)	(0.014)
Concentrate share		-0.055		-0.028		-0.020
		(0.035)		(0.026)		(0.023)
Feeding frequency		-0.013		-0.010		-0.007
		(0.012)		(0.010)		(0.010)
Veterinary visits		-0.001*		-0.001**		-0.001*
		(0.000)		(0.000)		(0.000)
Farm size		-0.005		-0.003		-0.004
		(0.006)		(0.004)		(0.004)
Heard size		0.007		0.007		0.009**
		(0.006)		(0.005)		(0.004)
On-site milking		0.019		0.024		0.001
		(0.024)		(0.021)		(0.019)
Fresh-cows separation		-0.014		-0.020		-0.016
		(0.028)		(0.020)		(0.017)
Milking reduction		-0.046		-0.056***		-0.046***
		(0.029)		(0.018)		(0.015)
Weeks since calving		0.002		0.000		0.001
		(0.004)		(0.003)		(0.003)
BCS		0.023		0.023		0.038*
		(0.031)		(0.026)		(0.020)
Parity		0.012***		0.009**		0.009**
		(0.004)		(0.004)		(0.004)
Last calf sex		-0.001		0.006		0.003
		(0.014)		(0.012)		(0.010)
Last calf stillborn		0.011		-0.004		-0.033***
		(0.039)		(0.035)		(0.011)
Constant	0.086***	0.021	0.066***	0.004	0.059***	-0.041
	(0.020)	(0.096)	(0.017)	(0.082)	(0.017)	(0.065)
Dependent variable mean	0.075	0.075	0.043	0.043	0.029	0.029
Observations	891	891	891	891	891	891
Region fixed effects	yes	yes	yes	yes	yes	yes

Notes: Coefficients estimated using linear regression models with Pr(ketosis=1) as the dependent variable. Clustered-Robust standard errors at the farm level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table A5: Regression results of risk aversion on ketosis by heard size

	Ketosis prevalence				
Covariates	(1)	(2)	(3)	(4)	(5)
Risk averse					
× Below median herd size	-0.036*	-0.025	-0.041*	-0.031	-0.030*
	(0.021)	(0.019)	(0.022)	(0.020)	(0.016)
Risk averse					
× Above median herd size	-0.032	-0.016	-0.033	-0.017	-0.003
	(0.020)	(0.021)	(0.021)	(0.023)	(0.018)
Constant	0.066***	-0.015	-0.004	-0.071	0.026
	(0.017)	(0.032)	(0.073)	(0.073)	(0.083)
Dependent variable mean	0.043	0.043	0.043	0.043	0.043
Observations	891	891	891	891	891
Farm-level controls	no	yes	no	yes	yes
Cow-level controls	no	no	yes	yes	yes
Region fixed effects	no	no	no	no	yes

Notes: Coefficients estimated using linear regression models with Pr(ketosis=1) as the dependent variable. Clustered-Robust standard errors at the farm level in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1