Risk-reducing incentives and preventive technologies in pasture-based dairies

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Abstract

This paper studies the relationship between risk aversion and ketosis, a metabolic disorder that negatively affects dairy farming. We identified farmers' risk preferences and their willingness to pay for information about cows' health status (WTP) using a lab-in-the-field experiment in Colombia. We also collected blood samples from dairy cows to test for the prevalence of the disease. Results show a lower likelihood of ketosis in cows managed by risk-averse farmers, which is consistent with a self-protection strategy under uncertainty. Further, experimental data show a positive relationship between risk aversion and WTP, which is comparable to risk-reducing investments related to veterinary services or on-farm diagnostic equipment. Further, we mostly find no significant differences in observed management across farmers' risk profiles, with the exception of some heterogeneous effects of farm practices related to concentrate feed and preventative care.

JEL classification: C93, D81, O33, Q12, Q16.
Keywords: risk aversion, technology adoption, agriculture, dairy, Colombia.

1 Introduction

Many of the world's low-income farmers are vulnerable to uncertain productive conditions but have limited options to manage risk. As a result, farmers often fail to adjust their decisions when confronted with biological and environmental threats. Moreover, attitudes and preferences towards risk shape farmers' responses to production risks, which helps to explain why some farmers under-invest in more profitable technologies. Given the choice of adopting improved inputs or modern practices, farmers may be reluctant to adopt if the risk on the return on adoption is too high (Magruder, 2018; Foster and Rosenzweig, 2010). Thus, risk aversion is often found to have a negative impact on technology adoption, especially under insurance, credit, and information constraints (Liu, 2013; Dercon and Christiaensen, 2011; Barrett et al., 2004).

This paper studies a case in which risk aversion can promote the use of preventive agricultural technologies. Compared with technologies intended to increase yield potential but that are too risky for farmers to adopt, preventive or risk-reducing technologies are practices and inputs that reduce risk exposure to events affecting farm yields. An oft-cited case is pesticides application (Sexton, 2007; Horowitz and Lichtenberg, 1994). However, not all individuals benefit from these investments. Risk-averse farmers have incentives to minimize preventable downside risks such as those caused by crop pests, livestock diseases, or extreme weather events, such as seasonal droughts or floods (Koundouri et al., 2006). Consequently, these incentives should generate demand for risk-reducing technologies that reduce losses a form of self-insurance, or that reduce the the occurrence of risk events as self-protection.

We focus in the case of pasture-based dairy farming in Colombia to study how risk preferences affect farm managements and outcomes. In particular, we study the relationship between risk aversion and the prevalence of ketosis, a metabolic disease affecting milk production, reproductive performance, and dairy cows' health (Ospina et al., 2010; Chapinal et al., 2011; McArt et al., 2012). To do so, we estimated the relationship between risk aversion and the likelihood of ketosis in dairy cows housed on pasture-based dairies in Colombia.

We collected blood samples from early lactation cows and tested these samples for concentrations of BHB, an organic compound of hepatic origin. This metabolite offers an objective metric to determine the prevalence of the disease, as the ratio of the number 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 when compared with dairy systems of industrialized countries (Knips, 2005). To close this gap and improve yields per animal, farmers' decisions on feed quality and frequency and the diagnostic and treatment of cattle diseases are crucial.[1]. However, in pasture-based dairies, especially those in developing countries, such tasks involve high uncertainty because the intake of forage per animal and overall feed quality are difficult to monitor and control. In consequence, this often results in lower yield per cow, lower profits, and potentially higher risks of nutritional deficiencies in dairy cows (Gillespie and Nehring, 2014; Hanrahan et al., 2018). For example, Colombia's dairy industry is comprised of primarily pasture-based farms that struggle to improve quality and yields to compete in increasingly globalized dairy markets (Carulla and Ortega, 2016; Villa-Arcila et al., 2017).

Similar to other settings, the extent to which risk affects outcomes is difficult to determine without an experimental design. So, we conducted a lab-in-the-field experiment to elicit the risk preferences of dairy farmers. Using lotteries, we present farmers with a trade-off between the cost of better feeding practices and the risk associated with the disease. Farmers' choice set in the experiment corresponds with situations in which farm management decisions represent upfront costs while benefits are uncertain. To allow for different levels of risk, we vary lottery probabilities in the game as an analogy for changes in the risk of the disease. In addition, we included a treatment condition in which we capture whether farmers have a positive willingness to pay for information about their cows' health status. The information provided simulates a *keto-meter*, the testing device we used to determine the prevalence of

[1]For instance, good early-lactation management should result in an adequate transition from non-productive to productive periods that minimizes metabolic disorders and other health problems, as a way to improve the productivity of dairy farms (Yepes et al., 2020; Ospina et al., 2013; Chapinal et al., 2011)

ketosis. This design helps us identify farmers' risk profiles using a framing tailored to this specific context, relating farmers' feeding practices with the likelihood of metabolic disorders.

Our results show that risk aversion is negatively associated with the prevalence of ketosis. We compare differences in the likelihood of ketosis across risk profiles, controlling for a rich set of farming practices, cow-level characteristics, and location-specific fixed effects. Consistent with an Expected Utility model, we find a lower prevalence of ketosis on cows managed by risk-averse individuals. Results indicate that during periods of high energetic stress, feeding and cow-level characteristics are associated with ketosis. For instance,the gradual milking reduction before the next lactation period decreases the likelihood of the disease, but it reduces yields in the short term. Further, higher distances to the milking parlor (which increases cows' energetic demands) and higher parity numbers are positively correlated with ketosis.

A possible explanation for these results is that risk-averse dairy farmers adopt practices that prevent metabolic diseases affecting cow's milk production. This idea is consistent with the idea that preventive health practices are risk management tools, since animal diseases are major barriers to higher dairy yields in developing countries (Hernández-Castellano et al., 2019). To test this explanation we focus on feeding practices, given that nutritional mismanagement directly affects cows' metabolic conditions. Experimental results show that risk aversion is positively correlated with farmers' WTP for information about cows' health status. Farmers' willingness to pay for information is a proxy for their demand for such testing devices or similar diagnostic services. Using observational data from surveys we find no significant mean differences for most farm practices between risk-averse and non risk-averse farmers. However, about 60% of ketosis cases in our sample occur in farms using no feed concentrates during the fresh period (a few weeks after calving), and results show that risk-averse farms are more likely to use some share of concentrates in cows' diet.

This paper is closely related to the agricultural technology adoption literature. Growing evidence for the demand for risk-reducing technologies has been documented in low-income countries. For instance, Emerick et al. (2016) find that the introduction of an improved drought-resistant rice variety leads to investments in modern practices in India. Shimamoto et al. (2017) shows that risk-averse farmers in Cambodia are more likely to adopt devices for moisture control in rice crops. In Ghana, Asravor (2018) reports that risk aversion increases the use of improved seeds and organic fertilizers, and Crentsil et al. (2020) find that risk-averse farmers were earlier adopters of fishing innovations improving disease and contamination resistance. In this paper, we show that risk aversion is related to a lower prevalence of a disease negatively affecting dairy yields. We also find evidence for practices help farmers manage cows' health status, including the use of commercial feed concentrates which are largely underutilized in pasture-based dairies of low-income countries (FAO et al., 2014; Duncan et al., 2013).

Second, we contribute to the experimental economics literature on risk preferences. Our findings suggest that experimental risk measures can explain the differences in the likelihood and management of preventable events affecting agricultural production. These results suggest a link between laboratory experiments and field observations to better understand how individuals' risk preferences affect economic outcomes when no direct observation or randomized evaluation is feasible. In addition, our risk profile classification procedure combines Eckel and Grossman (2002) and Holt and Laury (2002) designs, two widely used methods for risk elicitation, to incorporate changes in risk probabilities. In doing so, we provide a framework to classify risk profiles based on more precise calibration of the implied relative risk aversion parameters.

This paper is organized as follows. We first present a theoretical model explaining self-protection and self-insurance as risk-reducing strategies. We then present the experimental design we used to elicit the risk preferences of dairy farmers. In sections three and four, we describe the data and our empirical strategy to estimate the relationship between risk preferences and the prevalence of ketosis. In section five, we report the main results on disease prevalence, willingness to pay for information, and farm management. In the last section, we present a discussion of our results and relevant implications.

2 Risk-reducing incentives

We build an endogenous risk model to characterize farmers' behavior under uncertainty. Productive risk in dairy farming may arise from several sources. For instance, metabolic diseases affecting dairy cows, such that some cows are either sick or healthy. Payoffs are lower when cows are sick because the disease reduces yield, and its treatment increases production costs. While farmers can treat sick cows individually, most inputs and practices in pasture-based dairy production systems are determined at the herd level. So, investments are required to reduce the disease risk among all cows in a given herd. These investments may include inputs such as the adoption an improved variety of forage or feed supplements with better nutritional content (which increases yield potential). Alternatively, farmers may take preventive action by consulting animal nutritionists to formulate adequate diets, or hiring veterinary services to diagnose health problems (reducing the prevalence of the disease).

We model the decisions of farmers maximizing the expected utility of inputs and practices that reduce the likelihood and impact of risk events affecting yields (see equation 1). Farmers choose a level of inputs X and pre-event actions s to maximize the expected utility of consumption, $EU(c)$, which we assume to be function of farm profits such that $c = \Pi(f(X, s; \omega), p)$. Technology f in value terms is assumed to be increasing and convex in X and s. Per-unit input costs are p_x and the cost of preventive action is p_s. This framework is closely related to models developed to rationalize pest and disease control in agriculture Sexton (2007).

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

The production technology is given by $f(X, s; \omega) = h(X, \omega)\,(1 - d(s))$ with partial derivatives $f_X > 0$ and $f_s > 0$. $h(X, \omega)$ is potential output as a function of inputs X such that $h_X \geq 0$, and a random parameter ω affecting disease damage independent of X. Parameter

ω is indexed with respect states of nature. A higher realization of ω implies states of states of nature with high disease damage, hence less output. The term $d(s)$ captures the probability of risk event occurrence as the fraction of damaged output (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 $d(0) = d_0$ and $d_s(s) < 0$.

Farmers can (i) self-insure by reducing the severity of the risk event, and (ii) self-protect by reducing its likelihood (Archer and Shogren, 1996; Ehrlich and Becker, 1972). Post-event actions can work as self-insurance by reducing the the losses caused by risk events when they occur. For instance, inputs reduce the negative effects of a disease on output by increasing yield potential. An input is risk-reducing if the second derivative $f_{X,\omega}(X, s; \omega) < 0$, meaning that inputs increase production less when disease damage is high (Horowitz and Lichtenberg, 1994).[2] This implies that X is risk-reducing if $f_{X,\omega} = h_{X,\omega}(X, \omega)(1 - d(s))$. Since $(1 - d(s))$ is a non-negative fraction, $f_{X,\omega}$ and is negative if the marginal product of inputs is lower in less favorable states of nature such that $h_{X,\omega} < 0$.

Alternatively, farmers self-protect by influencing the conditions in which risk events happen to reduce their likelihood of occurrence. Preventive action always reduces risk since $f_{s,\omega} = -h_\omega(X, \omega)d_s(s) < 0$ for any non-zero value of s, X, and ω. Therefore, preventive action reduces damage more in bad states of nature, when the damage is high, via a lower fraction of damaged output. The main difference between X and s is that while inputs X go into production regardless of the damage level, pre-event actions s only happen to reduce the likelihood of damage. Thus, some inputs may not be risk-reducing, since $f_{X,\omega}$ may be zero or positive depending on the type of input used (Horowitz and Lichtenberg, 1994).

A risk-reducing strategy can also be defined as an input X or action s that a risk-averse producer will use more than a risk-neutral producer (Leathers and Quiggin, 1991). To see this, consider for instance the first order with respect to X is $\frac{\delta EU(c)}{\delta X} = E\big[U'(c)\big(f_X - p_x\big)\big] = 0$.

[2] Horowitz and Lichtenberg (1994) model for pest control includes other sources of uncertainty, in which yield potential is also affected by random factors independent of X and s. The definition of risk-reducing inputs in those cases cases when yield output is uncertain require additional assumptions about the correlation between those random factors and ω to determine the sign of $f_{X,\omega}$.

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 in (2) is the expected income effect, which does not affects risk-neutral individuals since $U'' = 0$, whereas $U'' < 0$ for the risk averse. The second term is the pure marginal productivity effect. This change in productivity affects all individuals regardless of their risk preferences. Therefore, changes in risk-reducing input use leads to higher expected utility for the risk-averse in worse states of nature.

This model suggests then that risk-averse individuals have more incentives to make risk-reducing investments. As long as these investments are cost-effective at reducing risk, risk-averse farmers get a higher expected utility from these investments whereas risk-neutral and risk-seeking behaviors get lower or even get negative expected payoffs. Risk-reducing investments are an alternative to commercial insurance covering the potential losses from harmful productivity shocks, especially under incomplete insurance markets. Notably, farm insurance is rare in low-income countries, and most policies rarely cover animal health. Moreover, if the information about the underlying risk is limited, risk events may become non-divisible, such that insurance providers may not satisfy farmers' demand for risk reductions. In situations like these, self-insurance and self-protection strategies offer a way to meet a demand for practices and inputs that mitigate downside risks.

Based on this framework, we formulate two expected effects for the case of dairy farmers facing risk of events such as metabolic diseases. First, risk-averse are more likely to invest in risk-reducing strategies than their non-risk averse counterparts. We should observe differences in practices that mitigate the prevalence of diseases across risk-profiles as a result, either via self-protection or self-insurance. In particular, the willingness to pay for information (WTP) about cows' health status is an investment that can potentially reduce risk. As a result, the WTP is expected to be higher among risk-averse farmers.

Second, we expect that preventive self-protection strategies decrease the likelihood of risk events such as diseases. Therefore, the prevalence of ketosis should be lower in farms managed by risk-averse individuals, conditional on all other factors affecting the prevalence of the disease independent of management. While some inputs and practices may reduce productivity risk, they do not affect the occurrence of risk events. So, pure self-insurance strategies should have no effect on the prevalence of ketosis.

Note that risk-reducing strategies are correlated with endowments, which suggest that herd-level management in pasture-based dairies mediates in farmers' ability to control diseases. The cost of inputs increases with heard size, whereas the cost of some preventive actions can be independent of the production scale. This is important because risk aversion is expected to decrease as endowments increase, such as income, land, and herd size. So, the benefits of risk-reducing inputs may disproportionately change with scale, which could make it less attractive to farmers with bigger farms.

3 Experimental design

We based our experiment on the design proposed by Eckel and Grossman (2002, EG henceforth) to elicit risk preferences, which we modified to capture effects on behavior due to changes in risk probabilities. In the EG design, participants choose one lottery from a set of binary lotteries with the same probability for both outcomes ($p = 0.5$) but with different expected payoffs. This framework allows us to empirically identify risk preferences by comparing the lotteries in a choice experiment, using the constant relative risk aversion parameter r as a metric. Individuals are classified as risk-averse if the constant relative risk aversion (CRRA) parameter implied from their choices yields $r > 0$, risk-neutral if $r = 0$, and risk-seeking when $r < 0$.[3]

We framed lotteries in our experiment to be analogous to the risk associated with feeding

[3]Using a group lotteries the CRRA parameter allows to identify preferences over risky options based on the cutoff points between pairs of adjacent lotteries (Dave et al., 2010). This classification process to derive r is depicted in appendix figure A1 for a well-behaved utility representation of preferences.

decisions made by farmers. Thus, the experiment mimics the economic trade-offs between higher investments in feed quality to reduce the likelihood of metabolic diseases. We simulate this environment by presenting lotteries as feed quality menus[4], in which payoffs depend on the prevalence of the disease, p. Farmers decide over three feed quality options (high, medium, and low) which yield different ranges for the CRRA parameter.[5] The experiment's framing conveys the idea that higher quality feeds reduce the monetary losses caused by the disease, at the expense of higher production costs. Contrary, cheaper and lower quality feed decrease costs, but it may also reduce overall profits if the disease is present on the farm.

Although the EG design helps us profile risk preferences, the classification of risk profiles depends entirely on a given risk probability p. Changes in the likelihood of outcomes can lead to different profile assignments, especially for ranges of r that include indifference points between lotteries. For instance, it may not be possible to distinguish between risk-neutral and risk-seeking behaviors when the CRRA parameter yields a range of $r \leq 0$.

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. For simplicity and since no prior information was available about the prevalence of ketosis in the study regions, we established three risk conditions in the experiment. The low-risk condition is when 20% of the herd is at risk of developing the disease, 50% in the medium-risk, and 80% in the high-risk condition. While these risk levels might be too high to represent the likelihood of an actual metabolic disease of this type in our study context, these levels aim to depict relative differences in prevalence levels in a way that makes it easy to distinguish between available options.[6]

Table 1 shows information about payoffs and probabilities of the lotteries as presented to the farmers. For each risk condition, participants decide over three feed quality options.

[4] In our experiment, feed quality refers to the combinations of quantity and frequency of different types of food (forage, feed concentrates, or supplements).

[5] These lotteries have the same characteristics of the lotteries presented in figure A1 in the appendix

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

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.

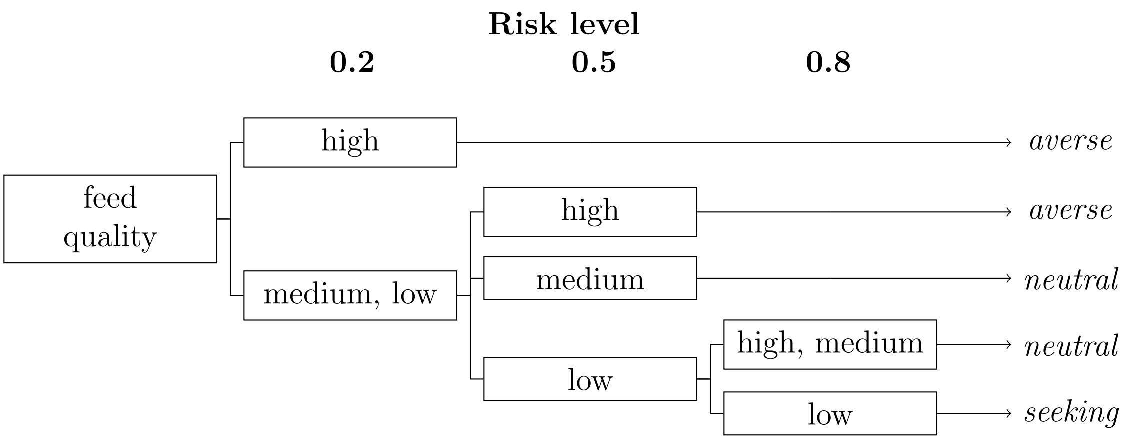
Additional information such as expected values, standard deviation, and CRRA cutoff points are included in table 1 but was not shown to the participants. These statistics are used in the EG procedure to identify risk preferences. For example, when the probability is $p = 0.2$, a risk-averse individual would choose option *high* because it has the lowest standard deviation, giving up potential gains in terms of expected value. A risk-neutral individual would choose the highest expected value, either by selecting either *medium* or *low*. If individuals select *low*, having the option to choose *medium* and get the same payoff with a lower standard deviation, they should exhibit risk-seeking behavior. However, this logic does not apply to all three risk conditions. Once the risk level increases, a classification procedure would require incorporating several cutoff points of the CRRA parameter.

We 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.[7] The basic case is when individuals choose the same option in all three

[7] 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 $3.02 \geq r \geq 6.26$.

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).

Figure 1: Risk profile classification based on lottery choices



Different combinations of choices provide more information about the individuals' risk preferences. For instance, a risk-averse individual is someone who chooses *medium* when $p = 0.2$ and chooses *high* in both $p = 0.5$ and $p = 0.8$ necessarily. This is because the implied CRRA is such that $3.02 \leq r \leq 6.26$, according to these choices. Figure 1 shows the classification procedure starting from the lowest prevalence-risk level, but results are independent of the order in which decisions are made. Finally, failure to be classified into a profile indicates a behavior inconsistent with the Expected Utility Theory. This situation is similar to switching back to a greater risk gamble after choosing the safe option in the Holt and Laury design (2002).

Finally, we included a treatment determining if there is a positive willingness to pay (WTP) for information about the health status of cows. Using the same basic experimental setup, we want individuals to reveal a positive WTP as a proxy for their demand for information. To do so, individuals can pay a fixed amount of money, c to know whether the cow is sick or healthy before choosing over the feed quality lotteries. Once the cow's health status is known, there is no uncertainty about the prevalence of the disease, and feed quality payoffs are lower than in the baseline case but certain.

The net benefit of this decision is given by comparing the expected payoff of paying for information of 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 for 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 corresponds to the utility of maximum payoff if the cow is healthy (sick), times the probability of a healthy (sick) cow. Then, the price of information was defined as $c = \$2$, such that $\mathrm{E}[x|c]$ equates the expected payoffs and standard deviations of the *medium* in each lottery set (see table 2).

Table 2: Expected payoffs net of payment for information

Risk condition	High payoff: $27-c$	Pr(healthy)	Low payoff: $14-c$	Pr(sick)	$\mathrm{E}[x\|c]$	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.

Note that this treatment does not change the game's payoff structure. Since risk probabilities remain the same, the only change is the amount of information available to farmers when making feeding decisions. By demanding this information, farmers can make better feeding decisions once the cows' health status is revealed. However, given the expected payoffs presented in table 2, paying for information does increase the expected payoffs since there is no difference in choosing the medium-quality option and rejecting to pay c before knowing the lottery's outcome.

3.1 Field protocol

The study was conducted in three of Colombia's main dairy farming regions (Cundinamarca, Antioquia, and Caldas).[8] We used field methods to collect information on three levels of analysis: cows, farms, and farmers. First, a group of veterinary students visited 56 farms and collected blood samples from more than 900 dairy cows to be tested for concentrations of BHB using a point-of-care device and determine the farm-level prevalence of ketosis. Farmers were recruited to participate through the extension program of two local universities using convenience sampling. From the pool of farms serviced by the universities, those willing to participate and meet two criteria were invited to be part of the study. These criteria are i) the farm has records of production, management practices, and basic cattle health status; ii) the farm herd size was large enough to guarantee a number of early lactation cows to be tested. In section 3, we discuss how farms in our sample compare to a conventional dairy in Colombia.

We conducted a blood test to estimate the level of ketone bodies in each cow. Specifically, we 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 the standard in most research studying ketosis prevalence in dairy cows (Ospina et al., 2010; Chapinal et al., 2011; Oetzel, 2004). However, cows with ketosis may not present clinical signs of the disease. Instead, ketosis may cause a drop in milk production while increasing the risk of developing other diseases and reproductive problems. Hence, the prevalence of the disease directly affects farm management via low productivity and cattle health-associated costs. In addition to the blood sample, information related to the cow's last calving and body condition score (BCS) for each cow was collected, which is an indicator of the general nutritional status of each cow by using a standardized five-points scale (Edmonson et al., 1989).

[8]The protocols for this study were approved by the Institutional Review Board for Human Participants (protocol XXXXXXXX), and the Animal Care and Use Committee (protocol XXXXXXXX) at XXXXXXXX.

After the animal sampling, a risk elicitation experiment and questionnaire were conducted with farmers. This survey collected information on farm characteristics and management, focusing on management practices before and after calving. Additionally, farm managers (whoever was in charge of the cows feeding decisions) took part in the choice experiment. A show-up fee of $5 USD was offered to each farmer before the game started. The instructions were read to each farmer in private, and the same researcher, a native Spanish speaker, conducted each session face to face with all farmers.[9]

In the experiment, farmers were informed that they had to make a total of six decisions. The first set of three decisions comprised the data used to establish the risk profiles of farmers. The second set of decisions were used to conduct a willingness to pay treatment for information on the health status of cows. The instructions explained that rounds were independent, such that the decision made in a given round did not affect the game dynamics or payoffs of any other round. Within each of the two sets 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 options of feed quality to use on their farm. As presented in table 1, each quality option had two payoffs, a higher payoff if the cow is healthy and a lower payoff if the disease is present. Participants were not given information on the cow's health status (healthy or sick) before deciding. Instead, a lottery determined this at the end of the game following the probabilities of each risk condition. For example, in the low-risk condition, the probabilities were framed as if "two out of ten cows in your farm are currently at risk of developing the disease". Also, they were told that only one of the six decisions will be used to determine final payoffs but that each round has the same possibility of being randomly selected.

In rounds 4 to 6, farmers were asked if they were willing to pay a fixed amount equivalent to $2 USD conduct the lottery before making their feed quality decisions. The new rounds were played as before, and the main difference is the reduction of each lottery's payoff,

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

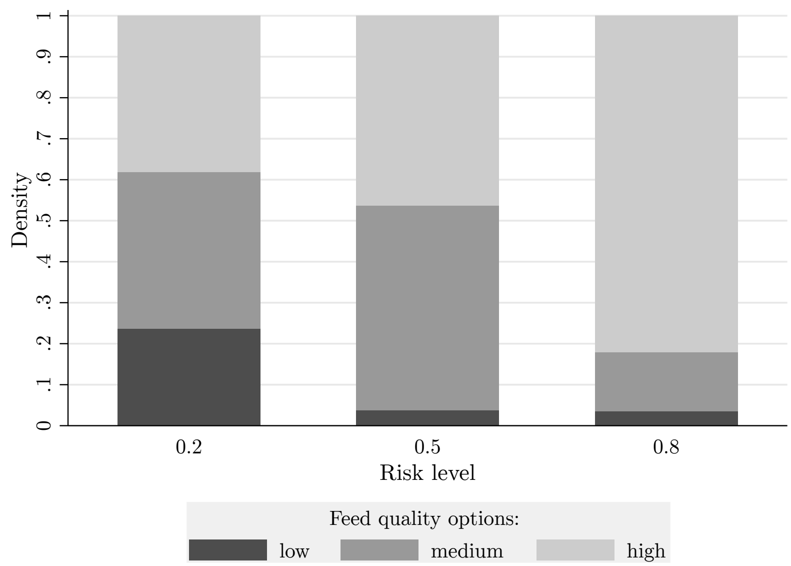
provided the farmer decided to pay to know whether the cow was sick or healthy. A new version of table 1 was presented to the farmers, showing the payoffs of each outcome after subtracting \$2. If they agree to pay this amount, we run a lottery to determine the cow's health status at the end of each round. After knowing the cow's health status, farmers decided on feed quality based on the same three quality options explained before.

Once all decisions were made, a bag filled with balls was used to determine the final payoffs of the game. First, six balls numbered from 1 to 6 were used to determine the round to be paid. Then, ten balls were divided between white balls representing the cow being healthy and red balls indicating the cow was sick. The risk condition determined the number of balls of each color group. For instance, when the risk condition was 0.5, half of the ten balls were white, and the other half were red. First, each participant randomly selected a ball from the bag to choose the round to be paid, and then they picked another ball to determine whether their cows were healthy or sick. After the lotteries, a short survey on socioeconomic information of farmers and their households was conducted. Finally, payments in cash were made according to the experiment payoffs.

4 Data

Figure 2 reports the distribution of choices in the risk experiment, showing that the 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. However, the low feed quality share shrinks as the risk of the disease increases. *High* is the option selected more often, 40 to 80 % of the time in all risk levels. In the moderate-risk condition, when $p = 0.5$, there is almost an even split between *high* and *medium* options. The share for the medium quality option expands when $p = 0.5$, but it has a large reduction when $p = 0.8$. This distribution of choices shows that the risk profile classification is dependent on the risk level, thereby affecting the estimation of the implied CRRA parameters. Furthermore, this distribution of choices suggests that there is the possibility of misclassification if only one probability condition is used to determine risk profiles. Thus, these experimental results validate the inclusion of several risk levels in our experimental design.

Figure 2: Distribution of choices by risk level



Following the classification procedure explained in section 2, the distribution of risk profiles is as follows: 65% of the managers are profiled as risk-averse, 26% as risk-neutral, and 9% as risk-seeking.[10] This distribution is somewhat similar to the literature when compared to risk elicitation studies using a single probability.[11] 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 condition.

Table 3 presents summary statistics of the variables used in our analysis. The top panel includes information at the animal level. Using estimates for the BHB concentration, we established that 4.3% of the cows in the sample were diagnosed with some ketosis level. The greatest number of cows with ketosis was found in Cundinamarca (9.4%), followed by

[10]We were unable to determine the risk profile of only 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.

[11]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.

Caldas (4.4%) and Antioquia (2.1%). Differences across regions were statistically significant for Cundinamarca versus Antioquia (Pearson's χ^2: 19.4, p-val: 0.00), and between Cundinamarca versus Caldas (Pearson's χ^2: 3.38, p-val: 0.07). [12]

Table 3: Summary statistics

	mean	S.D.	min	max
Panel A. Animal level, n=877				
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 (#)	3.11	1.99	1.00	12.00
Calf sex (male = 1)	0.49	0.50	0.00	1.00
Calf death (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 - fresh period (%)	19.50	19.51	0.00	80.00
Feeding frequency (times in a day)	3.90	1.06	2.00	6.00
Nutritionist visit (%)	85.45	35.58	0.00	100.00
Kikuyu pasture (%)	86.25	22.53	0.00	100.00
Stocking (animals/ha)	3.33	2.68	0.30	12.74
Distance to milking parlor (Km)	0.39	0.33	0.00	1.20
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

Other animal-level information shows that on average our sample is composed of primarily Holstein cows, more than 21 days after calving, around three previous pregnancies, with a mean body condition score (BCS) of 2.8/5.0. The veterinary medicine literature on early

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

lactation diseases has identified that risk factors for ketosis include increased parity, high BCS, Holstein cows, male calves, and other conditions related to the last calving.[13]

The second panel of table 3 shows information at the farm level. The average farm in our sample is characterized by a pasture-based production system with a daily production of about 20.4kg per cow/day, 3.5% fat in milk, and an estimated stocking density of about three cows per hectare. Values for a conventional dairy farm in Colombia respectively 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 our sample. These differences can be explained by the fact that relatively small, less professionally managed were excluded in our study. By design, our sample included farms with a large-enough number of cows, and good management information to properly identify the cows to be tested for Ketosis.

Other farm-level variables include the percentage concentrate in cows' diet in the fresh period (the first weeks after calving), the feeding frequency (including pasture and grain), 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 heard (fresh-cows separation), the number of animals per hectare (stocking density), and the daily distance cows walk to the milking parlor.

Lastly, the bottom panel of table 3 reports on farmers' information. Our sample includes mainly middle-aged male farmers with high-school education on average. Other variables include whether the farmer is the manager but not the owner of the farm and a dummy variable that captures farmers' access to credit (credit cards, input suppliers credit, and similar products).

5 Empirical strategy

We first focus on the relationship between risk aversion and the prevalence of ketosis. The basic specification presented in equation (3) relates the independent variable, Pr(Ketosis=1)

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

for cow i in farm j, to an indicator variable $Averse_j$ that equals one when the manager of the cow is a risk-averse farmer, zero otherwise. Moreover, the model assumes that a positive test for ketosis is determined by farm-level production practices, represented by vector Z_j, a set of cow characteristics X_{ij}, and potential differences in the productive and environmental conditions of the farm's location, captured by the region fixed effects indicator D_j. Additional unobserved variability in prevalence levels is captured by the error term ϵ_{ij}.

$$\Pr(\text{Ketosis=1})_{ij} = \alpha + \beta \mathbb{1}_{\{Averse_j=1\}} + \gamma Z_j + \eta X_{ij} + D_j + \epsilon_{ij} \tag{3}$$

Out objective is to test whether there is a negative and significant association between risk aversion and the prevalence of ketosis. Further, we anticipate that if there is an effect on prevalence levels of ketosis, a similar effect should be found for BHB estimates since higher concentrations increase the likelihood of ketosis to be diagnosed. This is because the Ketosis indicator is a function of the BHB blood concentration. Therefore, we use also estimate the model in equation 3 using the BHB blood concentration as dependent variables. Risk neutrality or risk-seeking behavior must imply that $\beta \geq 0$, so that estimate $\hat{\beta}$ is either positive or statistically insignificant. Our main hypothesis is that $\hat{\beta} < 0$. By identifying risk preferences in equation (3), we can focus on β as our parameter of interest to separate the marginal effect of risk aversion from the overall effect of risk factors affecting ketosis.

Second, we used the experiment and survey data to understand how risk aversion relates to the willingness to pay for information. We estimate a linear probability model that relates farmers' decisions during the treatment rounds to their risk profile (see equation 4). For each risk level, the independent variable is a binary variable WTP_j that equals one when farmers decide to pay for information about their cows' health status. In addition, we include an indicator variable $Averse_j = 1$ to identify when farmer j is risk-averse. Also, we control for farmers' socioeconomic characteristics, C, that have been found in risk elicitation literature to be important to explain behavior under risk. These include income, age, gender, education, and access to formal credit.

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

Additionally, we study differences in management practices between risk-averse and non-risk-averse farmers We consider management practices that can affect cows' health status, including risk factors affecting the prevalence of ketosis. Since the nutritional management of cows affects their health status, we primarily focus on feeding practices and inputs. Importantly, these variables are directly related to our measure of risk aversion since the risk profiles are based on the farmers' decisions about feeding inputs.

A critical challenge for identification is the adequate control for observed and unobservable confounders. Given the nature of our data, we cannot control for farm or individual-level fixed effects. Instead, we controlled for several confounding factors in our experimental design and used a rich set of farm, cow, and individual information. We control for technology choices that were identified to have an effect on the health status of cows in general and the likelihood of ketosis in particular. For instance, farmers could choose a pasture variety with higher nutritional content (Kolver, 2003; Compton et al., 2015; Garro et al., 2013; Daros et al., 2017; Wilkinson et al., 2019). In our sample, a single variety was predominant, Kikuyu pasture (*pennisetum clandestinum*), representing the largest percentage of pasture on the farm (see table 3). Also, farmers could gradually reduce the milking frequency before the dry-off or increase the feeding frequency to reduce the energetic demand of cows (González et al., 2008; Sahar et al., 2020; Yepes et al., 2020). In addition, a farmer may choose specific breeds of cows that are less prone to metabolic diseases. By design, we only included in our sample farms with Holstein cows and Holstein-crosses to reduce the potential variability across breeds. Moreover, we control for the cow's breed in our estimation.

Another relevant concern might be that the prevalence of ketosis is low. A large percentage of cows test negative for ketosis at the defined cut-off of 1.2 mmol/L BHB, leading to a relatively small number of ones in the dependent variable we use for the prevalence of the disease. Given the sample size, this makes the positive cases of ketosis a rare event in a statistical sense. For this reason, we consider alternative estimation methods for equation (3) to check the sensitivity of the estimates due to model selection and to correct for the potential finite sample bias in the presence of rare events. In particular, we estimated additional models using the standard procedure and another using the Penalized Maximum Likelihood Estimation proposed by Firth (1993).

6 Results

6.1 Disease prevalence

Table 4 reports the estimated coefficients of risk aversion on the prevalence of ketosis. We find a negative and significant coefficient for the risk aversion indicator variable, a result that is robust to all specifications. Column (5) in table 4 reports results for the model with all control variables and region fixed-effects, indicating that cows managed by risk-averse farmers are 3.7 percent points less likely to experience ketosis compared to farmers with other risk profiles (results for all variables are reported in A1 in the appendix). Coefficients in other models range from 3% to 5%, depending on the specification. Notably, the coefficient for risk aversion increases when farm-level controls on practices are included, maintaining its sign and statistical significance. In addition, results for the BHB blood concentration show a similar set of negative coefficients for the risk aversion variable (see table A2 in the appendix).

What are then the potential pathways through which risk aversion affects the likelihood of ketosis? To address this question, we study differences across farmers' risk profiles using two sets of data: experimental evidence on willingness to pay for information about cows' health status, and observational data on farm practices.

Table 4: Regression results of risk aversion on ketosis prevalence

Covariates	Ketosis prevalence (1)	(2)	(3)	(4)	(5)
Risk averse	-0.033*	-0.043**	-0.038*	-0.050**	-0.038**
	(0.019)	(0.017)	(0.020)	(0.019)	(0.016)
Constant	0.066***	0.074	0.071	0.041	0.101
	(0.017)	(0.055)	(0.100)	(0.112)	(0.120)
Dependent variable mean	0.043	0.043	0.043	0.043	0.043
Observations	877	877	877	877	877
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 a 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

6.2 Willingness to pay for information

Experimental results show suggest a positive relationship between risk aversion and willingness to pay for risk-reducing investments comparable to veterinary services or testing equipment such as the keto-meter. Table 5 shows results for the linear probability model of risk aversion on the willingness to pay for information about the health status of their cows (WTP). First, we find a positive coefficient for the risk aversion indicator (column 1), which is robust to the inclusion of farmer-level controls (see panel C in table 3). These results suggests that risk-averse farmers are more likely to demand information than their non-risk averse. Further, the WTP for information increases with risk level.

However, the estimated coefficients in columns 2 to 5 show that for the risk aversion coefficient are only statistically significant for the lowest risk level. In this condition, when there is only a 20% probability that the cow is sick, the likelihood that farmers pay for cows' health status in the experiment is about 32 percent points higher for the risk-averse. Note that the WTP for information significantly higher in the 50% risk condition, when the probability is ambiguous about the presence of the disease.

Table 5: Marginal effects of risk aversion on the willingness to pay for information

Covariates	Pooled WTP (1)	Risk=20% WTP (2)	Risk=50% WTP (3)	Risk=80% WTP (4)
Risk averse	0.204**	0.324**	0.051	0.237
	(0.096)	(0.119)	(0.187)	(0.167)
Risk 50%	0.254***			
	(0.092)			
Risk 80%	0.127			
	(0.091)			
Constant	0.585**	0.033	1.339***	0.764**
	(0.839)	(0.448)	(0.414)	(0.341)
Dependent variable mean	0.37	0.37	0.37	0.37
Individual-level controls	yes	yes	yes	yes
Observations	165	55	55	55
R^2	0.13	0.14	0.13	0.29

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 is that there exists an upper limit of risk for which more information on cows' health status is no longer valuable for the risk averse. In a scenario where the more likely outcome is that cows are sick, farmers may see a very high (or very low) prevalence of the disease as a strong signal that makes diagnostic information irrelevant to reduce risk when managing cows' health. For instance, farmers may limit pre-event action if they already expect a high enough number of sick cows in a given herd. This is consistent with cases when farmers may prioritize treatment over prevention. Evidence in dairy farming suggests that preparedness against vector-transmitted disease is expected to decrease with lower probability of disease introduction, larger spreads, and when post-event strategies are more effective relative to pre-event action (Elbakidze and McCarl, 2006).

6.3 Pasture-based management

Only a few practices predict the prevalence of the disease in our sample. We find that the higher the distance and the higher the parity number, the more likely is a dairy cow to experience ketosis (see column 1 of table A3 in the appendix). In line with previous research, the pressure on energetic demand caused by the stocking density and the daily traveled distance to the milking parlor Scott et al. (2014); Neave et al. (2021), as well as cow's age and reproductive history (Seifi et al., 2011; McArt et al., 2013; Benedet et al., 2019; Pralle et al., 2020) are contributing factors of metabolic diseases. We also find a negative and significant coefficient for milking reduction before dry-off in all specifications, which seems to improve cows' health despite their cost in terms of milk production.

In addition, we find no systematic differences in farm practices between risk-averse and non-risk-averse farms using simple statistical tests (see table 6). The only exception is the distance to the milking parlor, which on average is almost double for risk-averse farms (difference in means p-value = 0.009). In any case, small sample size issues make it difficult to detect true differences in management.

Table 6: Differences in farm practices between risk and non-risk averse

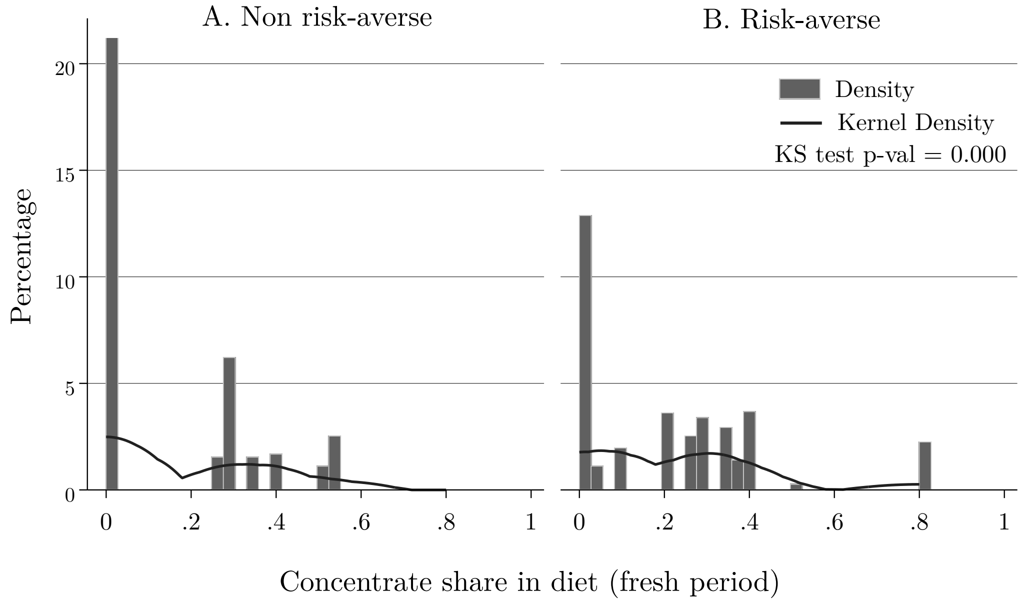
Practices	Non-risk averse mean	Risk averse mean	Diff. p-value
Concentrates share (%)	19.15	19.69	0.93
Feeding frequency (times)	3.94	3.88	0.70
Nutritionist visit (yes=1)	0.84	0.86	0.85
Kikuyo pasture (%)	86.72	85.01	0.29
Stocking density (herd size/area)	3.53	3.21	0.65
Distance to milking parlor (Km)	0.23	0.48	0.01
Fresh cows separation (yes = 1)	0.21	0.33	0.35
Milking reduction (yes = 1)	0.42	0.28	0.29

Notes: P-values calculated using two-tail differences in means tests.

Nevertheless, there could be heterogeneous effects of farm practices on ketosis between these types of management, which would suggest that risk aversion can affect ketosis in different ways depending on the distribution of each practice. For example, plenty of evidence suggests that concentrates may improve energy balance in pasture-based dairy cattle, reducing the risk of developing ketosis (Bargo et al., 2003; Pulido and Leaver, 2003; Wales et al., 2009; Hills et al., 2015; Auldist et al., 2016; García-Roche et al., 2021; Merino et al., 2021).

In our sample we observe no differences in concentrates means (p-value = 0.93). Also, regression results show negative coefficients of concentrates share on ketosis and BHB (see column 5 in tables A1 and A2), although not all are statistical significant. However, more than half of ketosis cases were detected in farms with zero concentrates in cows' diet. Further, figure 3 shows that the distribution of feed concentrate shares is more concentrated around zero and lower values in non-risk-averse farms. In contrast, the right-hand tail of distribution takes maximum values 30% higher than in non-risk-averse farms. The Kolmogorov-Smirnov test confirms that the two distribution are statistically different (p-value = 0.000).[14]

Figure 3: 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.

[14]When we replicate the preferred specification but restrict the sample to farms that use some positive share of feed concentrates in cows diets, the coefficient of risk aversion is still negative but in lower magnitude (see column 3 table A3). For the restricted sample of farms with only zero concentrate shares, the magnitude of the coefficient for risk aversion is double compared to the unrestricted sample.

To better understand how management affects the prevalence of ketosis via risk preferences we study the heterogeneous effects. Table 7 reports regression estimates for several farm practices on ketosis. Column 1 shows the main specification including animal-level controls and region fixed effects. In columns 2 and 3 we split the sample between risk and non-risk averse farmers. We find three types of results. First, we observe practices with the same results across the three specifications, showing that risk aversion does not mediates in their effect on ketosis. This is the case of Milking reduction at dry-off, which is negative and significant across all models.

Second, there are practices that only seem to matter for only risk averse farmers. In particular, we find a negative and significant coefficient for concentrates shares. Related to this we also find that the coefficient for nutritionist visit indicator variable is positive and significant, which seems to suggest a higher likelihood of ketosis. However, nutritionist visits and concentrates are highly correlated. The same of concentrates is 20% on average for farms visited by nutritionist, which significantly higher than the 11% shares in farms that do not hire nutritionist to formulate diets. In the second group of results, we also find positive and significant coefficients in the risk-averse sample for stocking density and distance to parlor. As discussed earlier, this distance is double for farms managed by risk-averse farmers (as well as farm size), so it makes sense that in this sub-sample we observe the negative effects of larger distances on cows health status. Similarly, stocking is also correlated with other practices, as a higher stocking may require a higher concentrate share, and a larger farm implies less herd density per pasture.

Third, we observe coefficients that cancel out when estimating the model with the fulll sample. Most of the effects mentioned before yield non-significant coefficients when both samples are pooled (see column 1). Even large and significant effects in the non-risk averse sample, as in the case of the share of the Kikuyu pasture variety that has a negative and significant coefficient in column 2, it is no longer significant for the full sample, as that effect is null among the risk averse. The net effects is still negative but statistically different than zero.

It is important to highlight that these results are not conclusive in the sense that we cannot reject alternative explanations to fully support a causal effect of risk preferences on ketosis via farm practices. Instead, they suggest that risk aversion matters mediates in how farm practices affect to ketosis. Another possibility is that these practices might be risk-reducing but not of the self-protection type. Instead, they may help self-insure farmers against the potential losses caused by ketosis, which we do not estimate because production data at the animal-level was not available in most farms in our sample. This is a limitation of our study, considering that most pasture-based farmers in developing countries do not track productivity at such granular level.

Other alternative might be that changes in risk levels do not influence farmers. In other words, the risk that farmers face does not trigger a managerial response that correspond to a specific set of preferences for risk. According to our framework, this means that the expected income effects are null relative to non-risk averse. This could be because the risk involved is not significant enough (a very low prevalence of the disease) or that farmers are unable to properly determine the risk level (diagnostic problems).

6.4 Limitations and additional robustness checks

While our findings are valuable to our understanding of how risk preferences affect farmers' technology choices, our study is limited by the nature of the problem and the available data. Here, we are not trying to establish the risk factors of ketosis, which requires epidemiological research beyond the scope of this paper. Instead, our goal is to understand how risk aversion may affect the prevalence of ketosis via management practices. Yet, the controls available in the data may not capture the entire variation in outcomes, such that potential unobservable characteristics correlated with risk aversion may affect the occurrence of ketosis, which can lead to an omitted variable bias.

To address this problem and given that we cannot control for farm-level fixed effects, we

Table 7: Heterogeneous effects and risk aversion

Covariates	Pooled (1) ketosis	Non risk-averse farms (2) ketosis	Risk-averse farms (3) ketosis
Risk averse	-0.038**		
	(0.016)		
Concentrates share	-0.031	0.038	-0.073*
	(0.033)	(0.105)	(0.037)
Feeding frequency	-0.008	-0.011	0.001
	(0.009)	(0.019)	(0.013)
Kikuyo pasture	-0.045	-0.253***	0.019
	(0.040)	(0.087)	(0.042)
Stocking density	0.002	-0.005	0.009***
	(0.003)	(0.003)	(0.003)
Distance to parlor	0.067***	0.026	0.089***
	(0.023)	(0.070)	(0.021)
Fresh cows separation	0.003	-0.019	0.019
	(0.015)	(0.031)	(0.013)
Milking reduction at dry-off	-0.051***	-0.079***	-0.050***
	(0.012)	(0.019)	(0.014)
Nutricionist visit	0.032	-0.023	0.081***
	(0.023)	(0.042)	(0.028)
Constant	0.067	0.136	-0.040
	(0.117)	(0.274)	(0.132)
Dependent variable mean	0.043	0.067	0.033
Observations	877	256	621
R-squared	0.054	0.065	0.074
Region Fixed Effects	yes	yes	yes
Animal-level controls	yes	yes	yes

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

included only certain breeds of cows and types of farms in our sample to minimize potential confounding factors by design. Further, we used a biological indicator used as an objective way to determine the prevalence of ketosis. Finally, we control for a rich set of farm and cow level covariates that were selected based on evidence from veterinary science regarding the determinants of ketosis. Nevertheless, further analysis is needed to address this limitation when identifying causal effects of farmers' preferences on farm-level outcomes.

An important concern is whether the magnitude of the omitted variable bias would drastically affect our results. We follow Oster (2017) procedure to correct for 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. We find a $\hat{\delta} = 7.2$, which suggests that unobservables would need to be seven times more important than our controls to result in 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 -0.041, which is similar to the estimates reported in table 4.

Finally, we conducted additional robustness checks for the prevalence of ketosis model. We focus on the model specification with all controls and fixed effects to check if the selection of the estimation model affects our results, in particular by correcting for potential bias caused by the low prevalence of ketosis in our sample (appendix table A4 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 -3.8% (for the probit model) and -4.9% (for the penalized maximum likelihood logit model). We conclude that the main results are robust to estimation, even when corrected for potential bias caused by the sample's relatively few positive cases of ketosis. So, we reported all main results using the linear probability model as it provides the most conservative estimate for the coefficient for risk aversion.

7 Discussion

Risk preferences can shape farm management in significant ways. The sources of uncertainty in dairy farming 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 change risk (Amamou et al., 2018). A handful of studies investigate farmers' attitudes toward these risks in dairy farming, showing differences in farming practices across different risk profiles of farm managers. For instance, some degree of risk aversion explains differences in the use of disease control practices (vaccination, prevention, and hygiene), concentrate use, veterinarian consulting, herd size, and public programs participation (Bishu et al., 2016; Bardhan et al., 2006; Tauer, 1986). However, the impact of these differences on dairy farming is yet to be fully understood, and these effects may compound if most of the dairy farmers are risk-averse, as the evidence suggests (Belhenniche et al., 2009; Tauer, 1986).

In this paper, we study the role of risk aversion in pasture-based dairy farms, focusing on the prevalence of metabolic diseases in cows as an outcome of farmers' technology choices. We argue that risk-reducing incentives can promote investments in risk-reducing management in dairy farming. When facing uncertain but preventable productivity shocks, such as the reduction of milk production or reproductive performance of cows caused by diseases such as ketosis, farmers have incentives to adopt practices that reduce their exposure to these events. However, not all farmers are willing to pay for this risk reduction. Our results indicate that farms with risk-averse managers exhibit a lower prevalence of ketosis, even after controlling for farm practices and cows' characteristics.

Moreover, our results indicate a lower risk level in farms with risk-averse managers. Our experimental results show that risk aversion is correlated with willingness to pay for information about cows' health status, which is comparable to veterinary consultation or the use of disease diagnostic tools such as the keto-meter, which is the testing device we used on the field to determine the presence of ketosis. If risk aversion leads to a willingness to pay for such risk reductions, then a potential demand for risk-reducing technologies may exist.

Recent evidence shows incentives to adopt post-harvesting practices, improved varieties, and electronic devices can help farmers reduce downside risks, especially among the risk-averse (Emerick et al., 2016; Shimamoto et al., 2017; Asravor, 2018; Crentsil et al., 2020). This demand for risk-reducing practices and inputs compares to cases documenting an otherwise negative effect of risk aversion on technology adoption.

These results suggest an important link between risk preferences and risk-reducing farm management. Our experimental design is based on the economic trade-off between the downside risks versus the cost of better farm management. In pasture-based dairies in low-income countries, this tension is often resolved in favor of management strategies that sacrifice cows' health and, as a result, dairy farms productivity. In this context, risk preferences are essential but mostly unobservable economic primitives affecting farm management, and our results highlight the importance of using experimental economics methods to study problems when no direct observation is available or when randomization can not be feasibly implemented in the field. Related research combines economic experiments and field observations in developing countries to test, for instance, theoretical predictions about social, other-regarding, and time preferences (Fehr and Leibbrandt, 2011; Carpenter and Seki, 2011). In our experiment, risk-averse individuals systematically chose higher feed quality options at the expense of lower expected returns. Using survey data, we also find show lower ketosis prevalence in farms that use concentrates in dairy cows' diet, which is especially relevant for pasture-based production systems where these and other nutritional supplements are mostly underutilized.

In addition, the identification of farmers' risk profiles is relevant for policy targeting and promoting agricultural innovations. Our results indicate that farmers that exhibit risk-neutral or risk-seeking behavior may be willing to endure higher levels of prevalence of diseases to avoid the cost of risk-reducing investments. Therefore, policies aiming at improving cattle health should consider farmers' risk preferences and target those farmers who have incentives to adopt risk-reducing technologies, especially when no other mechanisms are available such as insurance. For example, several government programs for dairy and livestock farming in Colombia include investments in vaccines, testing, and animal control to prevent the spread of viruses such as the one causing the foot-and-mouth disease. Given the steep potential losses of viral diseases, many of which are common in dairy and livestock production, understanding the heterogeneity of farmers' risk preferences and how they shape farmers' technology choices is crucial to improving the efficacy of such policies.

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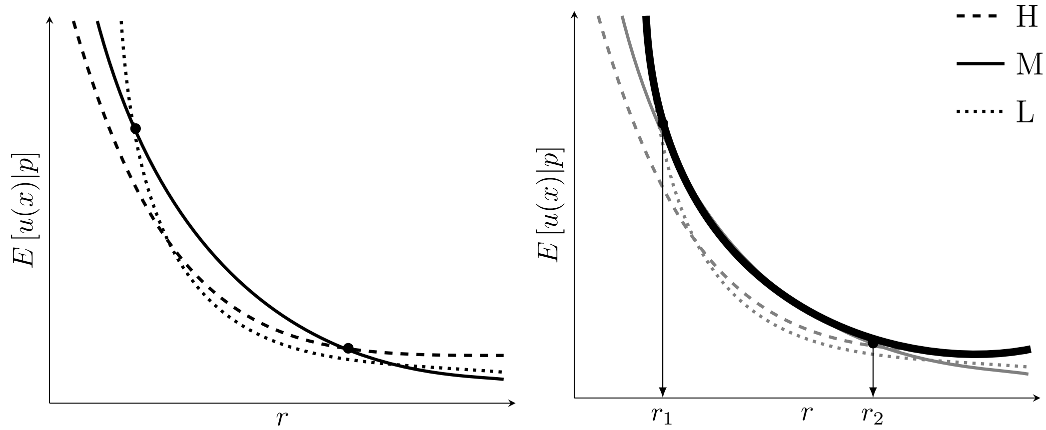
Appendix

Figure A1: Risk profile classification based on lottery choices



Notes: The x-axis is the Constant Relative Risk Aversion (CRRA) parameter r. The y-axis is the expected utility given probability p. The left panel shows the expected utility of three lotteries individually (H, M, L). The right panel shows their intersection points and the maximum expected utility of all three gambles as the envelope curve shown with a thick black line. Lottery H (L) provides a higher expected payoff for higher (lower) values of r, whereas lottery M yields the highest payoff for r in between lotteries H and L. For instance, to the right of point r_1 in figure 1, the values of the implied CRRA indicate that lottery L generates a higher expected utility than lotteries H and L. Similarly, between values r_1 and r_2, lottery M provides the highest expected utility of all three gambles.

Table A1: Ketosis prevalence: regression results

Covariates	(1) ketosis	(2) ketosis	(3) ketosis	(4) ketosis	(5) ketosis
Risk averse	-0.033*	-0.043**	-0.038*	-0.050**	-0.038**
	(0.019)	(0.017)	(0.020)	(0.019)	(0.016)
Concentrates share		0.012		0.012	-0.031
		(0.040)		(0.044)	(0.033)
Feeding frequency		0.012		0.014*	-0.008
		(0.008)		(0.008)	(0.009)
Kikuyo pasture		-0.095**		-0.081**	-0.045
		(0.037)		(0.038)	(0.040)
Fresh cows separation		-0.007		-0.008	0.003
		(0.016)		(0.016)	(0.015)
Stocking density		0.003		0.004	0.002
		(0.004)		(0.004)	(0.003)
Distance to parlor		0.041		0.046	0.067***
		(0.028)		(0.028)	(0.023)
Milking reduction at dry-off		-0.031**		-0.029**	-0.051***
		(0.013)		(0.014)	(0.012)
Nutricionist		0.026		0.028	0.032
		(0.020)		(0.022)	(0.023)
Days in Milk			-0.002	0.001	0.002
			(0.003)	(0.003)	(0.003)
BCS			0.017	0.018	0.022
			(0.025)	(0.026)	(0.026)
Parity			0.008**	0.008**	0.009**
			(0.004)	(0.004)	(0.004)
Male calf			0.006	0.006	0.006
			(0.013)	(0.013)	(0.013)
Calf dead			0.002	-0.006	-0.008
			(0.032)	(0.033)	(0.035)
Holstein cow			-0.071	-0.068	-0.060
			(0.061)	(0.064)	(0.061)
Constant	0.066***	0.062	0.071	0.030	0.067
	(0.017)	(0.054)	(0.100)	(0.107)	(0.117)
Observations	877	877	877	877	877
R-squared	0.005	0.032	0.016	0.041	0.054
Region Fixed Effects	no	no	no	no	yes

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

Table A2: BHB blood concentration: regression results

Covariates	(1) ketosis	(2) ketosis	(3) ketosis	(4) ketosis	(5) ketosis
Risk averse	-0.052	-0.090**	-0.065	-0.108**	-0.086**
	(0.049)	(0.046)	(0.052)	(0.051)	(0.044)
Concentrates share		-0.027		-0.022	-0.102
		(0.114)		(0.118)	(0.098)
Feeding frequency		0.011		0.011	-0.051*
		(0.019)		(0.020)	(0.031)
Kikuyo pasture		-0.244***		-0.241**	-0.208*
		(0.094)		(0.117)	(0.120)
Fresh cows separation		-0.015		-0.013	0.001
		(0.045)		(0.047)	(0.048)
Stocking density		0.005		0.006	0.001
		(0.008)		(0.009)	(0.006)
Distance to parlor		0.149**		0.159**	0.181***
		(0.063)		(0.064)	(0.059)
Milking reduction at dry-off		-0.040		-0.034	-0.084***
		(0.037)		(0.038)	(0.031)
Nutricionist		-0.059		-0.067	-0.084
		(0.078)		(0.080)	(0.071)
Days in Milk			-0.003	0.003	0.004
			(0.008)	(0.007)	(0.007)
BCS			0.074	0.088*	0.092*
			(0.055)	(0.050)	(0.050)
Parity			0.021***	0.023***	0.026***
			(0.008)	(0.008)	(0.008)
Male calf			-0.023	-0.027	-0.026
			(0.025)	(0.024)	(0.025)
Calf dead			-0.005	-0.033	-0.034
			(0.039)	(0.048)	(0.052)
Holstein cow			-0.152*	-0.082	-0.069
			(0.085)	(0.089)	(0.087)
Constant	0.636***	0.822***	0.543***	0.598***	0.783***
	(0.043)	(0.130)	(0.177)	(0.148)	(0.203)
Observations	877	877	877	877	877
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: Ketosis prevalence: regression results

Covariates	Pooled (1) ketosis	Concentrate share = 0 (2) ketosis	Concentrate share > 0 (3) ketosis
Risk averse	-0.038**	-0.076**	-0.038*
	(0.016)	(0.032)	(0.023)
Concentrates share	-0.031		-0.078**
	(0.033)		(0.035)
Feeding frequency	-0.008	0.004	-0.016
	(0.009)	(0.024)	(0.016)
Kikuyo pasture	-0.045	0.008	-0.191***
	(0.040)	(0.046)	(0.049)
Fresh cows separation	0.002	-0.010**	0.005
	(0.003)	(0.004)	(0.003)
Stocking density	0.003	-0.002	0.006
	(0.015)	(0.029)	(0.013)
Distance to parlor	0.067***	0.067	0.066***
	(0.023)	(0.050)	(0.019)
Milking reduction at dry-off	-0.051***	-0.043**	-0.052**
	(0.012)	(0.019)	(0.021)
Nutricionist	0.032	0.042	0.055**
	(0.023)	(0.038)	(0.025)
Days in Milk	0.002	0.003	0.001
	(0.003)	(0.005)	(0.005)
BCS	0.022	0.033	0.015
	(0.026)	(0.037)	(0.037)
Parity	0.009**	0.007	0.011**
	(0.004)	(0.007)	(0.005)
Male calf	0.006	0.002	0.007
	(0.013)	(0.022)	(0.014)
Calf dead	-0.008	-0.042	0.023
	(0.035)	(0.033)	(0.066)
Holstein cow	-0.060	-0.070	-0.146
	(0.061)	(0.076)	(0.105)
Constant	0.067	0.006	0.311*
	(0.117)	(0.176)	(0.183)
Observations	877	366	511
R-squared	0.054	0.064	0.081
Region Fixed Effects	yes	yes	yes

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

Table A4: Robustness Check: Model selection and rare-events correction bias

Covariates	(1) ketosis	(2) ketosis	(3) ketosis	(4) ketosis
Risk averse	-0.044**	-0.038**	-0.045**	-0.049*
	(0.019)	(0.016)	(0.019)	(0.027)
Concentrates share	-0.013	-0.021	-0.014	-0.013
	(0.036)	(0.032)	(0.035)	(0.046)
Feeding frequency	-0.003	-0.010	-0.004	-0.003
	(0.009)	(0.009)	(0.009)	(0.015)
Kikuyu pasture share	-0.044	-0.050	-0.050*	-0.046
	(0.029)	(0.039)	(0.029)	(0.042)
Stocking density	0.002	0.001	0.002	0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Distance to parlor	0.050**	0.064***	0.049**	0.055*
	(0.023)	(0.023)	(0.022)	(0.030)
Fresh cows separation	-0.009	-0.003	-0.006	-0.009
	(0.016)	(0.016)	(0.014)	(0.019)
Milking reduction at dry-off	-0.044***	-0.052***	-0.045***	-0.048**
	(0.012)	(0.012)	(0.012)	(0.020)
Days in Milk	0.003	0.002	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.004)
BCS	0.022	0.022	0.018	0.025
	(0.022)	(0.026)	(0.022)	(0.022)
Parity	0.008**	0.009**	0.008**	0.009**
	(0.003)	(0.004)	(0.003)	(0.004)
Male calf	0.012	0.005	0.013	0.013
	(0.013)	(0.012)	(0.013)	(0.016)
Calf dead	0.000	-0.007	0.008	0.015
	(0.045)	(0.036)	(0.042)	(0.041)
Holstein	-0.044	-0.057	-0.041	-0.053
	(0.028)	(0.062)	(0.032)	(0.032)
Observations	877	877	877	877
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) and the baseline groups are risk-neutral and risk-seeking profiles. Significance: *** p<0.01, ** p<0.05, * p<0.1