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Experiments in ranching: Rain-index insurance and investment in production and drought risk management

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Abstract
Rainfall is critical for financial viability in ranching, yet droughts are becoming more common. The USDA Pasture, Rangeland, and Forage rain-index insurance program seek to reduce drought-related financial risks. Using the DRIR-R model, we test the investment impact of rainfall-index insurance with two randomized control simulations, one with a general population and one with professional ranchers. We find no evidence of direct impacts of rainfall-index insurance on herd size or drought adaptation investments. These findings support the idea that the rain-index insurance policy limits moral hazard in a way that reduces the likelihood of overgrazing that could intensify drought stress.

KEYWORDS
agriculture, drought, experimental simulation, rain-index insurance, ranching

JEL CLASSIFICATION
Q18, C9, G22

Drought is the most serious risk to ranching productivity in the western United States (and globally). For example, the 2012–2013 North American drought caused widespread herd liquidations, leading to the smallest total US cattle herd size in 60 years (Waters, 2013). Even five years later, the market still had not recovered as operators faced high restocking costs. Most cattle ranching in the United States relies on rainfall and natural forage, not irrigated pasture (Conley, Eakin, Sheridan, & Hadley, 1999; Frisvold, Jackson, Pritchett, & Ritten, 2013; Gillam, 2012; McNew, Mapp, Duchon, & Merritt, 1991). Thus ranchers are vulnerable to rainfall volatility that affects forage production directly and through soil moisture (Reeves & Bagne, 2016). Moreover, extreme heat can reduce growth rates and increase mortality (Hahn, 1999). The extent of the vulnerability depends on the frequency and severity of drought and heat, the ranching system sensitivity to those hazards, and the adaptive capacity of the ranching system (Adger, 2006; Coppock, 2020; Derner et al., 2018; Roche, 2016).

The USDA Risk Management Agency offers rainfall-index insurance to help ranchers through periods of low rainfall that reduce forage production, cattle weight gain, and ultimately, ranch income. The Pasture Rangeland and Forage (PRF) rainfall-index insurance policy was rolled out in a few states in 2007 and expanded to the contiguous forty-eight states in 2016. The PRF policy pays an indemnity on insured acreage when precipitation falls below a threshold based on the historical average for the area. Because the payouts do not depend on actual losses, this type of insurance is meant to minimize the moral hazard that arises for many types of policies, especially when indemnities depend on crop losses (Smith & Goodwin, 1996; Wu, Goodwin, & Coble, 2020). While the PRF insurance is intended to help ranchers deal with drought risk, under certain conditions imperfect credit or risk markets (Karlan, Osei, Osei-akoto, & Udry, 2014), it could still create a subtle moral hazard for ranchers. Depending on how insured ranchers respond to the changes in risk exposure and expected future income, the PRF could incentivize behaviors that increase drought risk and decrease drought adaptation. Because the policy reduces the income risk of drought, it may increase the returns to investment in production inputs, such as herd size, and reduce the return on drought adaptation investments. As a result, the policy may affect the optimal size of the ranchers' herd and the optimal investment in drought adaptation in ways that have longer-term consequences for the vulnerability of ranching.

The goal of this study is to test how the rain-index insurance affects ranch management and whether it might increase or decrease vulnerability to drought. Specifically, we test the following two hypotheses, motivated by theoretical and empirical predictions (Karlan et al., 2014), with an experimental simulation:

> **H1.** The availability of rain-index insurance leads to an increase in the average size of cattle herds because the expected return on investment in cattle production will increase when the financial risks of drought are mitigated.

> **H2.** The availability of rain-index insurance will decrease investment in (i.e., crowd-out) other drought adaptation strategies because insurance serves as a substitute for risk mitigation.

To do this, we introduce the Drought Ranching Insurance Response R Model (DRIR-R), which to our knowledge is the first decision model to incorporate the USDA's rainfall-index insurance. Second, we test the model in two randomized control experiments, with a general population, and with professional ranchers.

The paper is organized as follows. Section 1 reviews the economic and policy background of agricultural insurance as well as the links between climate variability and range cattle production. Section 2 reviews the participants in the two studies, the coupled natural-human system model that drives the experimental simulations, and the experimental methods used in the simulations. Section 3 analyzes and discusses the experimental results. Finally, Section 4 offers conclusions from our experiments and suggestions for future research.

AGRICULTURAL INSURANCE: POLICY & THEORY

The United States has a long history of providing government assistance to the high-risk business of agriculture. With the Federal Crop Insurance Act of 1980 and the Agriculture and Food Act of 1981, policymakers shifted the policy trajectory towards heavier reliance on crop insurance to reduce the need for *ex post* weather and natural disaster assistance (Barnett, 2000; Coble & Barnett, 2012). Additional policies passed in 1994 and 2000 provided free catastrophic coverage and increased crop insurance subsidies (Coble & Barnett, 2012). Premium subsidies grew from 20 percent in the 1980s to the current levels of 60 percent for corn and soybeans (Annan & Schlenker, 2015).

As of 2016, U.S. ranchers have two main choices for federal insurance for their ranching operations: the Noninsured Crop Disaster Assistance Program (NAP) and the Pasture, Rangeland, and Forage (PRF) rain-index insurance. NAP supplies aid to producers of non-insurable crops (e.g., crops grown for livestock consumption) if a natural disaster results in crop losses or lower yields. The PRF rain-index insurance program is designed to provide insurance to rangeland, perennial pasture, or forage used to feed livestock, typically through direct grazing in our study region, against low precipitation that reduces forage available to livestock (U.S. Department of Agriculture, 2015). The PRF is indexed against gridded precipitation data from the National Oceanic and Atmospheric Administration Climate Prediction Center (NOAA CPC), rather than an individual producer's loss experience. PRF is the third-largest crop insurance program in the United States. Some 35,000 policies were in place in 2019, covering 140 million acres with $581 million in premiums paid and $292 million paid out to ranchers in indemnities (Coble et al., 2020; U.S. Department of Agriculture, 2016).

Insurance allows agricultural producers to reduce risk and smooth their income. In theory, a risk-averse producer would have positive demand for crop insurance at actuarially fair prices (Ahsan, Ali, & John Kurian, 1982). Yet we observe under-insurance even at subsidized premiums, which leads us to ask what other decision-making factors might be at play such as risk aversion, adverse selection, and moral hazard (Coble & Knight, 2002; Just, Calvin, & Quiggin, 1999).

Risk aversion is likely to increase demand for insurance while dampening the impact of the insurance on risk-taking behavior (Cleeton & Zellner, 1993; Pauly, 1968). We expect ranchers who are more risk averse to have a higher willingness to pay to avoid or reduce their risk. We would also expect that for a given level of insurance, more risk-averse producers remain more likely to hedge against residual risk.

Adverse selection in agriculture is not a straightforward story of agricultural producers knowing their own risks better than the insurers. Demand for insurance against weather-related risks may be hampered by decision-makers' cognitive errors when dealing with low-probability events (Kunreuther, 1996). Evidence suggests that decision-makers have a difficult time estimating the risk of low-probability events, like severe flood or drought (Burby, 2001; Kunreuther, 1996), leading them to underinsure. This problem is well established for non-agricultural disasters, but more research is needed to better understand the role that risk perception may play in agricultural insurance (Coble & Barnett, 2012; Du, Feng, & Hennessy, 2016).

Moral hazard is a major problem for crop insurance, particularly programs based on actual production or revenues. Evidence indicates that producers have responded to corn and soybean insurance by reducing adaptive behaviors that minimize the impact of extreme heat (Annan & Schlenker, 2015). Annan and Schlenker find that insured crop yields are 43% to 67% more sensitive to extreme heat than uninsured crops, implying that farmers invest less in protective behaviors when the losses are covered. They also find that insured crops are less sensitive to sub- or supra-optimal precipitation levels. Insuring loss may reduce the incentive to invest in other loss reduction measures. Hence, a major appeal of rain-index insurance is that it reduces moral hazard (Carter, Cheng, & Sarris, 2016) because indemnities depend on rain alone; no matter how producers respond to drought, they receive the same payouts. Yet, because rain-index insurance reduces the financial consequences of drought, it changes the payoffs to investments in drought protection (Fuchs & Wolff, 2011). As such, we would expect to see cattle ranchers substitute away from investments in drought adaptation. This substitution, paired with the increased profitability due to the income transfer of the PRF subsidy, leads us to hypothesize that ranching will become more profitable, which will lead to an intensification or expansion of cow-calf production, both for individual ranchers and for the industry as a whole.

Research on the impacts of rain-index insurance on risk management is limited, especially in the U.S. where such policies are relatively new. In a randomized control field study, Karlan et al., 2014 found that providing rain-index insurance to farmers in Ghana increases risk-taking behavior and increases investment in cultivation. For example, farmers increase the number of acres cultivated by 12.5% when they have rain-index insurance compared to a control group without insurance. They also increase the production of rainfall-sensitive corn by 9% and decrease other income-generating activities. Other studies that explore the impacts of weather-based insurance reinforce these findings (Cai, 2016; Cai, Chen, Fang, & Zhou, 2015; Cole et al., 2013). However, there is a key distinction between investment to increase production regardless of drought risk (e.g., increasing the size of the herd) and investment in drought risk reduction (e.g., feed supplements, trucking herds to rented pasture, or early sales).

THEORETICAL MODEL & DRIR-R MODEL

In this section, we review the Karlan model which forms the theoretical basis of our experimental hypotheses.

Karlan et al. (2014) developed a model of the impact of rain-index insurance on farmers who lack complete risk pooling for losses in revenue due to low levels of rainfall (hereafter referred to as "the Karlan model"). The Karlan model includes two periods $(t=0,1)$ with two states of the world $(s \in G, B)$. Preferences over consumption in the two periods are:

$$u\left(c^0\right)+\beta\sum_{s \in S}\pi_s u\left(c_s^1\right) \tag{1}$$

where π_s is the probability of state s and β is a discount factor.

With perfect credit markets, assets can be borrowed or lent at a risk-free interest rate of $R=1/\beta$. With complete risk pooling, the authors assume access to an informal ex-post risk pooling group that, regardless of whether a good or bad state occurs in the second period, each household obtains the expected value of its second-period consumption. In other words, $c_G^1=c_B^1=\sum_{s \in S}\pi_s u\left(c_s^1\right)$.

The rancher, or, in the Karlan model, the farmer, has a concave production function, $f_s(x)$, that takes a vector of inputs, x, committed in the first period to produce output in the second period. The model has two inputs: a risky input, x_r, and a hedging input, x_h. The risky input outperforms the hedging input in a high rainfall state $(s = G)$. Likewise, the hedging input outperforms the risky input in a low rainfall state $(s = B)$. In other words, the marginal product of x_r is lower in state B than in G and the marginal product of x_h is higher in state B than in G.

The risky inputs in the Karlan model are production inputs like "field preparation, fertilizer and pesticide use, weeding and cultivation activities" (Appendix S1, pg 1). In our study, the risky input is herd size. The marginal product of the herd size depends on rainfall with a higher marginal product in a high rainfall state than in a low rainfall state.

The hedging input in the Karlan model is irrigation. In this study, the hedging input is supplemental feed, a key drought adaptation investment for ranchers (Coppock, 2020; Haigh et al., 2021). The marginal product of supplemental feed is higher in the low rainfall state than in the high rainfall state.

The Karlan model predicts that under perfect capital and risk markets, rain-index insurance will not affect investment in risky or hedging inputs. However, under imperfect risk markets, rain-index insurance increases investment in risky inputs and decreases investment in the hedging inputs. In our study, we simulate perfect capital markets with unlimited borrowing at an interest rate of X% and imperfect risk markets with limited hedging instruments. Hence, we base our hypotheses on the perfect capital markets and imperfect risk markets case. If decision-makers fully operate as profit-maximizers, rain-index insurance should increase herd size [H1] and decrease investment in supplemental feed [H2]. We test these key predictions in this experiment.

METHODS

Experimental methods in economics research have become increasingly common (Latuszynkska, 2016) and computer simulations or "serious games" of risk and investment decisions have been used for decades in agriculture, especially as a teaching tool (Anderson, 1974; Babb & Eisgrubler, 1967; Pritchett, Kachergis, Parsons, Fernandez-Gimenez, & Ritten, 2012) and less often as a research instrument (Anderson, Ward, Koontz, Peel, & Trapp, 1998; Clark et al., 2020). Concerns about future climate change engendered a surge of agronomic and economic simulation in agriculture, building especially on crop yield modeling but then elaborating into agricultural systems simulation (Antle, 1996; Antle, Stoorvogel, & Valdivia, 2014). More recently farm and ranch enterprise simulation has become a common teaching and management tool (Hoag & Griffith, 2010), for example, the distribution of online risk scenarios and simulations by a consortium of university extension services called "RightRisk," several of which address ranching and drought (Hoag & Parsons, 2010). Multiple types of production and enterprise simulations are now available online to farm and ranch managers, though their use for research has yet to be reported in the literature. This study builds on this literature by developing and running a randomized control experiment with a PRF-like insurance treatment group using an incentive-compatible "serious game" built on a coupled rangeland and ranching production model (DRIR-R). Two studies were carried out: first with a non-expert sample of Americans and second with a population of experienced cattle ranchers in the Western US. Study protocols were pre-approved and monitored by the University of Colorado Boulder Institutional Review Board.

Participants

Study 1: We recruited 610 participants from the online Amazon Mechanical Turk community. Of those initial participants, 540 completed the study (88% completion rate). The study population was exclusively from the United States with a geographically diverse sample yielding at least one participant from every state. The average age of the study population was approximately 35 years old, 61% of the population identified as male, and 81% of the population identified as white. Most of the sample had no prior knowledge of cattle ranching (79%) and only one person in the study population reported having worked on a cattle ranch before taking part in the study.

Study 2: We recruited 108 participants via an article in The Fencepost, a regional agriculture newspaper. Of those, 98 completed the study (91% completion rate). On average, participants had over 13 years of ranching experience and earned 75% of their income from ranching. Half of the sample is from Colorado, the location of the simulated ranch, and the other half of the sample is located in the following states: Oregon, Arizona, California, Kansas, Wyoming, Louisiana, Texas, Montana, New Mexico, and Delaware. The average age of this sample is 40 years and 71% male. Nearly 30% of the sample self-identified as an environmentalist.[1]

DRIR-R model

In this coupled-natural-human-systems dynamic model, which we call DRIR-R, we build a simple grassland forage production model paired with a ranching production model and rainfall-index insurance model based on the USDA PRF Program. This model was developed with the guidance of rangeland and ranching specialists and the ranching production model was based on a decision spreadsheet developed by Colorado State University extension specialists (Tranel, Sharp, & Deering, 2011). The simulation was pilot tested with a focus group of ranching and extension professionals.

In the model-based simulation, ranchers maintain a herd of cows to produce calves for market and make annual hay purchase decisions to maintain sufficient forage. The model includes three stock variables: herd size, forage potential (i.e., rangeland health), and financial net worth. To produce calves at an ideal weight for market and to maintain a herd at the recommended carrying capacity, players must purchase supplemental hay in low rainfall years – but the optimal amount to purchase is uncertain because the investment must be made before the full year's rainfall (and rainfall index indemnity, if applicable) is known. Maintaining herds above the carrying capacity of the rangeland leads to slow declines in future forage potential; maintaining herds below the carrying capacity reduces the profitability of the operation. The DRIR-R model approximates the ranching management decision-making for a 3000-acre range in Eastern Colorado and draws from historical rain gauge records, monthly rainfall-based forage growth weights specific to the Central Plains Experimental Range. The rainfall-index insurance premiums and indemnities are based on USDA PRF data. The Appendix S1 for this paper contain the model documentation.

DRIR-R simulation experiment

The experimental simulations were conducted using a web-based randomized control user interface of the DRIR-R model. The model is coded in R and the web application is built with R Shiny and was made available online after the experiments were completed.[2]

In the "MTurkers study," the treatment group is required to have insurance every year while the control group is not offered insurance. In the "Ranchers study," the first two years of the simulation have no insurance for either the treatment or the control group to create a baseline measure of hay purchases, the following six years have the insurance required for only the treatment group, and the final two years have insurance offered as a choice for both the treatment and control group.

Participants are randomized into the insurance treatment group or the control group. To explain the experiment and the simulation, we provide participants with an instructional screen-cast that shows the practice simulation as it is run with a voice-over explaining the important information in each section. Participants take a brief quiz to ensure that they comprehend the instructions and understand that the simulation and lottery game after the simulation are incentive compatible with real-world payoffs. Then, participants complete a practice simulation that runs for 5 years followed by the main simulation that runs for 10 years and is incentive-compatible with the end-of-game net worth converted to an experiment payment bonus (Figure 1). The simulation uses historical rainfall from 1999–2008 for the grid that includes the USDA Central Plains Experimental Range in Colorado.

Each game-year is broken into four sections with the information provided in written and graphical form, with a summary of key variables on a side bar that is visible at all times (see Appendix S1 for screenshots of the experiment). First, the Winter Ranch Report is provided for participants to take account of their herd, range health, and financial status at the start of the grazing season in spring. In this section, those in the insurance treatment "pay" their insurance premium by entering the amount due for the year with the timing of the insurance bill reflecting that of the PRF program.

Second, participants make the Summer Adaptation Investment Decision where they learn about how much rainfall they have had from November to June alongside monthly historical averages. They are also given a weighted average expressed as a percentage of normal rainfall for the growing season and advice on how much hay they may want to buy for the rest of the year to have sufficient feed if low rainfall continues. The advice is broken down into optimal hay purchases for three different scenarios for rainfall in July through October: "normal" (average historical rainfall), "above average" (one standard deviation above the mean), and "below average" (one standard deviation below the mean). The amount of hay that is recommended in these scenarios depends on the rangeland condition, rainfall from November to June, and herd size. Purchasing hay is the only adaptation in this model and participants cannot sell unused hay or carry over hay year to year.

Third, at the End of Growing Season Report, participants learn how much rain they received from July through October. For the insurance treatment, they also learn whether they received an indemnity. If so, they are asked to type in the correct amount of the check to "deposit" it. Typing in the amount of both the premium and the indemnity is designed to increase the salience of the insurance policy for those in the insurance treatment.

In the Fall Cow and Calf Sales, participants learn about the number and average weight of the calves in their herd and decide how many cows and calves they will sell. If they are under the target weight of 600 pounds, they are told how much revenue they are missing due to the lack of weight gain. They are given a graphical and numerical estimate of how their selling decisions in this section will affect their herd size for the next two years. Participants must sell at least half of their calves because we assume that male calves have no economic value if kept in the herd. Participants are also reminded that the carrying capacity of their ranch is 600 cows and having a larger herd may damage their range health and decrease grass production.

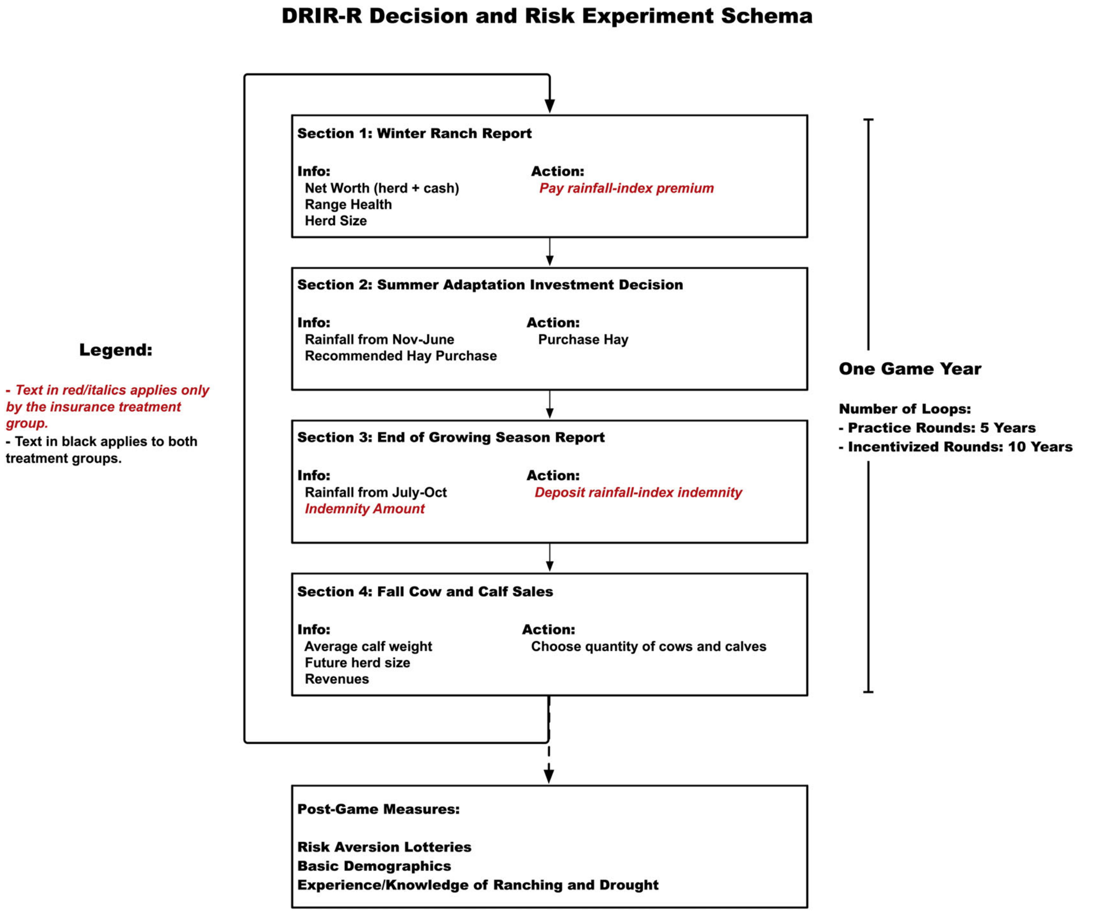

FIGURE 1 Graphical summary of the DRIR-R experimental simulation. Info: Indicates new information given in each section. Action: Indicates actions taken by the player. Text in red applied only to the insurance treatment group. Text in black applies to both treatment group

Finally, participants are given the revenues they will earn for the cow and calf sales numbers they have selected. Participants can change the number of cows and calves they may sell and watch the future herd size and revenues respond in real time. Once they are satisfied with their sales choices, they lock in the sales and move to the next year in the simulation.

After completing the game, participants choose between a series of lotteries designed to generate a measure of risk aversion (Holt & Laury, 2002). The lottery choices are incentive compatible–ten randomly chosen participants have one randomly selected lottery choice implemented and receive a second bonus according to their lottery payoffs.

Finally, participants answer a survey on demographics and questions specific to ranching and drought. The rancher population answers a larger array of questions about their cattle ranching operation, practices, and experience with drought.

Analysis

We first identified outliers and removed them from the data, and to reduce variation from people playing the simulation in ways that indicate inattention to the basics of the scenario, we removed the last year of the simulation data in the MTurkers study when many sold off their entire herds to attempt to maximize their payout (even though this was not a profit-maximizing strategy because game performance payments were based on net worth, including the value of the herd). After removing the last year of simulation data, we identified any participants who developed herd sizes more than twice the recommended level ($N = 9$) or less than half the recommended level ($N = 96$) and removed them from the data. None of the participants in the Ranchers study exceeded or fell below these herd size thresholds. Participant behavior in the simulation was far more varied in the MTurkers study than in the Ranchers study, likely due to inexperience with ranching and the kinds of complex decision scenarios like those faced in the simulation.

We estimated the risk aversion coefficient from the lottery choices following the methodology of Holt and Laury (2002). Participants who switched repeatedly between the high-risk and low-risk lotteries even as the odds became more favorable were recorded as a null measure of the risk coefficient (MTurkers: $N = 47$, 8.6% of the sample, Ranchers: $N = 0$).

Using Stata, we analyzed the experiment data to evaluate our initial hypotheses. Due to the time invariant variables of interest, herd size (H1) was evaluated using a random-effects model with robust errors clustered at the participant level. We included a single auto-regressive term to account for the temporal dependency in herd size. Our focal model for participant i in year t is as follows:

$$y_{it} = \beta_0 + \beta_1 T_i + \beta_2 r_i + \beta_3 T_i r_i + \beta_4 y_{i,t-1} + \gamma_i + \epsilon_{it} \tag{2}$$

where y_{it} is herd size of participant i in year t, T_i is a dummy variable for the insurance treatment, r_i is the coefficient for risk aversion, γ_i is the random effects. The model is evaluated for years 3 through 10 for the Ranchers study (removing the untreated baseline years) and years 1 through 9 for the MTurkers study.

We analyze hay purchases (H2) with the following model with the cluster robust errors:

$$h_{it} = \eta_0 + \eta_1 T_i + \eta_2 r_i + \eta_3 T_i r_i + \eta_4 y_{it} + \delta_t + \gamma_i + \epsilon_{it} \tag{3}$$

including year fixed effects, δ_t, to account for variations in rainfall, and herd size to account for hay demand per cow. In the Ranchers study, we leveraged the first two untreated years by calculating mean hay purchases for each participant and subtracting the mean from subsequent annual purchases.

To estimate the impact of the insurance treatment on the willingness to purchase rain-index insurance, we analyze two models with data from the Ranchers study: one with in-game purchases in the final two years and one with the reported likelihoods of purchasing PRF insurance for the participant's real-world ranch. In addition to the single-variate logistic regression of the treatment on insurance purchases, we also include models with the coefficient of risk aversion and an interaction term. Similarly, we use a logistic regression model of treatment, risk aversion, and an interaction term on a standardized Likert measure $(\mu = 0, \sigma = 1)$ of the reported likelihood of purchasing PRF insurance in the following year.

Finally, we estimate the effect of the insurance treatment and risk aversion on net worth, κ_t, by regressing the treatment dummy, risk aversion coefficient, and an interaction term on the net worth and net worth after subtracting the net transfer gained directly from the insurance program in an OLS model.

RESULTS

Herd size

One of the hypotheses of this study was that the presence of the insurance policy would lead to increased herd sizes (H1), an indication of moral hazard. Neither experiment found support for this hypothesis (Table 1, MTurkers 95% CI: [−0.636, 3.473], Ranchers 95% CI: [−0.581, 0.084]). Adding risk aversion to the model with and without an interaction term leaves the treatment effects largely unchanged and resulted in no significant relationships between herd size, treatment, and risk aversion. The MTurkers study had large variation in herd size between participants and over time with some participants attempting extreme herd building or herd liquidating strategies that were not profit-maximizing ($\bar{y} = 594.21$, $\sigma_y = 56.20$, $y \in [300, 1091]$). The Ranchers study, on the other hand, was marked by a close adherence to the recommended herd size of 600 cattle ($\bar{y} = 599.37$, $\sigma_y = 6.47$, $y \in [492, 616]$).

Overall, herd size was not systematically related to any of the variables under study. While caution must be taken in extrapolating these results to real-world ranching practices, within these simulations, the null findings for H1 indicate rain-index insurance is not creating a moral hazard for grazing intensity.

Hay purchase

The second hypothesis in this study was that the presence of insurance would decrease the investment in supplemental feed (H2). We did not find support for this hypothesis in either study, further indicating that in the context of the experimental game, the rain-index insurance does not create a moral hazard for drought adaptation (Table 2). Hay purchases in the insurance treatment were not significantly different from zero when regressing only the treatment and year dummies on hay purchase (MTurkers 95% CI: [−0.671, 3.471]; Ranchers 95% CI: [−0.946, 2.666]). The average effect of the insurance treatment remains indistinguishable from zero after adding covariates for risk aversion with and without an interaction with the treatment dummy (MTurkers 95% CI: [−9.534, 1.375]; Ranchers: 95% CI: [−3.575, 0.646]).

Overall, those with high levels of risk aversion buy less hay than those with lower levels of risk aversion, though the effect is not statistically significant (MTurkers 95% CI: [−6.525, 0.231]; Ranchers 95% CI: [−5.554, 1.791]). However, risk aversion played a strong role in the response to the treatment (Figure 2). Those with relatively high levels of risk aversion buy substantially more hay when they are in the insurance treatment group than when they are in the control group (MTurkers 95% CI: [0.892, 10.982]; Ranchers: 95% CI: [0.238, 21.464]). With an average annual hay purchase of $34,661 in the ranching study, ranchers with a high level of risk aversion in the insurance treatment purchased $8005 more than the average participant.

Those in the insurance treatment earn a positive net transfer from the insurance program, so we test to see if the relationship between the treatment and risk aversion is robust to the inclusion of cash assets at the point of hay purchase. The general pattern holds (MTurkers 95% CI: [0.952, 12.619]; Ranchers 95% CI: [−0.614, 16.697]). The cash assets available at the time of purchase have a small, but negative relationship with hay purchases in both studies, in all model specifications.

The strong response of risk-averse participants to the rain-index treatment offers insight into how the insurance may affect drought management behavior. Timely investments in drought

TABLE 1 Herd size with insurance treatment and risk aversion interactions

	(1)	(2)	(3)	(4)	(5)	(6)
Insurance	1.418	−0.248	1.026	−0.283	0.023	−0.158
	(1.048)	(0.170)	(1.018)	(0.184)	(1.969)	(0.130)
Coef. risk aversion			−0.788	−0.330	−1.201	−0.145
			(1.068)	(0.180)	(1.418)	(0.102)
Risk Aversion × Insurance					1.038	−0.531
					(2.122)	(0.531)
Prior Year Herd Size	0.920***	0.948***	0.914***	0.947***	0.914***	0.946***
	(0.026)	(0.016)	(0.031)	(0.016)	(0.031)	(0.016)
Constant	44.557**	31.451**	49.370**	31.883***	49.918**	32.196***
	(15.352)	(9.695)	(18.521)	(9.598)	(18.710)	(9.525)
Study Population	MTurkers	Ranchers	MTurkers	Ranchers	MTurkers	Ranchers
Observations	3951	784	3681	768	3681	768
Participants	439	98	409	96	409	96
Overall R^2	0.649	0.854	0.637	0.854	0.637	0.854

Note: Auto-regressive random-effects model of herd size with errors clustered at the participant-level. Robust standard errors are in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE 2 Annual drought adaptation investment (supplemental hay) with insurance treatment and risk aversion interactions

	(1)	(2)	(3)	(4)	(5)	(6)
Insurance	1.400	0.860	1.658	1.111	−4.080	−1.465
	(1.057)	(0.921)	(1.045)	(1.067)	(2.783)	(1.077)
Coef. risk aversion			−0.787	2.412	−3.147	−1.381
			(1.355)	(2.674)	(1.724)	(1.619)
Risk aversion × insurance					5.937*	10.851*
					(2.574)	(5.415)
Herd size	0.130***	0.082**	0.141***	0.084**	0.140***	0.085**
	(0.011)	(0.028)	(0.011)	(0.029)	(0.011)	(0.033)
Study population	MTurkers	Ranchers	MTurkers	Ranchers	MTurkers	Ranchers
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Baseline demeaned	No	Yes	No	Yes	No	Yes
Observations	3951	784	3681	768	3681	768
Participants	439	98	409	96	409	96
Overall R^2	0.685	0.926	0.710	0.925	0.711	0.928

Note: Random effects GLS model of herd size with errors clustered at the participant-level and year fixed effects. Robust standard errors are in parentheses. Baseline demeaned indicates that an untreated baseline of hay purchasing behavior for years 1 and 2 was averaged and subtracted from purchases in treated and comparison years (years 3–10). Annual hay purchase is the dependent variable and is in units of $1000's. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

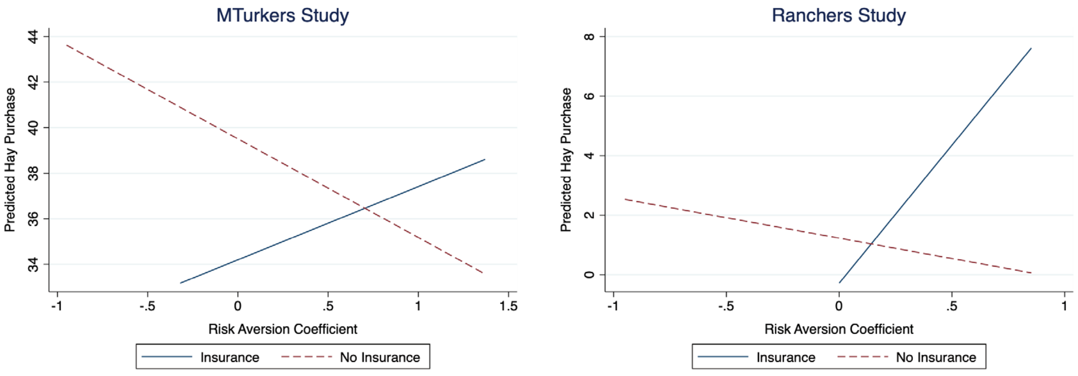

FIGURE 2 Interaction effect of insurance and risk aversion on drought risk mitigation investment

adaptation are critical to risk management, but they also hold an inherent risk of low return as the investments often must be made before it is clear whether rain will come and render those investments unnecessary (Shrum, Travis, Williams, & Lih, 2018). The risk averse may be especially hesitant to make investments that are irreversible like hay purchase, since excess hay does not carry over from year to year (in the real-world excess hay might be stored, though it loses nutritional value and most ranchers do not count on it as future feed). Theory predicts a decrease in investment, but we saw the opposite. It may be that risk-averse ranchers are behaving as if they are capital constrained and responding to the rain-index insurance as both an insurance mechanism and a cash grant (which, given the net transfer of income due to the subsidy, is accurate). In that case, if those who are risk averse perceive themselves to be cash constrained, then the subsidized insurance program may lead them to increase their investment in drought adaptation measures. For those who are not risk averse, we see the treatment effect of insurance trending in the direction predicted by the Karlan model even though the effect falls short of statistical significance.

Rain-index insurance purchase decisions

In the ranchers study, we provide the opportunity to opt-in to the rain-index insurance in the final two years of the simulation after requiring insurance for the treatment group and not offering it to the control group to test how experience with rain-index insurance affects demand for rain-index insurance. In the first year, it is offered as an opt-in, participants in the treatment group are nearly nine times more likely to purchase rain-index insurance (Odds Ratio = 8.944, 95% CI: [1.909,41.908]). In the second year, it is offered, participants in the treatment group are nearly twenty times more likely to purchase insurance than those in the control group (Odds Ratio = 19.593, 95% CI: [4.281,89.674]). Surprisingly, those with higher levels of risk aversion are no more or less likely to purchase rain-index insurance when it is offered in the simulation in either year. The null result is robust to the inclusion of the treatment dummy and an interaction term between risk aversion and treatment as well as a specification with only the risk aversion coefficient included (Table 3).

After the simulation, we asked how likely the Rancher participants were to buy PRF rain-index insurance in the following year for their actual ranch (Table 4). Focusing on the model with the risk aversion and treatment interaction term, those in the treatment group reported an increased likelihood of purchasing rain-index insurance for their ranch (95% CI: [0.261, 1.026]). We also find that those with higher levels of risk aversion reported a higher likelihood of purchasing PRF insurance (95% CI: [0.347, 1.997]). However, these increases in purchase intentions were not multiplicative for those with high levels of risk aversion in the treatment group. The negative coefficient on the interaction term (95% CI: [−0.961, −0.151]) cancels out the increase in likelihood from being in the treatment, leaving them with a total likelihood similar to those with high levels of risk aversion in the control group. Essentially, those with higher levels of risk aversion report very strong intentions to purchase PRF insurance in the following year, and the strength of those intentions do not differ between the treatment and control groups. For those with lower levels of risk aversion, going through the simulation in the treatment group increases their likelihood to buy PRF insurance compared to those with lower levels of risk aversion in the control group.

Net worth

Without accounting for the net transfer from the insurance program, on average, the insurance treatment led to a higher net worth in the simulation compared to the no insurance treatment in both studies (Table 5; MTurkers 95% CI: [$50,527, $97,645], Ranchers 95% CI: [$16,981, $50,806]). We focus the results on year 8 of the simulation to exclude years where insurance was optional for the Ranchers study.

The higher differential benefit of the insurance treatment in the MTurkers study is partly due to different insurance payouts. MTurkers in the treatment group have 8 years of insurance for a net gain of $73,869 as total payouts exceeded total premiums for this period for a net gain of $48,881. In both the studies, after subtracting the net transfer from the insurance program, the insurance treatment leads to insignificant differences between net worth in the treatment and control groups (MTurkers 95% CI: [−$55,083, $33,550]; Ranchers 95% CI: [−$9002, $33,871]). In the MTurkers study, risk aversion does not correlate with net worth, with or

TABLE 3 Simulation opt-in insurance purchase with insurance treatment and risk aversion interactions

	(1) Year 9	(2) Year 10	(3) Year 9	(4) Year 10	(5) Year 9	(6) Year 10
Insurance treatment	2.191**	2.975***	2.166**	3.098***	3.102*	4.321***
	(0.788)	(0.776)	(0.793)	(0.789)	(1.335)	(1.334)
Coef. risk aversion			−0.362	0.963	0.012	1.448
			(0.968)	(0.912)	(0.987)	(1.013)
Risk aversion × treatment					−3.039	−4.475
					(2.785)	(2.795)
Constant	0.944**	0.160	1.026*	−0.161	0.913*	−0.307
	(0.315)	(0.284)	(0.437)	(0.397)	(0.429)	(0.424)
Observations	98	98	96	96	96	96
Pseudo R^2	0.130	0.231	0.133	0.245	0.146	0.267

Note: Logistic regression of insurance purchase when it is available and optional for all participants in the final two years of the simulation. This study design was only available for the Ranchers study population. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE 4 Real-world intentions to purchase PRF insurance with insurance treatment and risk aversion interactions

	(1) likelihoodPRF	(2) likelihoodPRF	(3) likelihoodPRF
Insurance	0.626**	0.683***	0.644***
	(0.061)	(0.062)	(0.060)
Coef. risk aversion		0.502	1.172**
		(0.108)	(0.129)
trtXrisk			−0.556**
			(0.063)
Constant	−0.307***	−0.465***	−0.662***
	(0.042)	(0.053)	(0.056)
Observations	980	960	960
Adj. R^2	0.089	0.101	0.159

Note: OLS regression of the standardized reported likelihood of purchasing PRF insurance for the participant's own ranching operation. Standard errors in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

without a treatment interaction term. However, in the Ranchers study, including the risk aversion coefficient and an interaction term indicates that risk-averse participants in the insurance treatment group make substantially lower profits than risk-averse participants in the control group (95% CI: [−\$179,852, −\$61,524]). Taking the coefficient estimates together, the model predicts that those with high-risk aversion in the treatment group have \$59,373 less in net worth by the end of the 8th year of the simulation than those with high-risk aversion in the control group which appears to be driven by over-investment in supplemental feed (Table 2).

DISCUSSION AND CONCLUSIONS

This paper presents the DRIR-R model, a new ranching decision model that includes the USDA PRF rain-index insurance. DRIR-R is a coupled natural-human systems dynamic optimization model of cow-calf production on a northeastern Colorado range. Using the DRIR-R model, we built a user interface that allows us to run randomized control experiments that put real people instead of optimization criteria in the role as decision-makers. We ran two studies with this model, one with a non-ranching population recruited from Amazon MTurk and one with a population of professional cattle ranchers. The experiments tested two primary hypotheses:

The availability of rain-index insurance leads to increases in the average size of cattle herds because the expected return on investment in cattle production will increase when drought risk is mitigated.

The availability of rain-index insurance will decrease investment in (i.e., crowd-out) other drought adaptation strategies because insurance serves as a substitute.

H1 was definitively rejected. Insurance had no impact on average herd size in either study. Because rain-index insurance pays based on the acreage instead of the herd size, any production intensification driven by the insurance mechanism may manifest as an increase in the number

TABLE 5 Simulation net worth with insurance treatment and risk aversion interactions

	(1)	(2)	(3)	(4)	(5)	(6)
Insurance	71.706***	33.893***	68.046***	32.653***	63.102**	61.315***
	(9.919)	(8.520)	(9.236)	(8.801)	(22.543)	(10.793)
Coef. risk aversion			−9.707	−10.494	−11.738	31.701
			(10.395)	(15.337)	(13.404)	(17.614)
Risk aversion × insurance					5.114	−120.688***
					(21.269)	(29.789)
Constant	641.674***	876.923***	659.086***	879.722***	660.990***	867.291***
	(6.828)	(5.963)	(11.657)	(7.580)	(14.103)	(7.661)
Study population	MTurkers	Ranchers	MTurkers	Ranchers	MTurkers	Ranchers
Observations	439	98	409	96	409	96
Adj. R^2	0.105	0.133	0.114	0.123	0.112	0.248

Note: OLS regression of simulation net worth in year 8 on treatment, risk aversion, and an interaction term. Net worth is in USD 1000's. Standard errors in parentheses. $^{**}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

of acres under grazing rather than an increasing intensity of those acres. From a drought management perspective, this supports the idea that the rain-index insurance policy limits moral hazards in such a way that reduces the likelihood of overgrazing that could intensify drought stress. It remains to be seen, however, whether an overall increase in land in grazing could occur and whether that might drive marginally suitable lands into grazing rotations. Use-change on private lands is poorly tracked, but changing lease arrangements and formal programs like the Conservation Reserve Program have affected the land area utilized for grazing; the most recent Natural Resources Inventory (U.S. Department of Agriculture, 2020) showed almost 3 million acres moving to pasture on release from the CRP between 2012 and 2017, so the land for grazing expansion is available. It is also feasible that drought risk aversion affects the insurance strike level chosen by policyholders (we use 90% of average precipitation in the online experiment); lower strike levels incur less premium because they are less likely to be reached and pay an indemnity. But our study cannot assess whether costs or risk perception affect chosen strike levels. Moreover, because the PRF rain-index insurance program offers subsidized premiums, it may not only affect chosen strike levels but encourage entry into the cow-calf production market, discourage exit, and lead to an expansion of cattle ranching. The impact of the PRF program on the number of cattle ranchers or the number of acres grazed, rather than the intensity of the grazing on a ranch with a static size run by an individual rancher, is outside the scope of this study. However, these are important questions to resolve to understand the full impact of the PRF insurance on the production levels of the ranching industry as a whole.

H2 defined narrowly, was also rejected. On average, the insurance treatment did not affect investment in hay as a drought adaptation. However, we found important relationships between the level of risk aversion of the ranch manager, the rain-index insurance, and investment in supplemental feed. Decision-makers who exhibited higher levels of risk aversion in a lottery choice exercise (Holt & Laury, 2002) responded differently to the insurance treatment than those with lower levels of risk aversion. Those who were more risk averse responded to the insurance treatment and increased their investment in supplemental feed. It appears that the risk-averse ranchers are behaving as if they were credit constrained and the PRF insurance is treated as expected future revenue that allows them to increase investment in supplemental feed, as a hedging input.

In addition to these theory-driven hypotheses, we also used the study data to examine how the simulation affected demand for rain-index insurance within the game and intentions to purchase PRF insurance in the real-world. Study participants in the insurance treatment report higher intentions of buying PRF insurance for their ranching operation. Additionally, those with high levels of risk aversion also report higher intentions to buy PRF insurance, confirming a recent finding on PRF purchase decisions (Davidson & Goodrich, 2021).

This study is the first to address the question of whether rain-index insurance, designed in this experiment to imitate the PRF program, affects ranching production decisions. Overall, these findings can be taken as preliminary evidence that rain-index insurance is successful as a drought management tool for ranching, at least when it is used to cover the months of rainfall that matter most for forage production (the scenario studied in this experiment). We find no evidence of maladaptive moral hazard, although there is some evidence that highly risk-averse ranchers over-invest in adaptation measures when they have rain-index insurance. This study is, of course, not the first to observe deviations from rational economic models, or what one study of weather risk management among agriculturalists called "hazy hedging" (Findlater, Satterfield, & Kandlikar, 2019), where farmers satisfice rather than optimize, express different risk aversion to different levels of uncertainty, and deploy multiple risk management strategies, some of which reduce the expected value of others.

Observing behavior in a simulation has many advantages, namely controlling for the many variables that could affect decisions and fully observing decision-making choices and outcomes. Simulation, of course, has limitations. While participant behavior has been observed to correlate strongly with actual real-world behavior in other simulations, especially when the decisions are incentive-compatible, there is no guarantee that this will always be the case. Through the use of a non-expert and expert population, we demonstrate that while experimental simulations can provide useful insights into decision-making, there may be limits to using study populations without expertise relevant to the decision context, especially when the experimental simulations are complex. Comparisons between the general public and specialized populations (e.g., Clark et al., 2020) will help clarify the boundaries on how to design and implement experimental studies in applied research.

Moreover, even though the DRIR-R model was developed with guidance and feedback from rangeland and ranching experts as well as ranchers, the simplifying assumptions, parameter values, and limits on drought adaptation options could limit the value of simulation-based findings. While additional research questions can be addressed using the open-source DRIR-R model, ideally this work will also be followed by the analysis of empirical data as it accumulates to assess how this new, widespread drought risk management tool may impact critical ranching production decisions on the ground.

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DATA AVAILABILITY STATEMENT

The data and analytical code used in this work are publicly available at https://github.com/tshrum/rain-index-insurance-simulation

ENDNOTES

[1] See Appendix S1 for detailed demographic information broken down by treatment group.

[2] The DRIR-R simulation can be found and played online at https://earthlab.shinyapps.io/public_drought_decision_model/

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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