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Enrollment in Pasture, Rangeland, and Forage Rainfall Index Insurance: Awareness Matters

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Relatively little is known about producers' decisions to enroll in the Pasture, Rangeland and Forage Rainfall Index insurance (PRF-RI) program. Analyzing survey data from producers in the northeastern and southeastern United States, we show that assuming producers are aware of crop insurance options leads to false inferences about enrollment decisions. Full-time producers with more reliance on rented hay and pastureland and those who learned about PRF-RI from a crop insurance agent were more likely to enroll in PRF-RI. Livestock Revenue Insurance was found to be a complementary product to PRF-RI. Our study highlights the importance of targeted PRF-RI information campaigns.

Key words: cooperative extension, federal crop insurance program, hay production, livestock production, new insurance programs, risk exposure, risk management, risk preferences

Introduction

Pasture, Rangeland and Forage Rainfall Index insurance (PRF-RI) is a relatively new United States (U.S.) Federal Crop Insurance Corporation (FCIC) product that insures livestock and forage producers against low rainfall events. PRF-RI was introduced as a pilot program in 2007 and made available in all 48 contiguous states in 2016. The introduction of PRF-RI coincides with introductions of forage index insurance products in other countries, e.g., Canada and Spain, to mitigate the difficulties of measuring and, therefore, insuring grassland yields. Even though PRF-RI is highly subsidized and few other federal livestock insurance options are available, enrollment is much lower than other traditional crop insurance programs. In 2021, only 45% of eligible acreage in the U.S. was enrolled in PRF-RI, compared with 80-90% participation in traditional crop insurance programs (U.S. Department of Agriculture (USDA) Risk Management Agency (RMA), 2017, 2022; USDA National Agricultural Statistics Service (USDA NASS), 2017).

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PRF-RI is an index insurance product, i.e., indemnity payments are based on a calculated rainfall index rather than a producer's measured forage yields. A producer purchasing PRF-RI is subject to basis risk, or the risk that index measurements are imperfectly correlated with the producer's forage yields.[1] Several recent studies have explored issues with PRF-RI policy design such as quantifying the levels of basis risk in certain areas (Maples et al. 2016; Yu et al., 2019; Keeler and Saitone, 2022), how theoretical framing of the PRF-RI decision (e.g., profit maximization versus risk minimization) might affect specific PRF-RI policy decisions (Westerhold et al., 2018; Goodrich et al., 2020; Cho and Brorsen, 2021; Zapata and Garcia, 2022), and how the availability of PRF-RI might impact decisions to invest in production and drought risk management (Shrum and Travis, 2022).

Coble et al. (2020) conducted a review of PRF-RI and suggested policy changes such as restricting the time periods producers can insure, targeting viable forage producing areas, and increasing livestock and forage producer education. However, to our knowledge, relatively little is known about what influences participation in PRF-RI. Identifying factors that impact producers' enrollment decisions would ensure that changes to PRF-RI more effectively align with program objectives. This paper aims to determine how factors such as risk exposure, risk preferences, information and farm characteristics are related to a producer's decision to enroll in PRF-RI. We analyze survey data collected from roughly 250 livestock and forage producers in the northeastern and southeastern U.S. Only 48 percent of our sample was familiar with PRF-RI prior to this study, suggesting a primary limiting factor on the decision to enroll in PRF-RI is simply lack of awareness of the program. Thus, we utilize a sample selection model to first establish the factors related to whether a producer knows about PRF-RI and then we indicate the factors that relate to enrollment decisions given that he/she is aware of the program.

Common factors found to be associated with crop insurance enrollment decisions are the level of risk exposure, risk preferences, information dispersion through own and neighbors' prior experience with insurance, and other farm and operator characteristics (See for example, Sherrick et al., 2004; Jin et al., 2016, Santeramo, 2019; among others). For index insurance products like PRF-RI, increased basis risk has been shown to decrease enrollment (Elabed et al. 2013; Clarke, 2016). Roznik et al. (2019) explore factors affecting participation decisions in Canadian forage index insurance program and determine that lower feed reserves, higher perceived drought and weather risks, higher knowledge of crop insurance programs and younger farmers were more likely to purchase forage insurance. Specific to PRF-RI, we are aware of only one other study that offers some discussion of factors associated with the producer's decision to enroll. Davidson and Goodrich (2023) find modest evidence that a behavioral nudge framing PRF-RI as a risk management tool increases the likelihood that a producer enrolls in the program. The authors provide evidence that some measures of risk exposure and risk preferences are related to the enrollment decision, however the study relies on hypothetical choice data. Our current study expands on this topic, evaluating factors related to actual enrollment decisions and leveraging information about producer awareness of the program using simultaneously estimated sample selection methods.

The prior literature on the U.S. Federal Crop Insurance Program (FCIP) and Roznik et al. (2019) have assumed that producers are aware of the insurance products available to them. This assumption is likely accurate for traditional crops given the historical prevalence of crop insurance for traditional crops, but less likely for forage insurance products which have been introduced more recently. Our findings show that it is important for relatively new insurance products to consider producer awareness of the program in addition to the commonly identified factors that influence participation. For example, when awareness of PRF-RI is not accounted for, we find that if the participant has had a catastrophic forage loss and collected a payment from the Livestock Forage Disaster Program (LFP) in the last ten years, they are more likely to enroll in

[1] See Benami et al. (2021) for full discussion of the economic implications of false negatives and false positives in index insurance.

PRF-RI. However, when estimating the awareness and enrollment equations simultaneously, we find collecting a payment from LFP makes the producer more likely to be aware of PRF-RI, but has no relationship with whether or not the producer enrolls in PRF-RI. Without information on awareness, we would associate catastrophic forage losses with an increased demand for PRF-RI. Thus, some of the findings of Roznik et al. may be driven by lack of awareness of the relatively new forage insurance products in Canada (Vroege et al., 2019).

Our results show that farms with more hay and pasture acreage are more likely to be aware of PRF-RI, but are less likely to enroll. This contradicts previous studies that find that larger operations are more likely to purchase insurance (Coble et al., 1996; Jose and Valluru, 1997; and Sherrick et al., 2004). Though notably, each of the previous studies covers insurance demand for crop production not livestock. Operating more acreage as an input for livestock production may indicate more wealth, and as such more wealth can mean a higher risk-bearing capacity (Sherrick et al., 2004). We do not discover a relationship between the PRF-RI enrollment decision and a proxy for spatial basis risk.[2]

Our findings also have important implications for PRF-RI outreach. We find producers without prior access to a crop insurance agent are less likely to be aware of the program. Producers in the Southeast are more likely to be aware of PRF-RI than their Northeastern counterparts despite the product being available since 2011 in the Northeast and 2012 in the Southeast.[3] Thus, targeting information campaigns in the Northeast region and toward livestock producers without prior interactions with crop insurance agents may lead to higher awareness and enrollment in the program.

PRF-RI Background

PRF-RI is an area-based rainfall index insurance product, so rather than measuring farm-level forage production and losses, the product is based on a rainfall index calculated using the grid system developed by the National Oceanic and Atmospheric Administration Climate Prediction Center (NOAA CPC) data. Acreage is assigned to one or more NOAA grids, which measure 0.25 degrees in latitude and 0.25 degrees in longitude (17 x 17 miles at the equator). For each grid, a rainfall index is calculated for each of the eleven two-month increments from January to December so that average historic rainfall equals 100 for each grid-interval, i.e., a grid-interval index equal to 90 indicates rainfall at 10% below the historical average. Producers select the period during the year to insure by placing a percentage of value of the policy into non-overlapping two-month intervals. Indemnities are triggered when the calculated rainfall index for a two-month interval and grid falls below the coverage level the producer selected; coverage level options range from 70 to 90 percent of average rainfall. The opportunity to buy-up coverage is one factor that differentiates PRF-RI from the USDA Farm Service Agency's Noninsured Crop Disaster Assistance Program (NAP) and Livestock Forage Disaster Program (LFP), for which livestock producers also qualify. To receive a NAP or LFP indemnity, catastrophic levels of loss must occur to yield or inventory due to natural disasters. Rather than catastrophic coverage, PRF-RI covers losses that exceed 10 percent or more due to rainfall shortage, depending on the level of coverage selected.

Producers often learn about PRF-RI through a crop insurance agent or through USDA-funded risk management extension education programs. To enroll in PRF-RI, producers must make a

[2] We use average distance from the county centroid to four closest National Oceanic and Atmospheric Administration (NOAA) weather stations as a proxy for spatial basis risk.

[3] 80% of the Southeast sample came from the states of Alabama, Georgia, and Florida. Alabama had access to PRF-RI in 2008, Florida and Georgia received access to PRF-RI in 2012 (USDA RMA, 2018). 84% of the Northeast sample came from New York and Pennsylvania, in which select counties had access to PRF-RI beginning in 2007 (Pennsylvania), 2010 (New York), and all counties gained access in 2011 (USDA RMA, 2018).

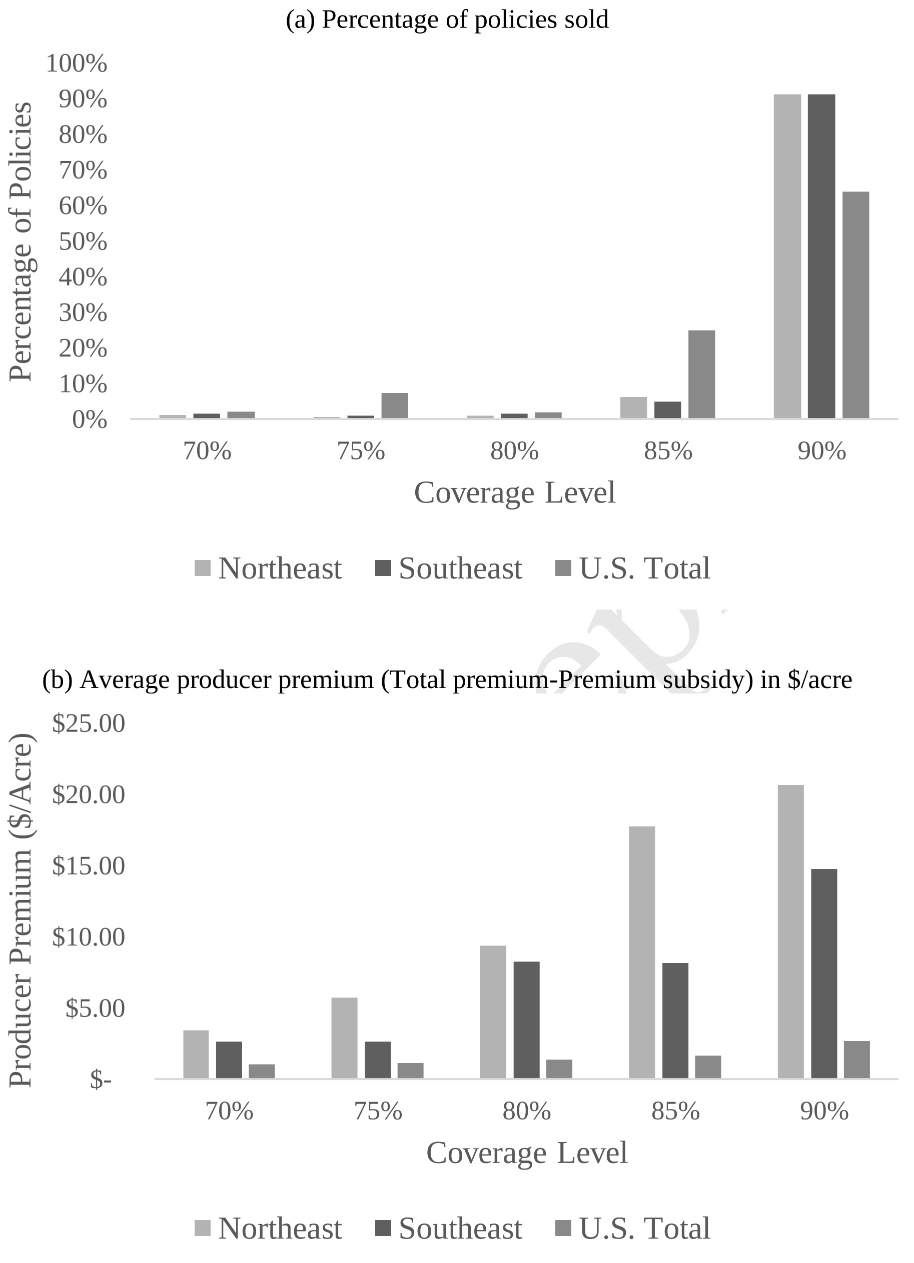

Figure 1 PRF-RI policy information by coverage level and region, 2020
Notes: Source: USDA RMA Summary of Business Data , 2020
Southeast states: AL, FL, GA, KY, MS, NC, SC, TN, VA
Northeast states: CT, DE, MA, MD, NY, OH, PA, RI, VT

series of decisions including type of forage production to insure (grazing or hay production), the number of acres to enroll, coverage level, irrigation practice, productivity factor, the two-month intervals to enroll, and the percent-of-value to assign in each interval. Premiums are calculated separately for each two-month interval to account for variability in rainfall during that period. Like other federal crop insurance policies, PRF-RI premiums are set by the FCIC. PRF-RI premiums are subsidized by the U.S. government, with subsidy levels varying based on the selected coverage level selected.[4] Producers must purchase their PRF-RI insurance policy through a certified crop insurance agent.

Figure 1 shows the distribution of participants across coverage levels (panel a) and average premiums paid per acre (panel b) for the Northeast, Southeast and entire U.S. for the 2020 crop year. Most producers throughout the U.S. enroll in higher coverage levels of 85% and 90%, despite the higher premiums per acre. In the Northeast and Southeast, over 90% of policies are sold at the highest coverage level of 90%. The Northeast and Southeast tend to pay higher premiums per acre than the rest of the U.S. due to regional differences in the value of forage acreage and/or variability in rainfall patterns.

Empirical Methodology

Following Smith and Baquet (1996), we assume a producer's insurance participation decision takes place in two steps 1) deciding whether or not to enroll in insurance and 2) specific policy decisions (coverage level, two-month intervals to insure, etc.). In this paper, we explore characteristics associated with the enrollment decision, and leave analysis of factors associated with the more specific policy decisions to future work. We model the PRF-RI enrollment decision as a Heckman-style sample selection problem using nonlinear methods outlined in Greene (2008). This model is most appropriate because of the omitted behavior that arises in our dataset, i.e., a person who is not aware of PRF-RI cannot decide whether or not to enroll in PRF-RI. Thus, the first equation represents whether the participant had prior knowledge of PRF-RI, and the second equation represents whether the participant enrolled in PRF-RI in a prior year given they had knowledge of the program.

The model takes the form:

$$Y^* = \boldsymbol{X\beta} + \epsilon \tag{1}$$

$$Y = \begin{cases} 1 \; when \; Y^* > 0 \\ 0 \; when \; Y^* < 0 \end{cases} \tag{2}$$

$$E^* = \boldsymbol{X_1\beta_1} + \mu \tag{3}$$

$$E = \begin{cases} 1 \; when \; E^* > 0 \\ 0 \; when \; E^* < 0 \end{cases} \tag{4}$$

where Y* is a latent variable for awareness of PRF-RI, and E* represents the enrollment decision, which is only observed if the participant had prior knowledge of PRF-RI (Y=1). ϵ and μ are error terms; ϵ is assumed to be distributed normally with mean zero and standard deviation one and $E[\mu|\epsilon] = \gamma\epsilon$. The independent variables, **X**, in (1) include those likely to be correlated with producer awareness of PRF-RI. The independent variables, $\mathbf{X_1}$, in (3) include those likely to be related to the enrollment decision. We use the *stats* and *MASS* packages in R to estimate the probit models of awareness and the enrollment decision. We use the *sampleSelection* package in R to simultaneously estimate the selection and outcome equations using maximum likelihood estimation (Toomet and Henningsen, 2008).

We combine results from Davidson and Goodrich and Roznik et al. with previous literature on demand for other crop insurance products to inform our hypotheses about the factors that may be related to actual PRF-RI enrollment decisions. Variable and expected coefficient signs are defined and outlined in Table 1 and discussed in the following paragraphs. Variables were collected through a survey instrument and are divided into the broad categories of factors related

[4] 70% and 75% coverage levels receive a 59% premium subsidy, 80% and 85% receive a 55% premium subsidy and 90% receives a 51% premium subsidy.

Table *1* PRF-RI Survey Data Variable Descriptions and Expected Relationship of Variables to Awareness of and Enrollment in PRF-RI

		Expected Relationship with	
Variable	**Values**	**Awareness (X in eq. 1)**	**Enrollment (X_1 in eq. 3)**
Aware of PRF-RI	Indicator variable equal to 1 if the participant had heard about PRF-RI prior to the survey and 0 otherwise		
Enrolled in PRF-RI	Indicator variable equal to 1 if the participant had enrolled in PRF-RI in previous years and 0 otherwise		
Risk Exposure			
Proportion Livestock	Proportion calculated as the sum of the proportion of total farm income from livestock and the proportion of total farm income from hay	+	+
Proportion Hay Sold	Proportion calculated as the amount of hay sold divided by the sum of hay produced and hay purchased		-
Livestock Margin Insurance	Indicator variable equal to 1 if the participant had enrolled within the last 10 years in Livestock Gross Margin Insurance (LGM) or Margin Protection Program for Dairy (MPP-Dairy) and 0 otherwise		-
Livestock Revenue Insurance	Indicator variable equal to 1 if the participant had enrolled within the last 10 years in Livestock Risk Protection (LRP) or Dairy Revenue Protection (Dairy-RP) and 0 otherwise		+
Rainfall Variability[a]	Variability measured as the maximum standard deviation in rainfall in the participant's NOAA grid during the participant's stated month intervals that are important for rainfall for forage growth	+	+
County Base Value[a]	PRF-RI County base value in $/acre for dryland hay production in a participant's county		+/-
LFP	Indicator variable equal to 1 if the participant had utilized Livestock Forage Disaster Program (LFP) in the last 10 years and 0 otherwise	+	+/-
Acres	Continuous variable equal to the participant's total number of acres dedicated to pasture land and hay production	+	+
Rent Proportion	Proportion of hay and pastureland rented over total hay and pastureland		+
Fulltime	Indicator variable equal to 1 if the participant identifies as a full-time farmer and 0 otherwise	+	+
Avg Dist to 4 Closest WS	Average distance in kilometers between the participant's county centroid and the four closest NOAA CPC weather stations		-
Risk Preferences			

Risk aversion	Constant relative risk aversion (CRRA) measured through a risk elicitation exercise with real payouts following Akay et al. (2012), Eckel and Grossman (2008), and Holt and Laury (2002). CRRA values calculated by the certainty-equivalent mid-point value at which a participant decided to switch from the sure payoff to the lottery. Possible CRRA values: -0.4, -0.2, -0.1, -0.03, 0.03, 0.1, 0.17, 0.24, 0.3, and 0.4	+	+
OtherInsurance	Ordered categorical variable equal to -1 if the participant did not grow crops, 0 if the participant grew field or specialty crops but did not enroll in crop Yield or Revenue protection, and 1 if the participant grew crops and previously enrolled in crop Yield or Revenue protection.		+
Information Spillover Effects			
Crop Insurance Agent	Indicator variable equal to 1 if the participant already has a crop insurance agent that they work with, 0 otherwise	+	
Info Source	Indicator variable equal to 1 if the participant learned about PRF-RI from that source and 0 otherwise. Possible sources are: News/media, Friend/Family Member/Neighboring farmer, Extension agent, and Crop insurance agent		+
Prop County Enrolled[a]	Hay and grazing acreage enrolled in PRF-RI for 2019 from USDA Summary of Business data divided by 2017 USDA Agricultural Census values for total hay and pasture acreage	+	+
Farm and Operator Characteristics			
Age	Participant's age in years	**?**	
Male	Indicator variable equal to 1 if the participant identifies as male, and 0 otherwise	**?**	
Dairy	Indicator variable equal to 1 if the participant indicated they operate a dairy and 0 otherwise	**?**	**?**
Beef	Indicator variable equal to 1 if the participant indicated they have beef cows and 0 otherwise	**?**	**?**
Region: SE	Indicator variable equal to 1 if the participant is located in the Southeast, 0 otherwise. Southeast states: AL, FL, GA, KY, MS, NC, SC, TN, and VA Northeast states: MA, CT, DE, MD, NY, OH, PA, RI, and VT	**?**	**?**
Farm income	Integer ranging from 1 to 7 representing the participants' agricultural gross sales in 2018: (1) <\$5,000 (2) \$5,000-\$9,999 (3) \$10,000-\$24,999 (4) \$25,000-\$49,999 (5) \$50,000-\$99,999 (6) \$100,000-\$249,999 (7) >\$250,000	+	-

to crop insurance awareness and enrollment: the level of risk exposure, risk preferences, information dispersion through own and neighbors' prior experience with insurance, and other farm and operator characteristics.

Variables Related to Awareness of and Enrollment in PRF-RI

To date, most literature investigating crop insurance demand uses expected utility theory to explain participation decisions. Following the theoretical model outlined by Roznik et al. (2019), factors that influence the level of risk exposure and farmer risk preferences are likely to impact the demand for PRF-RI insurance. Additionally, more recent literature has investigated the role of knowledge spillover from neighboring farmers on crop insurance decisions (Santeramo, 2019). While cumulative prospect theory as defined by Tversky and Kahneman (1992) has also been proposed as a model potentially fitting producer crop insurance decisions better than expected utility theory (Babcock, 2015; Cao et al., 2019; Luckstead and Devadoss, 2019), our summary focuses on the expected utility theory literature covering the U.S. FCIP as these findings are most directly relevant to our analysis of PRF-RI.

To our knowledge, no prior literature has explored awareness of specific programs offered by the U.S. FCIP when investigating insurance uptake. Though it has been investigated in the context of crop insurance in developing countries, e.g., Mukherjee and Parthapratim (2019). We expect many of the same factors related to crop insurance enrollment will impact a producer's awareness of insurance through motivating efforts to seek information about insurance products. Many variables associated with the enrollment decision could also influence choices of the specific policy decisions. For example, Westerhold et al. (2018), Goodrich et al. (2020), Cho and Brorsen (2021) and Zapata and Garcia (2022) show theoretically that risk preferences can impact the preferred choices of two-month intervals to insure. In this paper, we only measure characteristics associated with the enrollment decision, and leave analysis of factors associated with the more specific policy decisions to future work.

Level of Risk Exposure

Producers with greater levels of risk exposure are expected to be more likely to purchase crop insurance than those with lower levels of risk exposure. With traditional crop insurance, Sherrick et al. (2004) determine that farmers with higher debt-to-asset ratios, who perceive higher levels of yield variability, and who lease more land are more likely to purchase yield, revenue or hail insurance. Coble et al. (1996) find that producers with greater market return risk are more likely to enroll in Multiple Peril Crop Insurance (MPCI). Smith and Baquet (1996) show that higher perceived yield variability, more debt, and receiving disaster relief payments in the past increase the likelihood a farmer will purchase MPCI. Jose and Valluru (1997) determine that producers with a majority of farm income from crop production were more likely to purchase crop insurance than their counterparts with a majority of income from livestock production. Jose and Valluru also find that participation in other farm programs increased the likelihood of insurance purchase.

Roznik et al. (2019) conclude that higher perceived drought and weather risks and lower feed reserves increase the likelihood a producer participates in Canadian forage index insurance. Similarly, Davidson and Goodrich (2023) find that a higher proportion of hay sold leads to a lower likelihood of a producer enrolling in PRF-RI as producers can reduce risk exposure by using hay inventory to feed livestock in the instance of drought. Davidson and Goodrich also show that a higher proportion of total farm income coming from livestock or hay production and collecting a disaster payment from USDA livestock disaster programs at least once in the last 10 years increases the likelihood a producer enrolls in PRF-RI.

Following the previous literature, we include the following variables to measure the level of risk exposure of the participant which could relate to the decision to enroll in PRF-RI: proportion of farm income from livestock production (*Proportion Livestock*), proportion of hay produced on-farm that is sold (*Proportion Hay Sold*), whether in the past they have purchased livestock revenue or margin insurance products offered by USDA (*Livestock Margin Insurance* and *Livestock Revenue Insurance*), a measure of rainfall variability during the growing season in their NOAA grid (*Rainfall Variability*), whether they have collected a payment from LFP in the last ten years (*LFP*), number of acres of hay and pasture (*Acres*), the proportion of hay and pasture acreage that is rented (*Rent Proportion)*, the base value USDA RMA uses for dryland hay production to calculate the value of protection in a participant's county (*County Base Value*), and whether they are a full-time farmer (*Fulltime*). *Proportion Livestock*, *Acres*, and *Fulltime* are expected to increase overall risk exposure, therefore increasing the likelihood a producer will enroll in PRF-RI. *Rainfall Variability* is calculated as the maximum standard deviation of rainfall across growing season month intervals, where important growing season months were indicated by the participant during the survey. Like the measures of risk exposure in Sherrick et al. (2004), Smith and Baquet (1996), and Roznik et al. (2019), we expect higher *Rainfall Variability* during the growing season to be associated with a higher demand for PRF-RI.[5] Collecting an LFP payment in the last 10 years could indicate more variability in rainfall in the area, and/or an expectation that future catastrophic droughts will occur. Thus, *LFP* is expected to increase the likelihood of insurance uptake. Following Roznik et al. (2019) and Davidson and Goodrich (2023), we expect *Proportion of Hay Sold* to be negatively related to the insurance enrollment decision. *Livestock Margin Insurance* insures producers against unfavorable revenue and input cost movements, and might be viewed as a substitute for PRF-RI, thus decreasing risk exposure and their need for PRF-RI. *Livestock Revenue Insurance* protects producers from downward movements in revenue, thus PRF-RI may be viewed as a complementary insurance product.

The sign on the relationship between the *County Base Value* and enrollment is ambiguous due to conflicting incentives between the level of risk exposure and the premiums producers must pay. *County Base Values* are calculated by USDA RMA based on hay yields collected by USDA NASS. A higher *County Base Value* indicates a more productive area in terms of forage production, which would increase the level of risk exposure due to low precipitation, presumably making enrollment in PRF-RI more attractive. However, higher *County Base Values* increase premiums, which may lead to lower demand (Cabas et al. 2008).

Basis risk, one major factor inhibiting the uptake of index insurance, can be divided into three main components: design, spatial and temporal risks (Dalhaus and Finger, 2016). Spatial basis risk is particularly important in PRF-RI given that the precipitation indices are determined using a weighted average of precipitation data from at least the four closest reporting weather stations (NOAA CPC, 2021), which may not accurately depict the precipitation at a specific farm (Ritter et al. 2014). Thus, we include a proxy for spatial basis risk (*Avg Dist to 4 Closest WS*) which is the average distance from the centroid of a producer's county to the four closest NOAA CPC Climate Assessment Database (CADBv2) weather stations (NOAA CPC, 2020).[6] The larger the average distance, the less accurate the index will be at measuring the rainfall for locations within

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[5] Westerhold et al. (2018), Goodrich et al. (2020), and Cho and Brorsen (2021) show theoretically that if a producer is not risk averse, profit maximization results in a producer selecting two-month intervals with the highest rainfall variability to maximize the PRF-RI subsidy. This could translate to the enrollment decision, in which non-risk-averse producers might be more likely to enroll in areas with high rainfall variability. Thus, we include an interaction between *Rainfall Variability* and *Risk Aversion.*

[6] The NOAA CPC CADBv2 weather stations list contains 2933 weather stations for the contiguous U.S. (NOAA CPC, 2020), whereas the daily CPC Gauge Analysis procedure that underlies the rainfall index used by PRF-RI uses data from 8,000-9,000 weather stations on average (NOAA CPC, 2021). This number varies as not all stations report daily. As far as we are aware, NOAA CPC does not release the locations of all weather stations used in the CPC Gauge Analysis, so we use the CADBv2 locations as a proxy for the CPC Gauge Analysis weather stations. This assumes that counties with fewer nearby CADBv2 weather stations, i.e., a larger average distance to the four closest weather stations, will also have a larger average distance to the four closest CPC Gauge Analysis stations.

that county, increasing the spatial basis risk and making PRF-RI less attractive. Design risk, or how well precipitation alone predicts forage yields, is difficult to measure given the lack of information on forage yields. We assume design risk will be similar across all producers in these regions, so the region indicator variable (*Region: SE*) will control for any region-specific design risk. Temporal risk, or the risk that the index insurance does not insure the right time frame when precipitation impacts forage growth, can be alleviated by the fact that producers select which two-month intervals to insure throughout the year. This flexibility means that temporal basis risk should not impact a producer's decision to enroll in PRF-RI.

With regards to awareness of PRF-RI, we expect that producers with higher risk exposure will be more likely to seek out information regarding insurance and other risk management options. Thus, we expect *Proportion Livestock, Acres, Fulltime, LFP,* and *Rainfall Variability* variables to be positively related to PRF-RI awareness.

Risk Preferences

Literature on the role of risk aversion in crop insurance decisions is mixed. Petrolia et al. (2013), Simon and Fiorentino (2014), Jin et al. (2016), and Menapace et al. (2016) determine that as risk aversion increases insurance enrollment is more likely, while Just et al. (1999) and Goodwin (1993) suggest that risk aversion has little impact on crop insurance decisions in the U.S. However, Sherrick et al. (2004) find participants with high stated preferences for the importance of risk management were more likely to be crop insurance users. Greene et al. (2022) find that ranchers in the western U.S. purchase PRF-RI as part of their drought risk management strategy, indicating that risk preferences may have an impact on the decision to enroll. Results from Davidson and Goodrich (2023) and Shrum and Travis (2022) both suggest a positive relationship between the level of risk aversion and the hypothetical decision to enroll in PRF-RI. While Roznik et al. (2019) do not explicitly investigate risk aversion, they determine that producers with a better attitude toward forage index insurance are more likely to enroll, perhaps implicitly relaying attitudes towards risk preferences.

All survey participants engaged in an incentive-compatible exercise to elicit their risk preferences (*Risk Aversion*). A screen shot of the risk elicitation exercise is available in the appendix (Figure A1). In this risk elicitation exercise, one in six participants was randomly selected to earn real cash. The exercise followed Holt and Laury (2002), Eckel and Grossman (2008), and Akay et al. (2012). As *Risk Aversion* increases, we expect that in accordance with expected utility theory, the likelihood of enrollment in PRF-RI to increase. We also include an ordered categorical variable to represent whether the participant has purchased yield or revenue protection for traditional or specialty crops when they have access to those insurance products (*Other Insurance*). This variable could indicate a preference for insurance, so we expect having *Other Insurance* will increase the likelihood of enrollment in PRF-RI.

Regarding the relationship between risk preferences and awareness of PRF-RI, we expect producers who are more averse to risk to be more likely to seek out information about insurance and other risk management options. We also expect an interaction between *Rainfall Variability* and *Risk Aversion*, e.g., a highly risk averse producer in a highly variable precipitation area may be more likely to seek out information than a highly risk averse producer in a less variable area.

Information Spillover Effects

Santeramo (2019) explores the effects of information and experience on crop insurance decisions in Italy. Santeramo shows that the more farmers in a region that have crop insurance, the more likely a participant will enroll in crop insurance, suggesting information spillovers from other farmers have an impact on individual decisions. Additionally, Santeramo finds that prior experience with crop insurance increases the likelihood that a farmer will enroll. Similarly, Roznik et al. (2019) determine that a higher stated knowledge of agricultural insurance was associated with higher forage insurance uptake.

Following Santeramo (2019), we expect the higher the proportion of the hay and pasture acreage in their county that was enrolled in PRF-RI in 2019 (*Prop County Enrolled*) the more likely the participant will be aware of and enroll in PRF-RI due to information spillover effects. Relatedly, if the participant has already worked with a crop insurance agent (*Crop Insurance Agent*) for other USDA livestock or crop insurance programs, we expect them to be more likely to be aware of PRF-RI. We asked participants where they had learned about PRF-RI. We expect learning about PRF-RI from a friend, family member, neighbor, a Cooperative Extension Agent, or a crop insurance agent will increase the likelihood that they enroll compared to hearing about it from some other source (e.g., news, farm journal, internet, etc.), though we do not have expectations for how these sources will relate to one another.

Farm Characteristics

Multiple studies find a positive association between total farm acreage and crop insurance uptake (Coble et al., 1996; Jose and Valluru, 1997; and Sherrick et al., 2004). Using another measure of farm size, Coble et al. determine that farm net worth was negatively associated with crop insurance uptake. They also find regional differences in enrollment, potentially due to climatic differences or information transfer as farmers in the area learn more about participation. Davidson and Goodrich (2023) show that compared with beef producers, hay and other livestock producers are more likely to enroll in PRF-RI in a hypothetical setting, though the finding that other livestock producers are likely to enroll may suffer from hypothetical bias.

Assuming gross farm sales are correlated with farm wealth, like Coble et al (1996), we expect that as gross farm sales increase (*Farm income*), the participant will be more likely to be aware of PRF-RI but less likely to enroll in PRF-RI. We include indicator variables for whether the participant's operation had dairy (*Dairy*) or beef (*Beef*) cows, and whether the participant's operation is in the Southeast (*Region: SE*). We do not have expectations on how livestock operation or regional differences will relate to awareness and the enrollment decision.

Operator Characteristics

It is not immediately clear how characteristics about the farm operator will influence crop insurance decisions, however they will certainly impact the perceptions and preferences regarding risk, as well as have an impact on awareness through social networks and education. Sherrick et al. (2004) determine age to be positively associated with enrollment decisions, while Jose and Valluru (1997) show no effect of age on enrollment. Rosenik et al. (2019) find younger producers were more likely to participate in forage index insurance. Jose and Valluru, Smith and Baquet (1996), Sherrick et al., and Roznik et al. show no effect of education level on the farmer's decision to enroll in crop insurance.

Because the prior research provides mixed results for the effect of age on other crop insurance demand (Sherrick et al. 2004; Jose and Valluru, 1997), there does not seem to be a significant relationship between age and insurance demand in either direction. Thus, we do not include the participant's *Age* as a control for PRF-RI enrollment, but we do include it as a control variable for awareness of PRF-RI. We also include an indicator for the participant's gender (*Male*) as a control variable in the awareness equation. Both age and gender control for different levels of awareness because of differences in social networks or ways of accessing information, but we do not have expectations regarding the sign on either coefficient.

Table 1 Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Aware of PRF	254	0.48	0.50	0	0	1	1
Risk Aversion	254	0.04	0.23	-0.40	-0.10	0.24	0.40
Acres (thousands)	254	0.26	0.38	0.002	0.06	0.30	3.56
Rent Proportion	254	0.31	0.34	0.00	0.00	0.59	1.00
Farm Income	254	3.70	1.92	1	2	5	7
Age	254	46.62	16.23	19	32	60	86
Male	254	0.85	0.36	0	1	1	1
Prop Livestock Income	254	0.73	0.35	0.00	0.46	1.00	1.00
Prop Hay Sold	254	0.24	0.33	0	0	0.4	1
Rainfall Variability	254	82.97	18.19	46.53	66.51	95.02	143.69
Crop Insurance Agent	254	0.30	0.46	0	0	1	1
Livestock Revenue Insur.	254	0.12	0.32	0	0	0	1
Livestock Margin Insur.	254	0.07	0.26	0	0	0	1
LFP	254	0.15	0.36	0	0	0	1
Fulltime	254	0.35	0.48	0	0	1	1
Other Insurance	254	-0.08	0.60	-1	0	0	1
Prop County Enrolled	254	0.04	0.11	0	0	0.1	1
County Base Value	254	312.30	85.65	159	257	380	500
Beef	254	0.76	0.43	0	1	1	1
Dairy	254	0.13	0.33	0	0	0	1
Region: SE	254	0.52	0.50	0	0	1	1
Avg Dist (km) to 4 Closest WS	254	38.77	10.79	15.69	32.35	44.98	71.82
Enrolled in PRF	121	0.17	0.38	0	0	0	1
Info Source: News	121	0.19	0.39	0	0	0	1
Info Source: Friends	121	0.15	0.36	0	0	0	1
Info Source: Extension	121	0.34	0.48	0	0	1	1
Info Source: Agent	121	0.33	0.47	0	0	1	1

Survey Data

We conducted a survey of livestock and hay producers by convenience sampling at regional farm shows in the southeastern and northeastern U.S. in October 2019 and February 2020, respectively.[7,8] Participants were at least 18 years of age and self-reported as being the primary

[7] These regions were selected based on their relatively low PRF-RI enrollment numbers. As seen in Table 3, Northeast and Southeast enrollment were 2.6% and 13.0%, respectively, compared to 31% of enrollment nationwide.

[8] This data comes from a survey that accompanied an economic experiment (Davidson and Goodrich, 2023). Recruiting agricultural producers for economic experiments is difficult, time-intensive, and costly and response rates are often low (Weigel et al., 2020). Convenience samples reduce the cost and time associated with data collection and have been shown to represent the general class of farms as well as randomly selected samples (Luschei et al., 2009). Limitations of convenience sampling are that bias may arise and results may

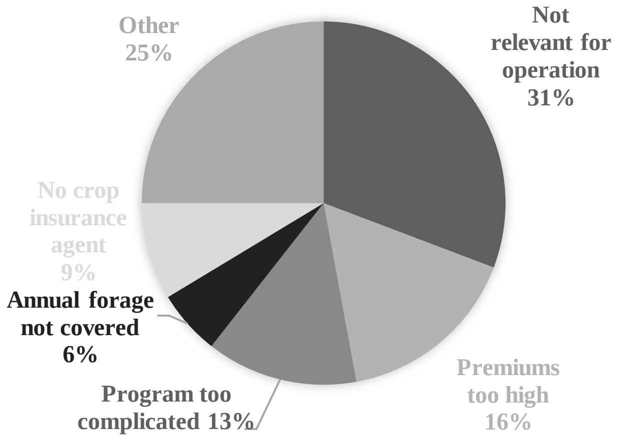

Figure 2. Percentage of participants who were aware of PRF-RI by stated reason for not enrolling (N=104)

decision-maker on their operation. The survey completion time was approximately 30 minutes and participants were compensated $20 with the potential to earn up to an additional $40 during the risk elicitation exercise.

Table 2 shows summary statistics for the survey data. The sample includes 133 farmers from the Southeast and 121 from the Northeast. On average, participants had 260 acres of hay and pasture, of which an average of 31% is rented. Livestock and hay production accounts for 73% of farm income on average, and 24% of hay produced is sold. The average participant coefficient of constant relative risk aversion (CRRA) is 0.04, indicating that participants are close to risk neutral, on average. Of those who were aware of PRF-RI, 17% had enrolled in PRF-RI in a prior year, 34% learned about it from Cooperative Extension, and 33% learned of it from a crop insurance agent. Less than 20% of those aware of PRF-RI learned about it from news/media or friends/family/neighboring farmers. 30% of the sample had already worked with a crop insurance agent in the past, 12% had purchased livestock revenue insurance, and 7% had purchased livestock margin insurance. Out of the 197 producers that produced row and/or specialty crops, 18% had purchased yield or revenue crop insurance. 15% of participants had collected a payment from LFP at least once in the last 10 years. Over one-third of participants (35%) considered themselves full-time farmers.

Table 3 displays a comparison of our sample with the corresponding population in the Northeast and Southeast from the 2017 USDA Agricultural Census.[9] Values for the total U.S. are also included. The average age of producers in our sample is younger than the average age of the population.[10] The sample represents less than 1% of operations with cattle in each of the regions, however the distributions of cattle operations with respect to the types of cattle and the proportion of hay and pasture acreage is similar to the population in each region.

not be generalizable (Stratton, 2021). However, given the comparison with the population shown in Table 3 and corresponding discussion, it does not seem that our sample suffers from significant bias.

[9] Figures S1 and S2 in the online Supplementary Materials show the comparison of gross farm sales categories for our sample and the population in the Northeast and Southeast, respectively.

[10] Our sample includes only cattle and hay producers, whereas the U.S. Census data only provides producer age in aggregate.

Table *3* Sample representativeness compared to producers enrolled in PRF-RI in the Northeast and Southeast

	Northeast		Southeast		U.S.
	Pop.	Sample	Pop.	Sample	Pop.
Operator Age	56	47	58	46	58
Operations with Cattle	51,545	112	87,367	142	768,542
Percentage of Cattle Operations: with Beef Cows	78.7%	80.4%	98.8%	97.0%	94.9%
with Dairy Cows	26.2%	28.3%	2.9%	4.5%	7.1%
Total Hay and Pasture Acreage	7,064,803	26,145	13,031,943	41,112	50,466,457
Percentage Hay Acreage	50.9%	67.9%	25.4%	27.8%	11%
Percentage Pasture Acreage	49.1%	32.1%	74.6%	72.2%	89%
Percentage Hay and Pasture Acreage Enrolled in PRF-RI in 2019	2.6%	2.6%	13.0%	6.8%	31%
Distance (kilometers) from county centroid to 4 closest NOAA weather stations	34.72	39.74	38.63	38.01	42.86

Notes: Population Sources: 2017 USDA Agricultural Census, USDA RMA Summary of Business, NOAA CPC Station Library (https://ftp.cpc.ncep.noaa.gov/cadb_v2/library/)
Census statistics for operations with cow inventories in 2017. Only those states that represented at least 2% of the participants in our sample were included in population and sample calculations. Northeast states included Delaware, New York, Pennsylvania, Vermont and Virginia, and Southeast states included Alabama, Florida, Georgia, and Tennessee

Table 3 shows the percentage of hay and pastureland enrolled in PRF-RI in 2019 and the measure of spatial basis risk in each region and for the total U.S., compared with the sampled counties. The counties sampled in the Northeast were identical to the population in terms of PRF-RI enrollment in 2019, while in the Southeast, roughly 7% of the sampled area was enrolled in PRF-RI compared to 13% of the population area. The population average in the Southeast is brought up substantially by the state of Florida which had almost a third of acreage enrolled in PRF-RI in 2019. Only 16% of the sample in the Southeast came from the state of Florida, so the sample average is much more in line with the other states' enrolled proportions ranging from 5-8%. Both the Northeast and Southeast regions lag behind the U.S. average of 31% of hay and

Table 4 Average Awareness of PRF-RI and Source of Information by Region

	Northeast	Southeast	Unequal Variance t-test P-value (Null: Population means differ)
Aware of PRF-RI	36%	58%	0.00
Info Source: News	30%	13%	0.04
Info Source: Friends	5%	21%	0.00
Info Source: Extension	30%	36%	0.44
Info Source: Crop Insurance Agent	27%	36%	0.30

pasture acreage enrolled in PRF-RI. In terms of spatial basis risk, the sampled counties in the Northeast on average had a higher distance to the four closest weather stations than the population, and in the Southeast the population and sample basis risk measures were similar. The population measures in each region were lower than the U.S. average, suggesting that on average the Northeast and Southeast have lower spatial basis risk than the U.S. as a whole. Combined, acreage enrolled in PRF-RI in the Northeast and Southeast made up about 1% of the total acreage enrolled in PRF-RI in 2019.

Table 4 shows values for producer awareness of PRF-RI and information sources by region. 57% of the Southeast sample were aware of PRF-RI prior to our study, compared with only 36% of those in the Northeast. Sources of information about PRF-RI also seem to differ by region. In the Northeast, 30% of those aware of PRF-RI had heard about it through a news source, compared to 13% of those in the Southeast. Consistent with the relatively higher rates of enrollment in the Southeast, 21% of those aware of PRF-RI in the Southeast had heard about it from a friend, family member or neighbor, compared with only 5% of those in the Northeast. The Southeast had slightly higher percentages of those who had heard about PRF-RI from Cooperative Extension and crop insurance agents, though these differences were not determined to be statistically significant.

To gather additional information, we asked participants who were aware of PRF-RI prior to the study but had not enrolled to indicate their reason for not enrolling. Figure 2 shows the results. The most common response was that PRF-RI was not relevant for the farmer's operation (31%), however only farmers qualifying for PRF-RI were allowed to participate in our study. This likely indicates even though these participants were aware of PRF-RI, they did not fully understand its purpose either due to lack of adequate information or the complexity of the program. Similarly, 13% of producers stated the complexity of PRF-RI caused them not to enroll. Both findings indicate additional education is necessary to increase enrollment.

Results

Table A1 in the appendix shows the probit regressions for the dependent variables: awareness of and enrollment in PRF-RI.[11] As expected, results change once sample selection is controlled for. Table 5 displays the results of the simultaneously estimated sample selection regressions (equations (1-4)) for the dependent variables: awareness of and enrollment in PRF-RI. The estimated correlation between error terms (ρ) is significant at the 1% level, suggesting the sample selection estimates should be used.

The only statistically significant variables associated with awareness of PRF-RI were *Acres*, *Crop Insurance Agent*, *LFP,* and *Region: SE.* Larger farms, in terms of acreage, were more likely

[11] Table S1 in the online Supplementary Materials displays Pearson correlation coefficients between the explanatory variables and the two dependent variables.

Table 2 Sample Selection Regressions of Awareness of PRF-RI and Prior Enrollment in PRF-RI on Regressors

	Dependent variable:	
	Aware of PRF-RI (1)	**Enrolled in PRF-RI (2)**
Acres (thousands)	0.65* (0.34)	-0.15* (0.09)
Beef	0.42 (0.29)	-0.10 (0.15)
Dairy	-0.05 (0.39)	-0.18 (0.21)
Risk Aversion	0.67 (1.66)	0.38 (0.74)
Rainfall Variability	-0.003 (0.01)	-0.001 (0.003)
Farm Income	0.08 (0.06)	-0.03 (0.02)
Fulltime	-0.22 (0.22)	0.21** (0.09)
Info Source: Extension		0.06 (0.07)
Info Source: Friends		-0.07 (0.09)
Info Source: Agent		0.19** (0.08)
Other Insurance		0.02 (0.06)
Prop Livestock Income	0.10 (0.25)	0.11 (0.11)
Age	0.004 (0.005)	
Male	0.08 (0.22)	
Crop Insurance Agent	0.44** (0.22)	
Prop Hay Sold		-0.05 (0.12)
Livestock Revenue Insurance		0.25** (0.11)
Livestock Margin Insurance		-0.004 (0.18)
LFP	0.65** (0.27)	0.06 (0.10)
Prop County Enrolled	-0.89 (0.83)	0.45 (0.45)
Rent Proportion		0.19** (0.09)
County Base Value: Hay,Not irrigated		-0.001* (0.0005)
Avg Distance 4 close WS		0.0003 (0.003)
Region: SE	0.49** (0.25)	-0.13 (0.13)
CARA x Rainfall Var	-0.01 (0.02)	-0.004 (0.01)
Constant	-1.29** (0.61)	0.70** (0.34)
Observations	254	
Log Likelihood	-188.10	
ρ	-0.74*** (0.17)	

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

to be aware of PRF-RI. Farmers who already had a crop insurance agent they work with regularly were more likely to be aware of PRF-RI, and those who had collected an LFP payment in the last ten years were more likely to be aware of PRF-RI. The regional variable shows that farmers in the Southeast were more likely to be aware of PRF-RI.

The following variables all had the expected positive relationship with enrollment: *Fulltime, Info Source: Agent, Livestock Revenue Insurance,* and *Rent Proportion.* One notable finding when comparing the probit regressions in the appendix Table A1 and the sample selection regression in Table 5 is that the relationship between LFP and enrollment is positive and significant in the probit regressions, but statistically insignificant when awareness of PRF-RI is accounted for.

Full time farmers were not more likely to be aware of PRF-RI, but were more likely to enrolled, showing the role higher risk exposure can play in enrollment decisions. Table 5 shows that larger farms in terms of hay and pasture acreage are more likely to be aware of PRF-RI, but contrary to results of prior literature on crop insurance, are less likely to be enrolled. Mishra and El-Osta (2009) showed that dairy and livestock operations are associated with higher wealth accumulation than operations with other types of production, likely due to the capital-intensive nature of such operations. Acres of hay and pasture are an input to livestock and dairy production, so more acres likely mean a larger livestock operation and more wealth accumulation. As discussed in Sherrick et al. (2004), if larger farms have more wealth, they may have higher risk-bearing capacity, which could present one reason for the negative association with these variables and PRF-RI enrollment. Like Sherrick et al. (2004), Table 5 shows that a higher proportion of rented hay and pasture acreage is associated with a higher likelihood of enrollment. Those with higher levels of ownership of land are likely to have more wealth and therefore more risk-bearing capacity. The coefficient on *County Base Value* is negative and statistically significant, suggesting that the large premiums associated with more valuable land outweigh the impact of the productive land on risk exposure, leading to lower levels of enrollment for more productive land. Enrollment in livestock revenue insurance programs is related to an increase in the likelihood a producer enrolled in PRF-RI, suggesting that as hypothesized, these insurance programs insure different parts of the producer's profitability consideration and are complementary. There was no significant relationship between the other measures of risk exposure and the enrollment decision, including the proxy for spatial basis risk.

Similar to previous studies of FCIC insurance demand, the level of risk aversion did not have a statistically significant association with the demand for PRF-RI. The coefficients on rainfall variability and the interaction term between the risk aversion and rainfall variability variables were not statistically significant.[12] Potentially, the small sample size does not provide enough power to estimate these effects, especially with regards to risk aversion given it was elicited into only 10 levels. Additionally, there may be conflicting effects with rainfall variability. Because PRF-RI premiums are actuarily fair, higher variability means higher premiums for enrolling in those months. Thus, the large premiums from high rainfall variability during the growing season may lead to lower demand (Cabas et al. 2008), counteracting the increased demand from higher risk exposure.

Surprisingly, the proportion of the producer's county acreage enrolled in PRF-RI had no statistically significant relationship with the awareness of PRF-RI or the decision to enroll in PRF-RI. Given the median was 0, there may not be enough awareness and current enrollment in PRF-RI for information spillover effects to take place. Learning about PRF-RI from a crop insurance agent is associated with an increase in the likelihood a farmer enrolled in PRF-RI in the past. This makes sense given the crop insurance agent has the ability and incentive to sell PRF-RI policies.

Conclusion

Pasture, Rangeland and Forage Rainfall Index insurance program has been available in the contiguous U.S. since 2016, however to date it has experienced relatively low enrollment rates. This paper explores characteristics related to the awareness of and enrollment in PRF-RI to inform policy makers and researchers assessing potential changes to the program, and to assist USDA RMA and extension educators tasked with growing awareness of this risk management tool.

[12] Additional models were run without the interaction variable, and a rainfall variability measure which was an average of the standard deviations in rainfall over growing season months. Results were similar.

We find that of those who were aware of PRF-RI but did not enroll, 13% said the program was too complicated and 31% perceived PRF-RI as not relevant for their operation, even though any non-qualifying farmers were screened out of the survey. Thus, additional education is necessary. Producers without prior access to a crop insurance agent and producers in the Northeast were less likely to be aware of PRF-RI which suggests a need for targeted information campaigns to increase awareness and enrollment. In recent years, USDA RMA has offered funding for education in "Targeted States" where crop insurance participation has traditionally been low. Many of these states are in the Northeast, so our results provide support for this initiative.

We find that full-time producers with less hay and pasture acreage and a lower proportion of owned forage land are more likely to enroll in PRF-RI when they are aware of the program. Thus, relatively small producers with more risk from land tenure agreements are participating in PRF-RI. Producers who enrolled in other livestock revenue insurance products were more likely to enroll in PRF-RI, suggesting revenue protection products are complementary to input cost protection products like PRF-RI.

Producers that have received a payment from catastrophic losses through the Livestock Forage Disaster Program (LFP) in the last 10 years are more likely to be aware of PRF-RI, but not more likely to enroll when these equations are estimated simultaneously. Relatedly, producers who had learned about PRF-RI from a crop insurance agent were more likely to enroll in PRF-RI. This demonstrates that participation in other USDA crop insurance and disaster programs can be a catalyst for educating producers about the various program options available, though these approaches may need to be more intentional to translate into increased enrollment.

One limitation of this analysis is that we cannot make causal inferences. As with all surveys, one must balance the length of the survey with the respondent burden, so we could not control for all confounding factors that might have a direct impact on insurance decisions, e.g., debt-asset-ratios, drought risk perceptions of producers, etc. We also acknowledge the limited statistical power of our analysis. Our small sample size is directly related to low awareness and enrollment rates in PRF-RI in the Northeast and Southeast regions. Less than half of survey participants were aware of PRF-RI, and only 17% of those aware enrolled in PRF-RI. As PRF-RI awareness and enrollment increases, future survey analyses may have additional statistical power.

Despite these limitations, we contribute to the relatively sparse literature covering PRF-RI, identifying significant relationships between awareness and enrollment in this relatively new insurance product which has important implications for policy design and extension education. Most importantly, our study shows it is useful to account for producer awareness of new insurance products when making inferences about insurance uptake. Such analyses can serve dual purposes through providing information for targeted education efforts, in addition to indicating segments of the population that are aware of the insurance but not utilizing it, potentially narrowing in on ways to improve the policy for wider enrollment.

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Appendix

Description of lottery basket: For this task, a ball will be drawn from a basket that contains 5 white balls and 5 orange balls. This means there is a 50% chance of drawing a white ball and a 50% chance of drawing an orange ball.

Your decision: Decide when you want to begin choosing Option B (the sure amount). You may decide to first choose Option B in choice 1 or in any other choice in the list.

Choice	**Option A**		**Your Decision**	**Option B**
	Play the lottery			**Sure amount**
	The likelihood/chance of a white ball being drawn is: **50%** Payoff if white (U.S. Dollar)	The likelihood/chance of a orange ball being drawn is: **50%** Payoff if orange (U.S. Dollar)		Payoff of the sure amount (U.S. Dollar)
1	0	40	**A** ◉ ○ **B**	10.59
2	0	40	**A** ◉ ○ **B**	13.73
3	0	40	**A** ◉ ○ **B**	15.46
4	0	40	**A** ○ ◉ **B**	16.71
5	0	40	**A** ○ ◉ **B**	17.94
6	0	40	**A** ○ ◉ **B**	19.05
7	0	40	**A** ○ ◉ **B**	19.99
8	0	40	**A** ○ ◉ **B**	20.85
9	0	40	**A** ○ ◉ **B**	21.88
10	0	40	**A** ○ ◉ **B**	23.44

Submit

Figure A1. Screen Shot of Risk Elicitation Exercise in Survey

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Table A1 Probit Regressions of Awareness of PRF-RI and Prior Enrollment in PRF-RI on Regressors

	Dependent variable:	
	Aware of PRF-RI	**Enrolled in PRF-RI**
	(1)	**(2)**
Acres (thousands)	0.60* (0.34)	-0.80 (0.65)
Beef	0.43 (0.29)	4.19 (292.71)
Dairy	-0.02 (0.39)	2.57 (292.71)
Risk Aversion	0.24 (1.66)	-0.78 (5.17)
Rainfall Variability	-0.002 (0.01)	-0.003 (0.02)
Farm Income	0.10 (0.06)	-0.22 (0.16)
Fulltime	-0.18 (0.22)	1.34** (0.56)
Info Source: Extension		0.30 (0.42)
Info Source: Friends		-0.94 (0.85)
Info Source: Agent		1.31*** (0.47)
Other Insurance		0.14 (0.32)
Prop Livestock Income	0.09 (0.25)	1.09 (0.79)
Age	0.002 (0.01)	
Male	-0.003 (0.24)	
Crop Insurance Agent	0.12 (0.20)	
Prop Hay Sold		0.17 (0.63)
Livestock Revenue Insurance		1.48** (0.69)
Livestock Margin Insurance		1.16 (1.59)
LFP	0.63** (0.27)	0.86* (0.47)
Prop County Enrolled	-0.71 (0.82)	2.87 (2.70)
Rent Proportion		1.51** (0.66)
County Base Value: Hay,Not irrigated		-0.01* (0.003)
Avg Distance 4 close WS		0.01 (0.02)
Region: SE	0.48* (0.25)	-0.42 (0.82)
CARA x Rainfall Var	-0.01 (0.02)	0.003 (0.06)
Constant	-1.15* (0.62)	-5.21 (292.72)
Observations	254	121
Log Likelihood	-155.61	-35.40
Akaike Inf. Crit.	343.23	116.79

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.