THREE ESSAYS REGARDING U.S. CROP POLICY AND RISK

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by
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The undersigned, appointed by the Dean of the Graduate School, have examined the thesis entitled

THREE ESSAYS REGARDING U.S. CROP POLICY AND RISK

Presented by Scott Gerlt

A candidate for the degree of Doctor of Philosophy

And hereby certify that in their opinion it is worthy of acceptance.

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hard. I believe this lesson paid off as I finished a PhD with a family and while working full-time.

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ABSTRACT

Agricultural policy is an important component of risk management in U.S. agriculture. This dissertation focuses on various aspects of this topic. In the first essay, we find that baselines generated for policy analysis can serve as viable forecasts of season average farm prices. Specifically, simple alternatives of a time-series model and a futures-based forecast failed to perform better or contain all of the information for corn and soybean prices in the baselines. The result is that the baselines provide a resource to the public beyond just their use for scenario analysis.

Crop underinsurance is examined in the second essay. Producers purchase some crop insurance options that expected utility theory (EUT) suggests they should not select. The essay examines several of the explanations that have been proposed for this outcome and finds that a budget constraint, asymmetric information and cumulative prospect theory under the correct condition are plausible explanations. Analysis from a survey finds that producers in the Plains and the South are more likely to underinsure. Furthermore, producers more sensitive to premiums are less likely to underinsure.

The survey used in the second essay also revealed that 64% of respondents believe that they lose money on crop insurance over time. Given program design and past performance, this result is surprising. The third essay examines this result and finds that a recent indemnity is a significant factor in explaining this outcome, which is evidence of recency bias in the perception of crop insurance. However, we fail to find this perception is related to actual crop insurance decisions.

1. INTRODUCTION

Risk is inherent to crop production. Annual crops are planted and must grow for many months before reaching harvest maturity. During that time, they are dependent on many environmental factors to determine the final yield. These environmental factors such as temperature, rainfall and pests are beyond the control of the producer. Yet, the grower makes a substantial investment to establish the crop despite the unknown environmental conditions that will ultimately determine the total production.

Stochastic environmental factors are not the only risk for producers. Crop farmers are subject to market risk as well. Many of the crops grown in North America are annuals, meaning there is only one harvest per year. The biological delay between planting and harvest allows a period when output prices can substantially change, and no single farmer can subsequently alter their actions to influence the price. For instance, according to the 2017 Census of Agriculture, the average farm with corn had 278 acres of the crop, and only 370 farms had more than 5,000 acres of corn (USDA-NASS, 2019). Yet there were 90.2 million acres of corn planted that year (USDA-NASS, 2023). A complete crop failure of one individual farm likely wouldn't even appear as a rounding error in the national statistics.

The farmer must make a large investment to plant the crop, then must wait months while the environment determines the size of the crop and market conditions determine the price for any portion of the crop that is not pre-sold. Given that most U.S. crops are planted in the spring and harvested in the fall, the producer generally faces a scenario where the crops are faced with a very similar set of environmental conditions. This means that there the output from the farm occurs nearly simultaneously and is highly correlated. If the result isn't sufficient to cash flow until the next year, the farmer may be forced to exit the marketplace. The production process doesn't allow the natural hedging that occurs with more frequent and less correlated outcomes.

These risk factors have been drivers of U.S. farm policy (Coppess, 2018). While the policies have evolved since their introduction in 1933, the current suite of programs focuses on price and yield risks (Zulauf and Orden, 2016). This dissertation focuses on different aspects of those policies and risks.

The first paper focuses on one particular aspect of the agricultural policy making process- baselines. Baselines serve as the starting point against which to evaluate agricultural policy changes. For instance, if Congress wanted to increase the support price for a particular commodity, scenario analysis could estimate the potential market effects and government costs. However, the scenario would need to be compared against a point of reference, which is the baseline. For this reason, baselines must extend far enough into the future to cover the period potentially affected by policy changes. For budgetary purposes, Congress generally focuses on impacts over the next ten years, so a baseline extending ten years into the future may be the appropriate point of reference for examining scenarios.

Two baselines in the agricultural space have long track records. They are from the Food and Agricultural Policy Research Institute (FAPRI) and the United States Department of Agriculture (USDA). This research investigates how they have performed compared to actual outcomes. It also looks at whether simpler, less costly options could provide at least as much information about future market prices. In other words, do the baselines provide useful information compared to simple alternatives about outcomes in the future? We find that the baselines do provide information not available from the simpler approaches explored.

The second and third papers in this dissertation are based upon a farmer survey covering crop insurance. Crop insurance is delivered to farmers by private providers, but USDA sets premium rates and provides premium subsidies. Legislation requires that premium rates be actuarially fair (Du, Feng and Hennessy, 2016). In other words, the indemnities are designed to match the premiums before subsidies over time. After subsidies are taken into account, producers should receive more in indemnities than they pay in premiums over time. The subsidy rates are dependent upon the coverage level (deductible) chosen. As a result, there are some coverage options that a risk adverse producer should not choose. Yet, in practice some producers do choose coverage options that are suboptimal if producers behave as EUT theory suggests.

The second paper examines why producers select suboptimal crop insurance levels. It utilizes information from the survey about crop insurance selections, demographic information, farm characteristics, attitudes about crop insurance and motivation for purchase to construct a regression testing the significance of various factors. The paper also examines the theoretical underpinnings of various explanations that have been proposed in the literature and finds that additional assumptions are sometimes required for the explanation to be viable.

The third and last paper specifically examines producer beliefs about whether they receive more in indemnities than they pay in premiums through time. While program design would indicate that they should, our survey indicates producer beliefs do not align with *a priori* expectations. We investigate what influences this belief among producers by examining demographic information, program experience, farm characteristics and motivations for purchasing crop insurance. We also test whether this belief influences crop insurance selection.

These three papers contain varying subjects but have the thread of agricultural policy and risk running through each. The research contributes to understanding in the field while having practical significance for agricultural policy. Federal funding supports each of the topics examined, and this work has practical implications for continuing or modifying the programs and levels of support.

1.1 References

Coppes, J. (2018). *The Fault Lines of Farm Policy: A Legislatie and Political History of the Farm Bill*. University of Nebraska Press.

Du, X., Feng, H., & Hennessy, D. A. (2016). Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics, 99*(3), 732-756.

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2. EVALUATION OF THE PERFORMANCE OF LARGE-SCALE ECONOMIC MODELS

The USDA and FAPRI generate agricultural baselines from large scale models. Despite warnings that the baselines are not forecasts, they are often used in this manner. This research examined their suitability as predictions by constructing simpler forecast generating procedures as lower-cost alternatives. We fail to find that the alternatives perform better or contained all information in the baselines. This indicates that these publicly available options present a low-cost forecast resource to the public.

2.1 Introduction

Agriculture market forecasting has a long history with many papers dedicated to evaluating performance. Yet, large scale models (LSM's) have largely escaped *ex post* analysis. The Food and Agricultural Policy Research Institute (FAPRI) and the USDA Economic Research Service (ERS) both maintain LSM's. These models include representation of many commodities such as crops, biofuels, livestock, dairy and poultry throughout much of the world. The systems can include hundreds or thousands of equations and require coordination among many people for maintenance.

The stated purpose of the LSM's is the evaluation of changes such as farm bills, exchange rate movements, etc. (FAPRI-MU; O'Donoghue, 2018). As such, they are not intended to produce price forecasts. Instead, these models are designed to quantity the effects of changes in the agriculture sector and are thus econometric, structural equation models. This places the focus of the LSM's on the magnitude and interaction of elasticities within the system.

However, scenarios require a starting point against which to make changes. This starting point is referred to as a baseline and is produced once per year for both the USDA and FAPRI, although the latter updates the numbers midway between baselines. The baselines assume no policy changes, normal weather and general status quo conditions. Consider a scenario that evaluates the cost of altering a government program. The LSM would be reprogrammed to reflect the change and would produce a new outcome consistent with the policy change. Subtracting the baseline results from those of the scenario provides an estimate of the effects of the policy change on government costs, market outcomes and other indicators.

The process of preparing baselines varies by institution but always involves some combination of econometric models and analyst judgement. For example, in preparing its 10-year baseline FAPRI will look at initial results from the econometric equations and adjust them with addfactors to be in line with the analysts' market expectations. The addfactors are simply adjustment terms in the equations that allow analysts to incorporate beliefs or additional information. Bachman (1994) argues that the addfactors allow adjustments in models that cannot possibly capture all of reality. Oftentimes, other current events and policy changes are incorporated into the baselines through these addfactors. After the first few years, there is little extraneous knowledge, and the factors are often held constant. After an initial baseline in November, FAPRI presents the numbers to outside reviewers and makes revisions that are released in March (Meyers, Westhoff, F. Fabiosa, & Hayes, 2012).

The USDA follows a similar approach to FAPRI. However, many key variables are agreed upon by a panel for the first year or two and the addfactors in the models are calibrated to return those numbers. The USDA starts in process in August but releases the baseline in February. The process receives input from ten different agencies within USDA (O'Donoghue, 2018).

Given that baselines are merely a step in the scenario process and not a final product, why is so much effort put into the process of producing them? The answer is twofold. First, scenario analysis is not path independent. In other words, the results of scenario analysis can be very reliant upon the starting points in the baselines. Imagine a policy that pays when market prices fall below a trigger. The cost savings from removing the program are dependent upon the baseline price. If it is above the trigger, removing the program would be deemed to have no cost savings with a deterministic model. The better the forecasting ability of a baseline, the more accurate the scenario analysis, *ceteris paribus*.

Second, baselines are often used as forecasts, i.e. predictions. Users are cautioned against using baselines as forecasts as they generally hold policy constant through the projection period which is a condition that will likely not hold. However, since the 1996 farm bill U.S. government support has been largely decoupled which minimizes the effect of the caveat. As a result, FAPRI and USDA prices are often used in outlook work. The numbers have been used in farm marketing and budgeting work, bank stress tests and by producers choosing between farm bill options. Despite warnings, there is little distinction between baselines and forecasts among the public.

As a result, the lack of studies that evaluate the performance of these LSM's is problematic. These models are not suited for cross validation types of tests. The models are designed to be forward looking to evaluate future scenarios. The functional forms may not be appropriate to recreate history. Additionally, the models are constantly evolving which makes cross validation results no longer relevant with the next iteration. Fortunately, both the USDA and FAPRI LSM's have been generating baselines for many years[1]. This creates a data set upon which to conduct tests.

The question this research intends to answer is, "Do FAPRI and USDA baselines have any forecasting value?" The efficient market hypothesis (EMH) posits that all relevant information is already incorporated in prices. Therefore, futures prices establish a benchmark against which to compare results. Furthermore, much simpler time series processes can be used to generate forecasts. This research intends to compare LSM baselines against these other forecasts to answer the research question.

2.2 Literature review

Forecasting has long been a focus of agricultural economics (Allen, 1994). Literature has thus followed evaluating the performance of different techniques. The simplest method is the use of futures prices. The efficient market hypothesis implicates that the markets are the gold standard and cannot be outperformed on average. Several studies have tested this in agricultural markets. Garcia, Leuthold, Fortenbery, and Sarassoro (1988) found that the live cattle futures market did not outperform econometric, time series and composite models based on Mean Squared Error (MSE). However, the differences would create only minimal trading opportunities. In other words, the futures markets could not confidently be outperformed. Similarly, Kastens and Schroeder (1996) found the Kansas City wheat market was efficient as their models were

[1] Over 35 years for FAPRI and 25 years of public releases for the USDA.

unable to provide any trading gains over the historical test period. Kastens, Jones, and Schroeder (1998) evaluated multiple crops and livestock markets in the Midwest to find the most accurate predictor of local cash prices. The authors found that in 395 out of 420 commodity/timeline scenarios, the futures price plus an average basis performed at least as well as competing naïve estimates. They concluded that added complexity was usually unwarranted.

Contrary to the studies of futures market efficiency, Bessler and Brandt (1992) found that cattle markets are outperformed by experts. For hogs, the two perform about equally. Colino and Irwin (2010) determined that outlook forecasts from experts rarely have smaller MSE than futures-based forecasts in the cattle and hog markets. However, they argued that according to the EMH, the markets should encompass all available information. In other words, outlook forecasts should contain no new information. They failed to reject this null hypothesis in about half of their tests. Colino, Irwin, and Garcia (2011) conducted a similar study on hog price outlooks from Iowa State but also added a comparison with time series techniques. The authors concluded based on MSE that the futures markets have a clear advantage over the outlook one quarter out, but that it diminishes in the second quarter and disappears in the third. Encompassing tests are not as conclusive. Last of all, composite forecasts that combine the Iowa State numbers with time series output consistently outperformed the simple outlook. Likewise, Colino, Irwin, Garcia, and Etienne (2012) find that futures markets are difficult to outperform in the short-run but composite forecasts provide significant tradeable gains over public outlook forecasts.

Some effort has been made to evaluate the USDA's World Agricultural Supply and Demand Estimates (WASDE) forecasts. This publication provides frequent short-term projections for supply, use and farm prices of many major commodities. Kastens, Schroeder, and Plain (1998) collected forecast estimates over multiple years via survey. They concluded that WASDE and private forecasts generally outperform comparable university extension numbers for crops but not livestock. However, composite forecasts from the surveys prove better than the WASDE. Sanders and Manfredo (2005) also argue for encompassing as the true test of the EMH. They found in the fluid milk market that futures do not encompass the WASDE information in the second quarter. This encompassing result has also been shown for corn, soybeans and wheat (L. Hoffman, Irwin, & Toasa, 2007). L. A. Hoffman, Etienne, Irwin, Colino, and Toasa (2015) showed that WASDE corn price projections have lower RMSE's over some periods and provide incremental information not contained in the futures market.

Literature evaluating the LSM's has been relatively scarce compared to similar work on the WASDE. Bora, Katchova and Kuethe (2022) recently examined accuracy and informativeness of FAPRI and USDA baselines. They found that the accuracy of the projections decreases across the horizon. The authors noticed several systemic biases. For example, both FAPRI and USDA underpredicted soybean acres while overpredicting wheat acres. However, both did reasonably well with yield predictions. The study found that the forecasts have predictive value for up to four to five years. The authors concluded that neither set of projections consistently outperforms the other, with the exception of net cash income and crop receipts where FAPRI did better and corn price and soybean yield where USDA did better.

Beyond Bora, et al. (2022), the literature examining LSM's tends to be much older. Just and Rausser (1981) evaluate several forecasts from large scale models. They find that livestock forecasts tend to perform better relative to the futures market than crop forecasts. The authors also report that the timeline's effect on accuracy depends upon volatility in the market. Forecasts tend to perform better in the short term for more stable markets and better in the long term for more volatile markets. Last of all, Just and Rausser (1981) found that futures markets are less biased but have larger forecast error than forecasts from LSM's. Similarly, Wisner, McVey, and Baumel examined baselines from FAPRI and the USDA and find an upward bias in corn and soybean export projections. They use baselines from 1997 to 2000 and find a simple trend performs better. Wisner et al. acknowledge that baselines are not intended as projections as does Baumel (2001). The latter concluded that a linear trend outperforms FAPRI export projections for corn and wheat but not for soybeans. Likewise, USDA baselines from 1997 to 2000 had consistently overestimated exports of the same three crops.

A few smaller studies have attempted to address the performance of the LSM's. Miller, Baumel, Wisner, and McVey (2004) find that a five-year moving average has lower RMSE and bias than FAPRI and USDA for corn and wheat but not for soybeans, beef and pork exports. Irwin and Good (2015) fail to find meaningful differences between the USDA projections and futures-based forecasts for corn, soybean and wheat prices. Similarly, Westhoff (2015) finds mixed performance between FAPRI, USDA and futures markets for the same three commodities.

Given the amount of work done on price forecasting, why should a study be warranted over LSM's? These models are often used for policy making which has a long timeline. Policy makers are concerned about effects over the lifespan of the policy. In contrast, most outlooks that have been studied are only concerned about the current year. Their main purpose is to help producers market their products. This study adds to the literature by not only evaluating the performance of the LSM's but also comparing to simpler alternatives that don't require the time or expense to maintain.

2.3 Conceptual framework

A natural point of comparison in the short run for forecasts from FAPRI and ERS are the futures markets. In the nearby periods, markets for many commodities are well-traded. This study will limit its scope to corn and soybeans, both of which have well-functioning futures markets. The traditional understanding of the EMH posits that futures prices cannot be outperformed in terms of MSE. It bears consideration that this study is using futures prices to predict MYA farm prices, so it is not a pure test of this hypothesis. While the traditional EMH interpretation bears consideration, as Colino and Irwin (2010) and Sanders and Manfredo (2005) argue, encompassing is the true test of the EMH. If markets capture all relevant information, then other forecasts have no marginal value. Using the equations and notation from Sanders and Manfredo (2005), let f_t be the futures price in *t* and f_{t-n} be the price for the same contract *n* periods in advance. The returns from holding a contract for *n* periods must be unrelated to the information at time at *t-n* if the EMH holds. This can be tested by the null hypothesis of whether β equals a vector of zeroes in the regression equation:

(1) $$f_t - f_{t-n} = \alpha + \beta X_{t-n} + \varepsilon$$

where X_{t-n} is a matrix of the relevant information at time *t-n*. Let X_{t-n} contain profits from using an alternative forecast, f^{a}_{t-n}. Equation 1 then becomes:

(2) $$f_t - f_{t-n} = \alpha + \lambda(f^{a}_{t-n} - f_{t-n}) + \varepsilon.$$

where λ is a scalar that is one component of β. The authors show that with some rearranging this results in:

(3) $$f_t - f_{t-n} = \alpha + \lambda[(f_t - f_{t-n}) - (f_t - f^{a}_{t-n})] + \varepsilon$$

which can be written as:

(4) $$e_1 = \alpha + \lambda(e_1 - e_2) + \varepsilon$$

where e_1 is the error from the market model and e_2 is the error from the competing model. If the null cannot be rejected, the competing forecasts may hold marginal value and is not necessarily encompassed by the market. If α=0, this is equivalent to an encompassing test (D. I. Harvey, Leybourne, & Newbold, 1998). Sanders and Manfredo (2005) also explain that for *K* alternative forecasts, the equation becomes:

(5) $$e_1 = \alpha + \sum_{k=2}^{K+1} \lambda_k(e_1 - e_k) + \varepsilon$$

and the null hypothesis is that $\lambda_1 = \lambda_2 = \cdots = \lambda_K = 0$. If the null is rejected, the optimal forecast, f^{*}_{t-n}, is the combination:

(6) $$f^{*}_{t-n} = (1 - \sum_{k=2}^{K+1} \lambda_k) f_{t-n} + \sum_{k=2}^{K+1} \lambda_k f^{k}_{t-n}$$

where f^{k}_{t-n} is the *k*-1 alternate forecast at time *t-n*.

Yet, an encompassing test on the FAPRI and USDA baselines alone would not fully answer the question of whether the baseline processes are justified. Both sets of projections have high costs of production. Simpler time series models present an alternative without the need for the intensive processes of data generation. A Bayesian

Vector Auto-Regression (BVAR) will also be included as an alternate forecast to test whether the LSM's have marginal value with the simpler alternative.

In the long-run, futures markets are too thin or even non-existent to serve as a benchmark. In this case, the time-series model presents the lone alternative to the LSM's considered here. Therefore, the test becomes whether the BVAR has significantly smaller MSE from the LSM's. If it does, does the time series forecast encompass those from LSM's? In that case, using long-term forecasts from FAPRI and USDA is inefficient.

2.4 Methods

Data

The LSM's produce eleven-year projections of many variables. This study will focus on prices for both corn and soybeans. FAPRI and ERS use marketing year average (MYA) farm prices reported by the National Agricultural Statistics Service (NASS) of the USDA. This metric represents the average price received by all producers within the marketing year for a crop. Projections for the MYA for corn and soybeans were obtained from the past baselines for both groups.

Data for futures markets were obtained from the Chicago Mercantile Exchange. FAPRI baselines are released around the first of March and the USDA around the first of February so futures prices on the close of March 1 were used as a comparison. However, futures markets correspond to a specific delivery day and not a marketing year average. Furthermore, they need a national basis adjustment to be comparable to prices received by farmers. Therefore, the following formula was used to convert futures prices to a comparable MYA price:

(7) $$p_{c,y}^{f.MYA} = \sum_{m=1}^{12} \left[\frac{1}{5}\sum_{t=1}^{5} w_{c,y-t,m}\right]\left[p_{c,y,m}^{f} + \frac{1}{5}\sum_{t=1}^{5}\left(p_{c,y-t,m}^{MYA} - p_{c,y-t,m}^{f}\right)\right]$$

where *c*, *y*, and *m* are indices for crop, year and month of the marketing year, respectively, $p^{f.MYA}$is the futures equivalent farm MYA price on March 1, *w* is the percent of the crop marketed in each month as reported by NASS[2], p^f is the deferred futures price on March 1 for year *y* and month *m*, and p^{MYA} is the same only for the monthly average farm price as reported by NASS. This formula takes a weighted average of a basis adjusted futures prices for months within the marketing year. A five-year moving average of actual weights for each month is used to determine the expected weight. Likewise, a five-year moving average of the basis for the month is used to calculate the expected basis as previous research has shown this to outperform more complex models (Kastens, Jones, et al., 1998). If a futures contract does not exist for a month, its weight, *w*, was divided equally between the preceding and succeeding months.

Time Series Forecast

Restricted vector autoregressions (VAR) have been shown to have good predictive power in commodity forecasting (Colino et al., 2011; Kaylen, 1988). The VAR model with *k* variables and *m* lags is specified as:

(8) $$y_t = A + \sum_{l=1}^{m} B_l y_{t-l} + \epsilon_t$$

where y_t is a *k*x1 vector of variables at time *t*, A is a *k*x1 vector of intercepts, B_l *k*x*k* matrix of coefficients and ϵ_t is a *k*x1 stochastic error term assumed to be multivariate normal with means of zero. This specification results in $mk^2 + k$ parameters to be

[2] The NASS marketing data correspond to the delivery date, not the date the contract was signed for the grain. As a result, the market prices during that period could be significantly different than the amount paid for the delivered crop. On average, this effect should equal zero though.

estimated. This potentially large number can lead to efficiency issues with OLS and has led to various alternatives. One common estimator is the Bayesian VAR with a Minnesota prior (Colino et al., 2011). This often used prior is not truly Bayesian in spirit but is closer to empirical Bayesian procedures. It uses initial data to estimate hyperparameters.

The priors for each coefficient matrix, B_l, are as follows:

$$\begin{gathered} b_{ii} \sim N(1, \tau_{ii}) \\ b_{ij} \sim N\left(0, \tau_{ij}\right) \end{gathered} \tag{9}$$

This prior assumes that lagged dependents are meaningful while other lags are not with the respective means of one and zero. The variance parameters, τ_{ij}, are determined by the following equation:

$$\begin{gathered} \tau_{ii} = \frac{\gamma}{l^k} \\ \tau_{ij} = \frac{\gamma w s_i}{l^k s_j} \end{gathered} \tag{10}$$

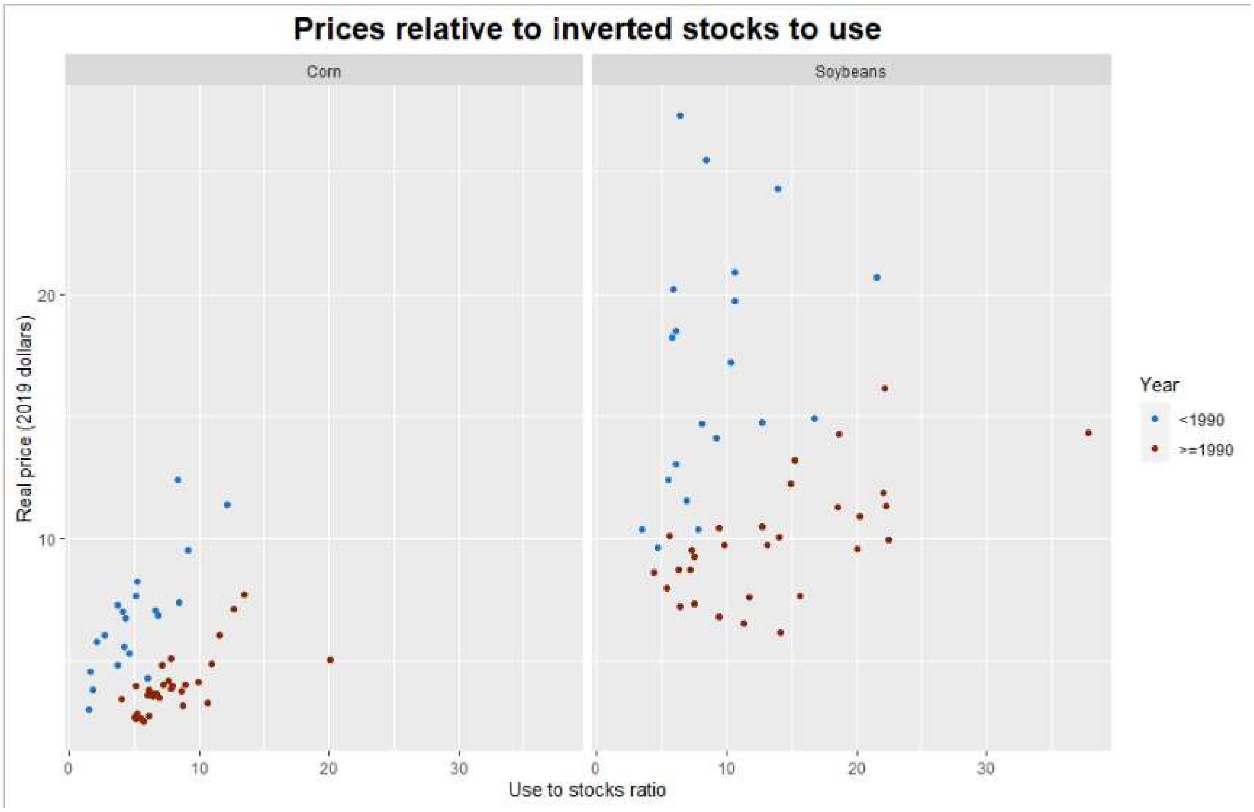
where s_i and s_j are the standard residuals from univariate autoregressions, γ sets the overall tightness for the prior, k controls the rate of decay and w allows for a stronger prior on other lags. Following Colino et al. (2011), γ, k and w are set to .1, 1 and .5, respectively, and l is the lag number. The prior for A is a flat prior and Var(ϵ_t) is assumed to be $.9s_i$ on the *i*th diagonal and zero otherwise following Doan, Litterman, and Sims (1984). The optimal number of lags is chosen by minimizing the Bayesian Information Criteria.

The choice of variables for the BVAR is not inconsequential. Given that this analysis is concerned with price forecasting, the challenge is to determine the minimum set of additional variables that sufficiently capture the dynamics that determine prices.

One common measure strongly associated with price is the stocks to use ratio. This value contains information on many other variables such as production and use. A high ratio indicates that the marketing year ended with large amounts of the crop relative to what is needed and is thus associated with a lower price. The converse is also true.

Figure 1 shows the relationship between stocks to use and price for corn and soybeans. Prices are in real amounts with a base year of 2019. The stocks to use ratio is inverted to the use to stocks ratio as the former exhibits an inverse function pattern and the inversion linearizes it. The years displayed in the charts are from 1970 to 2019. Over the entire period, there appears to be almost no relationship between the variables. However, breaking the time series into pre-1990 and 1990 and beyond shows a different story. At that breakpoint, there is a clear lowering of the real price relative to use to supply. In fact, there is almost no comingling of the datapoints between the two subsets. For this reason, the structural break renders the pre-1990 observations unsuitable for more recent estimation and thus will be excluded.

Figure 1: Prices relative to inverted stocks to use



BVAR estimation with up to five lags was tried, but one lag returned the lowest BIC.

Table 1shows the results.

Table 1: BVAR results based on years 1990 to 2019

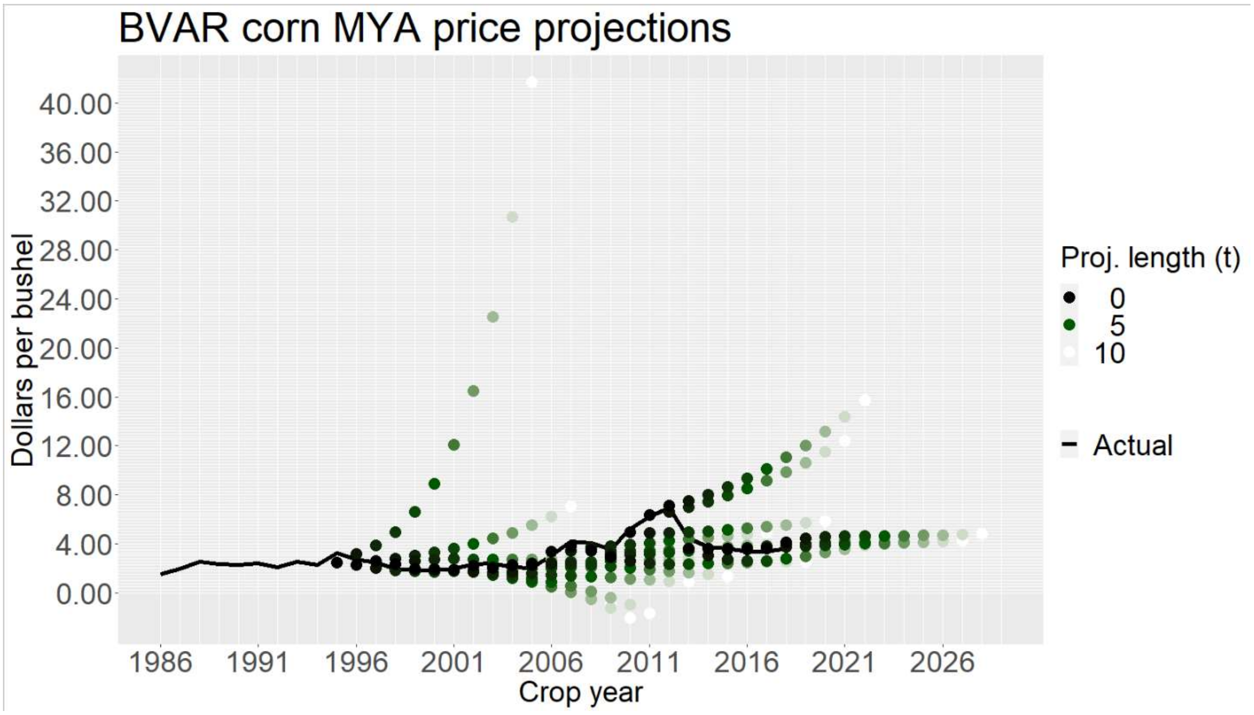
	$pcorn_{(t)}$	$psoy_{(t)}$	$uscorn_{(t)}$	$ussoy_{(t)}$
Intercept	1.334	1.456	4.042	-1.026
	(0.617)	(1.044)	(2.123)	(3.749)
$pcorn_{(t-1)}$	0.999	0.314	0.164	1.124
	(0.181)	(0.306)	(0.497)	(0.719)
$psoy_{(t-1)}$	-0.054	0.811	0.002	-0.010
	(0.114)	(0.165)	(0.309)	(0.456)
$uscorn_{(t-1)}$	-0.056	0.044	0.545	0.243
	(0.056)	(0.098)	(0.155)	(0.289)
$ussoy_{(t-1)}$	-0.024	-0.086	-0.071	0.619
	(0.027)	(0.046)	(0.09)	(0.138)

Values in parenthesis are the posterior standard errors. **pcorn** is the real corn price with base year 2019, **psoy** is the real soybean price with base year 2019, **uscorn** is the use to stocks ratio for corn and **ussoy** is the use to stocks ratio for soybeans.

The BVAR model can be used to construct historical eleven year forecasts. The estimation starts in 1996 and uses the data starting in 1990 and ending in the previous year. The number of lags is chosen to optimize BIC and is subject to the number of observations. While this is a short timespan, Bayesian methods can help offset limited observations. The GDP deflator is measured by the U.S. Bureau of Economic Analysis. For this study, it is considered independent of agricultural markets and is log-transformed and forecasted as an ARIMA model. The model is chosen by optimizing AICc. Since the GDP deflator is independent, it can take advantage of a longer time series. As a result, the starting year for the data is 1970. Using the full time period from 1970 to 2019 results in an ARIMA(0, 1, 2) model with drift. Since it is log-transformed, this is equivalent to modeling the growth rate of the variable as an MA(2) process.

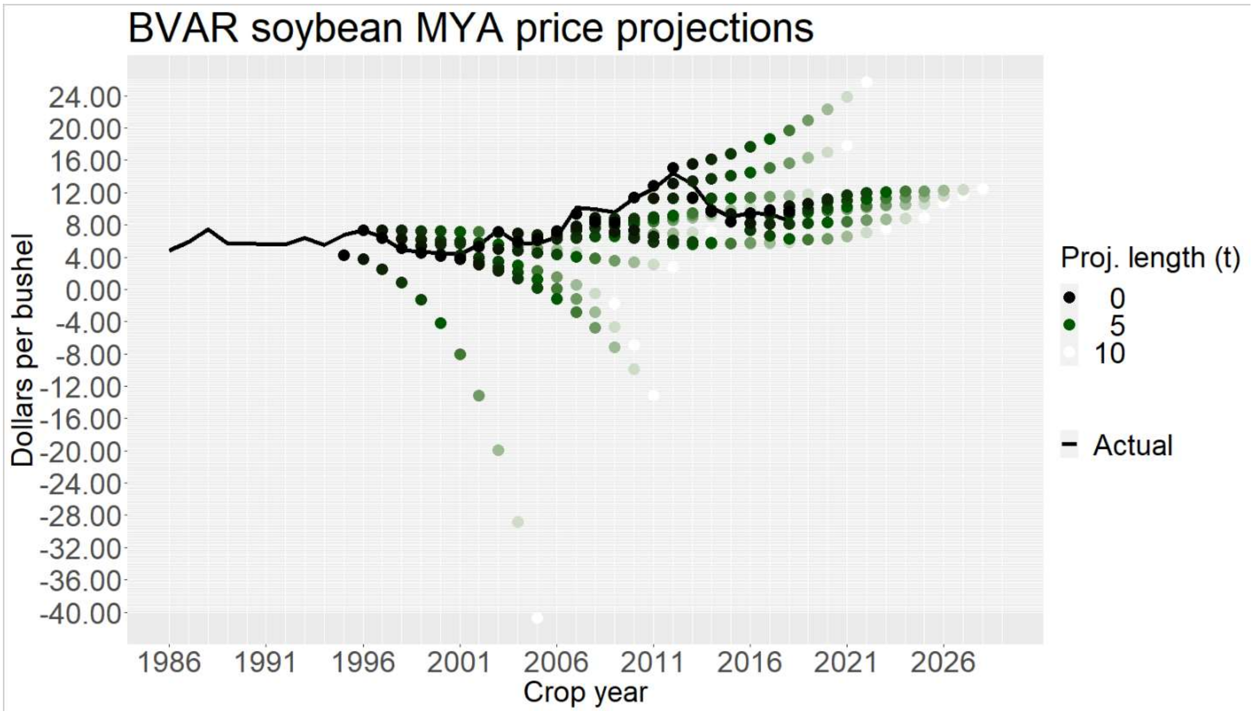
Figure 2 and Figure 3 display the BVAR results for nominal corn and soybean prices, respectively. The Bayesian methods were not adequate to compensate for the limited observations. One price projection for corn is over \$40 per bushel in the early 2000s. Likewise, one projection for soybeans is -\$40 per bushel around the same period. Obviously, these projections are not viable candidates as alternatives to LSMs[3].

Figure 2: BVAR corn MYA price projections



[3] The BVAR model with just corn and soybean prices was also tried, but performance was still an issue.

Figure 3: BVAR soybean MYA price projections



The issue is that some of the variables in the BVAR model are not stationary over certain time periods. Table 2 shows the results of Augmented Dickey-Fuller tests on the variables. The first set of values are integrated of order zero, or in other words not differenced. No matter how many years of data are used, none of the variables can be concluded to be nonstationary. The second set of values is integrated of order one, i.e. first differenced. These perform slightly better, but many of the variables still appear to be stationary. Part of this is the that the ADF test is not powerful enough to detect nonstationary in the small sample sizes. While not shown, differencing and detrending does not lead to more sensible results.

Table 2: Augmented Dickey Fuller test p-values with data starting in 1996 and ending in "Year"

	I(0)				I(1)			
Year	pcorn	psoybean	sucorn	susoybean	pcorn	psoybean	sucorn	susoybean
1996	NA	NA	NA	NA	NA	NA	NA	NA
1997	NA	NA	NA	NA	NA	NA	NA	NA
1998	0.870	0.521	0.823	0.729	NA	NA	NA	NA
1999	0.984	0.836	0.952	0.815	0.924	0.946	0.832	0.962
2000	0.942	0.966	0.936	0.696	0.789	0.699	0.724	0.669
2001	0.696	0.963	0.796	0.869	0.567	0.010	0.664	0.010
2002	0.456	0.912	0.623	0.679	0.660	0.083	0.707	0.023
2003	0.321	0.740	0.519	0.578	0.823	0.906	0.737	0.429
2004	0.256	0.820	0.506	0.567	0.728	0.958	0.704	0.434
2005	0.085	0.599	0.365	0.390	0.536	0.699	0.535	0.319
2006	0.072	0.615	0.294	0.599	0.482	0.676	0.462	0.457
2007	0.591	0.699	0.300	0.782	0.490	0.624	0.368	0.316
2008	0.885	0.933	0.240	0.232	0.514	0.490	0.301	0.043
2009	0.730	0.897	0.183	0.317	0.145	0.242	0.225	0.021
2010	0.533	0.903	0.159	0.133	0.049	0.151	0.174	0.049
2011	0.972	0.955	0.232	0.111	0.084	0.164	0.144	0.045
2012	0.985	0.950	0.312	0.188	0.062	0.123	0.110	0.032
2013	0.990	0.974	0.383	0.184	0.044	0.090	0.083	0.023
2014	0.647	0.865	0.313	0.203	0.012	0.057	0.053	0.017
2015	0.538	0.636	0.196	0.125	0.015	0.274	0.060	0.011
2016	0.466	0.561	0.154	0.100	0.016	0.309	0.046	0.010
2017	0.506	0.545	0.141	0.075	0.055	0.168	0.043	0.010
2018	0.526	0.593	0.128	0.095	0.044	0.150	0.033	0.010
2019	0.788	0.799	0.311	0.849	0.036	0.131	0.025	0.081

Therefore, the BVAR model was abandoned and a much simpler approach adopted as an alternative time series model. Miller, Baumel, Wisner and McVey (2004) found that a five year moving average could outperform LSM's in some cases. As a result, the five year moving average was adopted. The February WASDE projections for the current marketing year were used as the t=0 forecast since that information would have been available at the beginning of March. While alternative time series regressions would likely suffer from nonstationarity, this method should be robust to the issue.

Hypothesis testing

The Modified Diebold-Mariano (MDM) test is often used for forecast comparison (Colino & Irwin, 2010; Colino et al., 2011; Colino et al., 2012; L. Hoffman et al., 2007; L. A. Hoffman et al., 2015; Sanders & Manfredo, 2005; Bora et al., 2022). This test allows the testing of differences between functions of two different error series with null that $d_t = 0$ where:

(11) $$d_t = g(e_{1t}) - g(e_{2t})$$

and e_{1t} and e_{2t} are the error series from two different forecasts with t=1,…,n, and g is a loss function. If $g(e) = e^2$ then the MDM tests for differences in MSE. The test statistic is as follows (D. Harvey, Leybourne, & Newbold, 1997):

(12) $$MDM = \left[\frac{n+1-2h+n^{-1}h(h-1)}{n}\right]\left[\frac{1}{n}\left(\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right)\right]^{-1/2}\bar{d}$$

where $\gamma_k = \sum_{t=k+1}^{n}\left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right)$ is the autocovariance of d_t, $\bar{d}$ is the mean of the same data series and h is the forecast horizon. In other words, h is the number of periods ahead of the time at the forecast generation. The MDM statistic is distributed as a t distribution with n-1 degrees of freedom and does not require unbiasedness or lack of serial correlation.

Alternatively, d_t can be respecified as:

(13) $$d_t = e_{1t}(e_{1t} - e_{2t})$$

and the MDM test used to determine whether f_t encompasses f_t^a, i.e., $\lambda = 0$ (D. I. Harvey et al., 1998). This allows for pairwise comparisons. D. Harvey and Newbold (2000) extend this to allow testing of multiple forecast encompassing, $\lambda_1 = \cdots = \lambda_k = 0$. For *K* alternative forecasts,

(14) $$d_{it} = e_{1t}(e_{1t} - e_{i+1,t})$$

where i=1,…,K-1. The test statistic is then:

(15) $$MS = \frac{(n-K+1)}{(K-1)(n-1)} \bar{d}' V^{-1} \bar{d}$$

where $\bar{d} = [\bar{d}_1\ \bar{d}_2\ \dots\ \bar{d}_{K-1}]$, $\bar{d}_i = \frac{1}{n}\sum_{t=1}^{n} d_{it}$ and V "is the sample covariance matrix" (D. Harvey & Newbold, 2000). The $(i, j)^{th}$ element is calculated as:

(16) $$v_{ij} = n^{-1}[n + 1 - 2h + n^{-1}h(h-1)]^{-1} \times \Big[\sum_{t=1}^{n}(d_{it} - \bar{d}_i)(d_{jt} - \bar{d}_j) + \sum_{m=1}^{h-1}\sum_{t=m+1}^{n}(d_{it} - \bar{d}_i)(d_{j,t-m} - \bar{d}_j) + \sum_{m=1}^{h-1}\sum_{t=m+1}^{n}(d_{i,t-m} - \bar{d}_i)(d_{jt} - \bar{d}_j)\Big]$$

which is distributed as an F distribution with parameters (K - 1, n – K + 1).

2.5 Results

Forecasts

FAPRI's forecasts for corn and soybeans through the 2020 baselines are in Figure 4 and Figure 5, respectively, which plots FAPRI projections against actual prices. Black dots are the forecast in March for the current marketing year, which is partially over at that point. Unsurprisingly, the error rate is small for the intra-year projections. The other end of the spectrum is the white dots which are the projection for the last year of the baseline. There is considerably more error in the more distant forecast. From 1986 to around 2005, there wasn't much variation in the annual corn and soybean prices. The FAPRI baselines didn't predict the sudden acceleration in prices that happened after that. The price peak in 2012 was largely due to a severe drought, and FAPRI accurately projected that the prices would not stay at those levels.

Figure 4: FAPRI corn MYA price projections

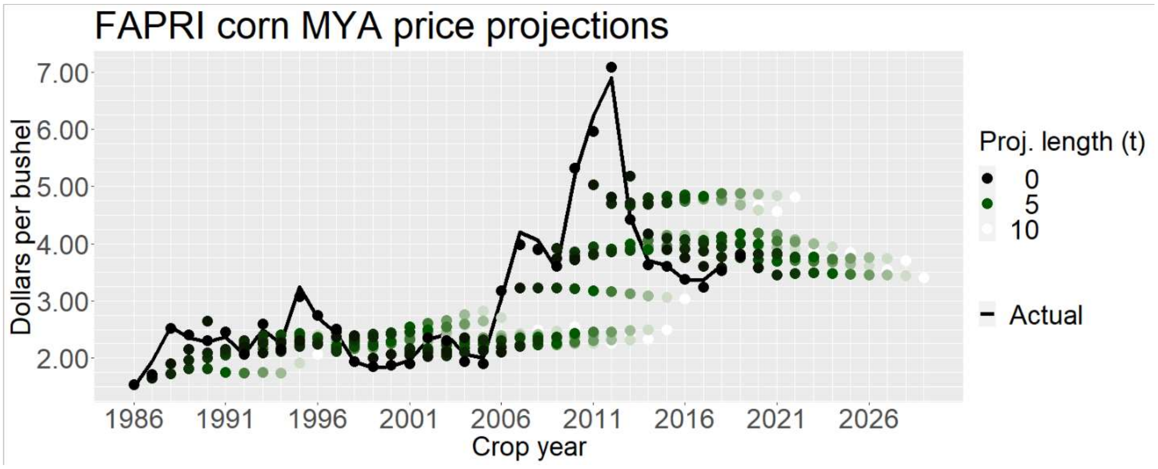


Figure 5: FAPRI soybean MYA price projections

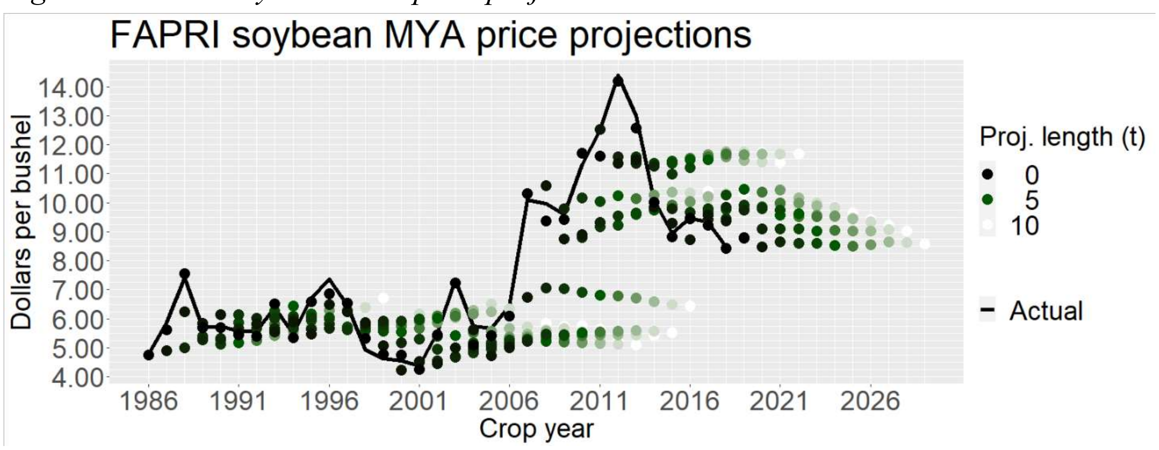


Figure 6 and Figure 7 present similar data, only for USDA ERS's corn and soybean price projections. These data series did not start until 1996. The pattern is not dissimilar from FAPRI's baselines. While the t=0 errors are a generally little larger than FAPRI's, ERS's baseline is released earlier and thus has less year-to-date data available.

Figure 6: ERS corn MYA price projections

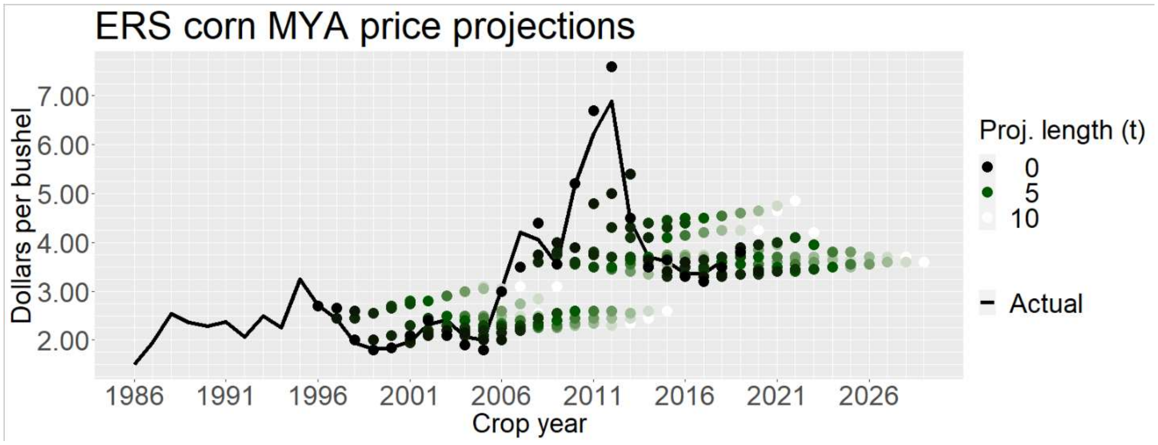
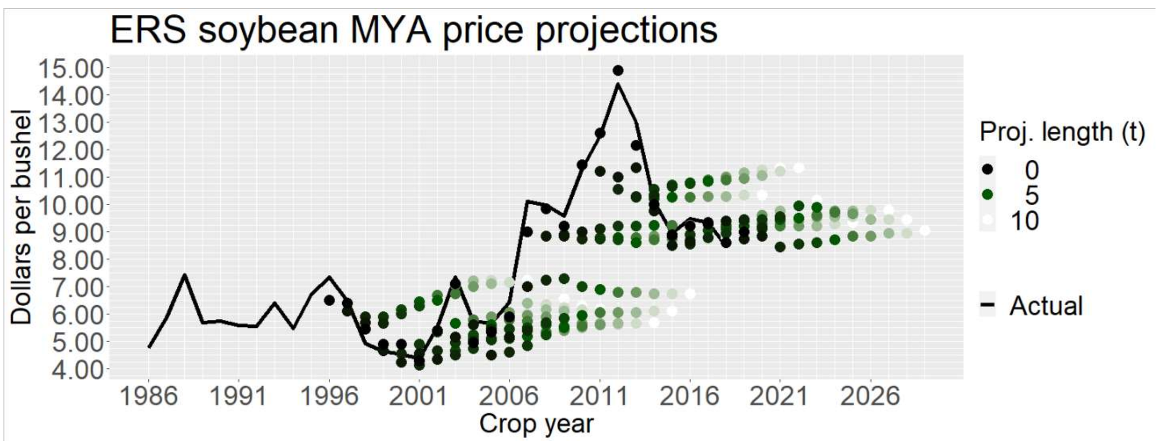


Figure 7: ERS soybean MYA price projections



Likewise, Figure 8 and Figure 9 show results for the five-year rolling average models that use the WASDE forecasts for the first year of the projection. After the first year, the time series forecasts are naïve as they don't take into account new information. As such, they revert to the recent mean. The forecasts starting from around 2011 present a much more dispersed array of prices going forward than those from the LSM's.

Figure 8: ARIMA corn MYA price projections

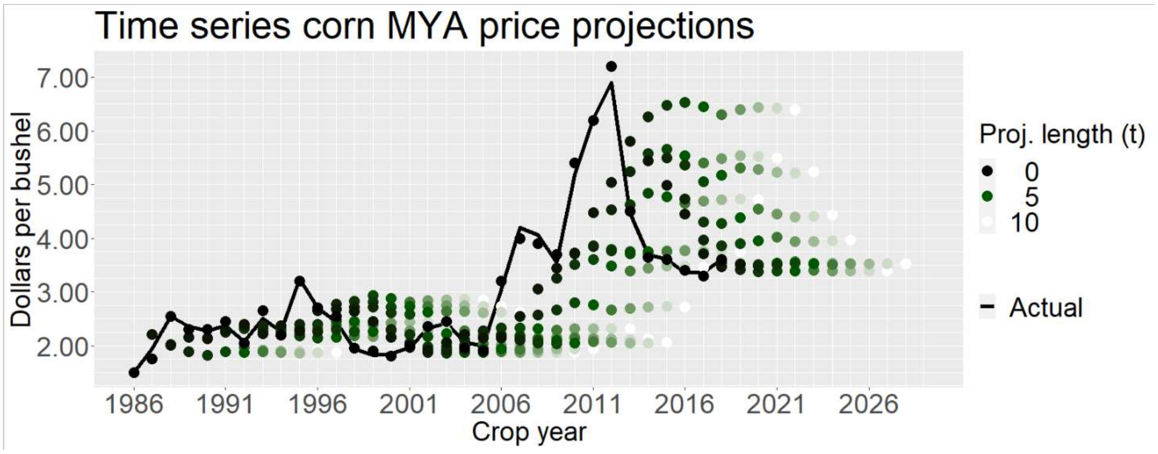


Figure 9: Time series soybean MYA price projections

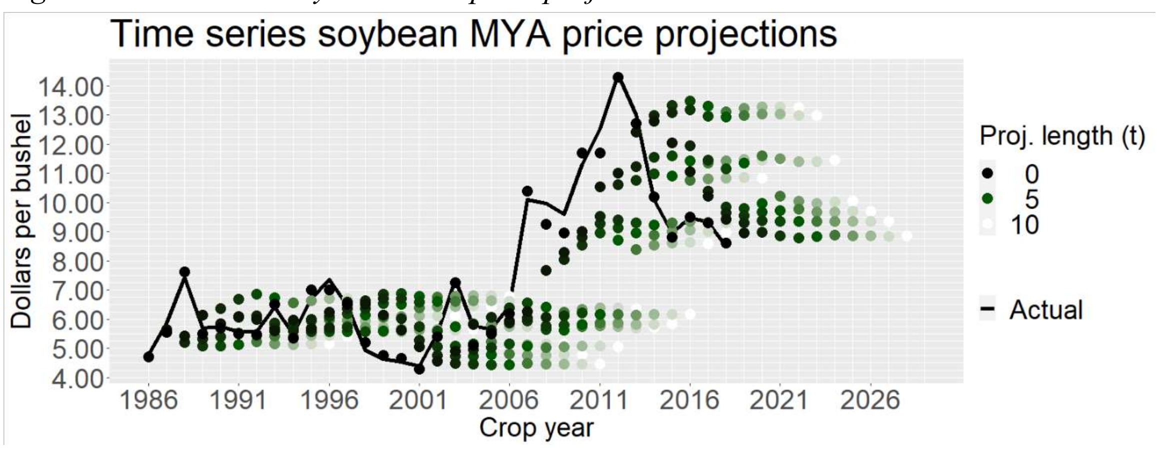


Figure 4 contains projections for the next marketing year for FAPRI, ERS, time series and an MYA adjusted futures price corresponding to information available on the first trading day of March in the baseline year. Corn and soybean futures markets are thinly traded beyond this time frame, so only projections for the subsequent year are considered for the futures market adjust prices. The 2008 MYA adjusted futures price presents an outlier as the new crop futures markets were significantly above the realized farm prices for that year. The backward-looking nature of the time series forecast is apparent as the projections tend to mimic the recent past.

Figure 10: Corn price projections for t=1

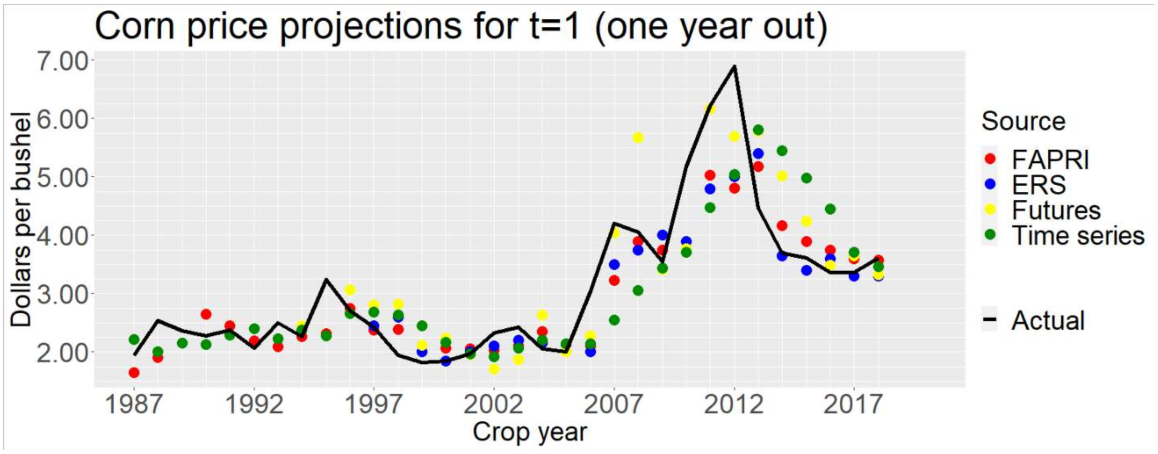


Figure 11: Soybean price projections for t=1

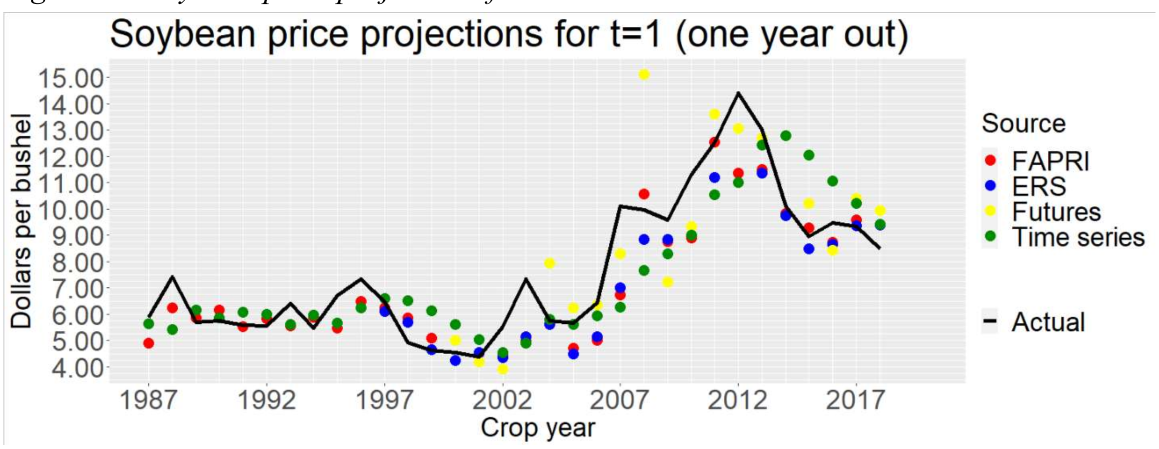


Figure 12 and

Figure 13 present the mean squared error of the different projections across the different horizons. The sample size (n) is unique for each projection horizon. An observation was only used if all forecasts made the projection in that year for the marketing year (this only applies to the futures forecast in t=1). The sample size falls as the horizon increases due to fewer observed projection years. The soybean t=1 observations drop to 19 as the marketing weights for soybeans which are used to convert the futures prices are not available prior to 1995. The adjusted futures prices rely on a moving five-year average of the weights which prevents the calculation before 2000.

The MSE's tend to increase through time, which is consistent with *a priori* expectations of less information for more distant horizons. The futures price has a larger MSE than both FAPRI and ERS t=1 projections. The difference between the LSM and time series forecasts will likely increase for the out years as more history is observed. Some of the time series forecasts are still heavily influenced by 2012 and thus project much higher levels for the next few years than FAPRI or ERS, both of which appear on track to perform better if recent price levels continue.

The p-values in the chart are from an MDM test for equality of MSE's. There are not enough observations at the t=10 level to conduct the test. It is worth noting that only t=7 for corn is significant at the alpha=.05 level, which given that there are 10 independent tests for each commodity, cannot be ruled out as a coincidental result. In fact, applying the Bonferroni correction would necessitate a p-value of less than .005 to reject. The test does not have enough power with the small sample size to reject the null hypothesis that the MSE's are the same. In other words, it cannot be concluded that any of the forecasts performs better than the others.

Figure 12: Corn mean squared error of projections

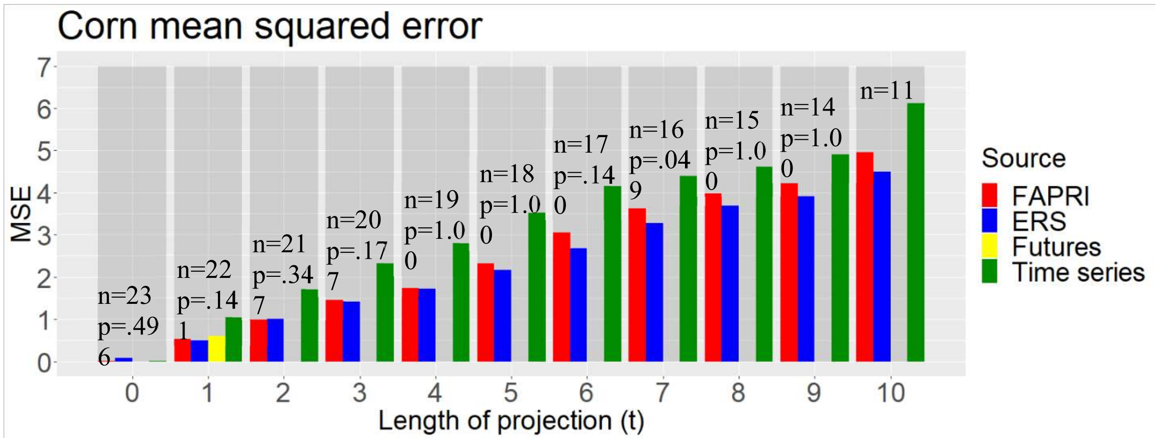


Figure 13: Soybean mean squared error of projections

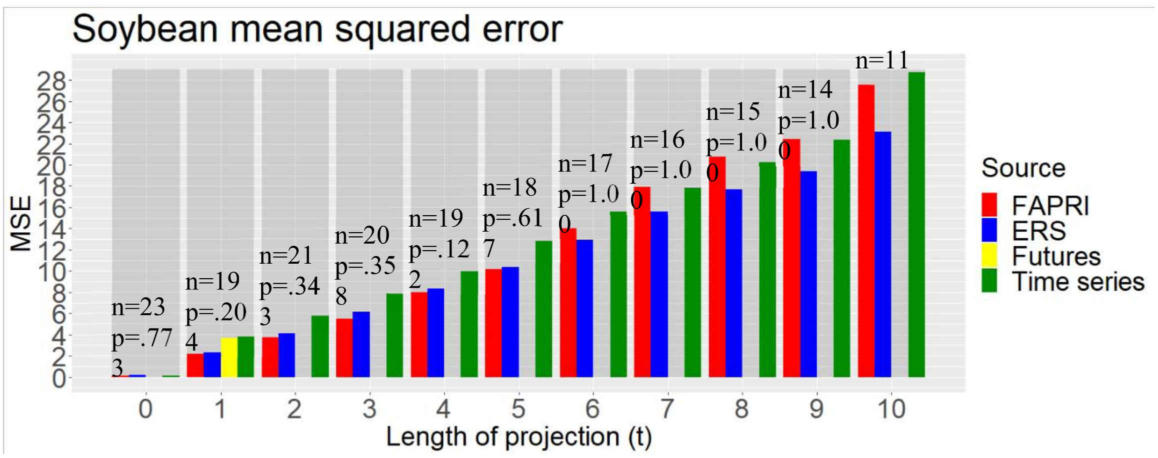


Table 3 contains the results of the encompassing tests. Each column is the test of whether that forecast encompasses the information in the other forecasts for the commodity. The rows are the forecast horizon. Like the MSE test, t=7 for corn is the only set of outcomes that is significant at alpha=.05. The Bonferroni correction would require p-values of less than .0016 to reject at the same significance level for each crop. None meet this criterion. In other words, it cannot be concluded that any of the forecasts contain the information in the others.

Table 3: Encompassing tests (p-values)

t	Corn				Soybeans			
	FAPRI	ERS	Futures	Time series	FAPRI	ERS	Futures	Time series
0	0.769	0.388		0.546	0.693	0.497		0.793
1	0.087	0.764	0.286	0.408	1.000	0.241	0.219	0.080
2	0.334	0.097		0.274	0.758	0.275		0.142
3	0.104	0.069		0.159	0.627	0.739		0.285
4	0.206	0.211		0.136	0.715	0.393		0.074
5	0.273	0.350		0.395	0.607	0.632		0.800
6	1.000	1.000		0.206	1.000	0.739		0.806
7	0.036	0.004		0.063	1.000	1.000		1.000
8	1.000	1.000		1.000	1.000	1.000		1.000
9	1.000	1.000		1.000	1.000	1.000		1.000
10								

2.6 Conclusions

Large scale models are very important for agricultural policy work. The USDA and FAPRI maintain systems for these purposes. The baselines from these systems are not intended to be projections, according to both, but are often used as such. This work sought to determine whether that use is appropriate. The statistical tests of performance and encompassing failed to reject the nulls. In other words, we failed to find evidence that the alternative forecasts performed better and contained all the information already in the LSM projections.

Harvey and Newbold (2000) point out that failure to reject forecast encompassing does not necessarily equate result in the conclusion that the base forecast is preferred. Failure to reject the null can be caused by a high degree of correlation between the forecasts, which is the case between the FAPRI and ERS models. Furthermore, large variability in prices and limited observations also negatively impact the test's ability to detect differences.

While a failure to reject the null should not be confused with confirming the null, the alternative forecasts generally have higher MSE's. This is because the futures-based forecast has several outliers and the time series model is unable to incorporate extraneous information. The differences may not be statistically significant, but the practical differences are enough that practitioners should pause before passing up the LSM forecasts in their favor. Additionally, while not every possible alternative forecast was considered, care should be taken when considering the number of potential alternatives as the limited sample size could easily lead to an incorrect conclusion.

Furthermore, it is worth noting that the study did not directly test the efficient market hypothesis. Futures prices were used to predict the MYA price. A test of the EMH would be the reverse. The two types of prices, although related, are fundamentally different measures. The tests presented herein did not test whether gains can be achieved in the futures markets from the LSM forecasts.

This research confirms Bora et al.'s (2022) finding that the FAPRI and ERS baselines do contain useful information for predicting the MYA price, which is useful for policy analysis and understanding farm level impacts. The alternative forecasts considered were intentionally simple. Another complex model might be able to perform better but wouldn't necessarily achieve productivity gains. Instead, this research shows that the publicly available projections are good options with a low cost for those needing to forecast prices. As a result, the release of the baselines appears to provide a benefit to the public through the additional information.

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Wisner, R. N., McVey, M., & Baumel, C. P. *Are Large-Scale Agricultural-Sector Economic Models Suitable for Forecasting?*

3. UNDERSTANDING THE DETERMINANTS OF CROP (UNDER)INSURANCE PURCHASES

Crop insurance literature has identified that some producers are buying lower levels of crop insurance than would be anticipated under expected utility theory (EUT). A risk-averse producer should never select a coverage level if the marginal subsidy rate is non-decreasing. We investigate the theoretical reasoning for this and find that a binding budget constraint, asymmetric information and cumulative prospect theory with the premium included in the anchor are plausible explanations. A national survey was given to producers. The results indicate that producers in the South and Plains are more likely to be underinsured, and that those more sensitive to premiums are less likely to be underinsured.

3.1 Introduction

Crop insurance has become a cornerstone of U.S. agricultural policy. Subsidies to the program have grown from less than \$3 million in 1988 to over \$6 billion in 2018 (USDA-RMA, 2019). During the 2018 farm bill debate, one of the recurring themes was to first do no harm to crop insurance (Fatka, 2019). Research has focused on producer demand for crop insurance and its effects on production. A developing theme in the literature is that expected utility theory fails to explain observed producer behavior. The research presented here investigates various proposed reasons for this failure.

Crop insurance has a long history but for much of that period, program participation was limited[4]. The federal crop insurance program was created in 1938 by an act of Congress. For decades, participation remained low, and the program was largely viewed as a failure. Ad hoc disaster payments were common due to a lack of insurance coverage by many producers. This pattern changed starting with the Federal Crop Insurance Reform Act of 1994. The legislation created a catastrophic (CAT) insurance product that provided low levels of coverage but did not charge a premium. Additional subsidies were provided for "buy up" policies with higher levels of coverage that did charge a premium. Premium subsidies were again increased in 1999 and 2000 for buy up policies. Program participation increased in response to the increased subsidy levels, and the relative importance of ad hoc disaster assistance has declined.

Literature that focuses on crop insurance participation tends to take one of two tracks. The first is econometrically estimating crop insurance demand. Goodwin, Vandeveer, and John (2004) develop a system of equations for crop insurance demand and determine it to be quite price inelastic with respect to producer-paid premiums. O'Donoghue (2014) estimates the demand for crop insurance with a two stage least squares regression and finds that producers tend to increase coverage levels rather than enroll new acres with an increase in subsidies. The author also estimates crop insurance demand to be inelastic, although not to the same level as Goodwin et al. (2004). Du, Feng, and Hennessy (2016) estimate crop insurance demand using a mixed logit model and also find it to be inelastic. Two subsequent papers have seized on the endogeneity issue first identified in O'Donoghue (2014) and argued that failure to account for it has

[4] See Glauber (2013) and Hennessy, Feng, and Du (2016) for a detailed narrative of U.S. crop insurance participation.

resulted in the inelastic estimates (Woodard and Yi and Yu, Smith, and Sumner, 2017). The endogeneity occurs when premiums are used as an independent variable while estimating crop insurance demand since premiums are a function of the selected coverage level and are therefore likely correlated with the error term.

The other track taken when investigating producer demand for crop insurance is based on expected utility theory. For example, Bulut, Collins, and Zacharias (2012) use a mean-variance utility function as a basis for proofs to show that under actuarially fair premiums, farmers will always prefer individual insurance to group insurance. Furthermore, Du, Hennessy, and Feng (2013) show that higher coverage levels are often preferred by corn, soybean and wheat producers in less risky areas under risk neutrality. The authors also find revenue insurance is preferred over yield insurance in those areas. This is somewhat surprising since the negative correlation between prices and yields is stronger in the more productive regions.

Several studies combine the effects of crop insurance and farm bill programs on producer's decisions under expected utility theory. Vedenov and Power (2008) examine whether farm bill programs proposed at the time replicated crop insurance coverage. They find in high production regions that revenue insurance is preferable over farm bill price supports with yield insurance. The authors determine that a proposed farm bill revenue program may replicate revenue insurance to some extent. These results were obtained with a constant relative risk aversion (CRRA) utility function. Likewise, Power, Vedenov, and Hong (2009) use the same utility form to study the 2009 farm bill ACRE program. Unlike Vedenov and Power (2008), the authors find that ACRE doesn't reduce crop insurance effectiveness and that revenue insurance is always preferable. However, both studies consider programs with different mechanisms. Barnett and Coble (2011) also evaluate the ACRE program under CRRA with crop insurance and conclude that adding crop insurance does not change the optimal farm program decision. Similarly, Bulut and Collins (2014) used a CRRA utility function to analyze the new farm bill programs and crop insurance options in the 2014 farm bill and find that farm bill Title I programs don't generally cause a reduction in crop insurance utilization, but SCO and STAX can substitute for higher coverage levels.

Even though the CRRA utility function is ubiquitous in the literature, it has a well-understood shortcoming with regard to crop insurance. Given that crop insurance is subsidized and rated to be actuarially fair before the subsidy, any non-risk loving agent should at least maximize the subsidy levels. However, this is not what the empirical evidence suggests (Du et al., 2016). Figure 14 shows the number of corn, soybean, wheat and cotton acres enrolled in Yield Protection (YP), Revenue Protection (RP) and Revenue Protection with Harvest Price Exclusion (RPHPE) policies with Enterprise units in 2020. These common policies represent a significant share of the insured acres. Given the constant 80% subsidy rate for Enterprise units for coverage levels up to 70%, no risk-averse utility maximizing producer should select a lower coverage level. While the number of acres for these four major crops insured at the lower coverage levels is not large, it does vary by crop.

Figure 15 shows similar data, only for rice. In this case, the 50% coverage level has the third highest participation rate. The CRRA utility function cannot easily explain the observed behavior.

Figure 14: Corn, soybean, wheat and cotton acres enrolled in Enterprise units and YP, RP and RPHPE policies in 2021

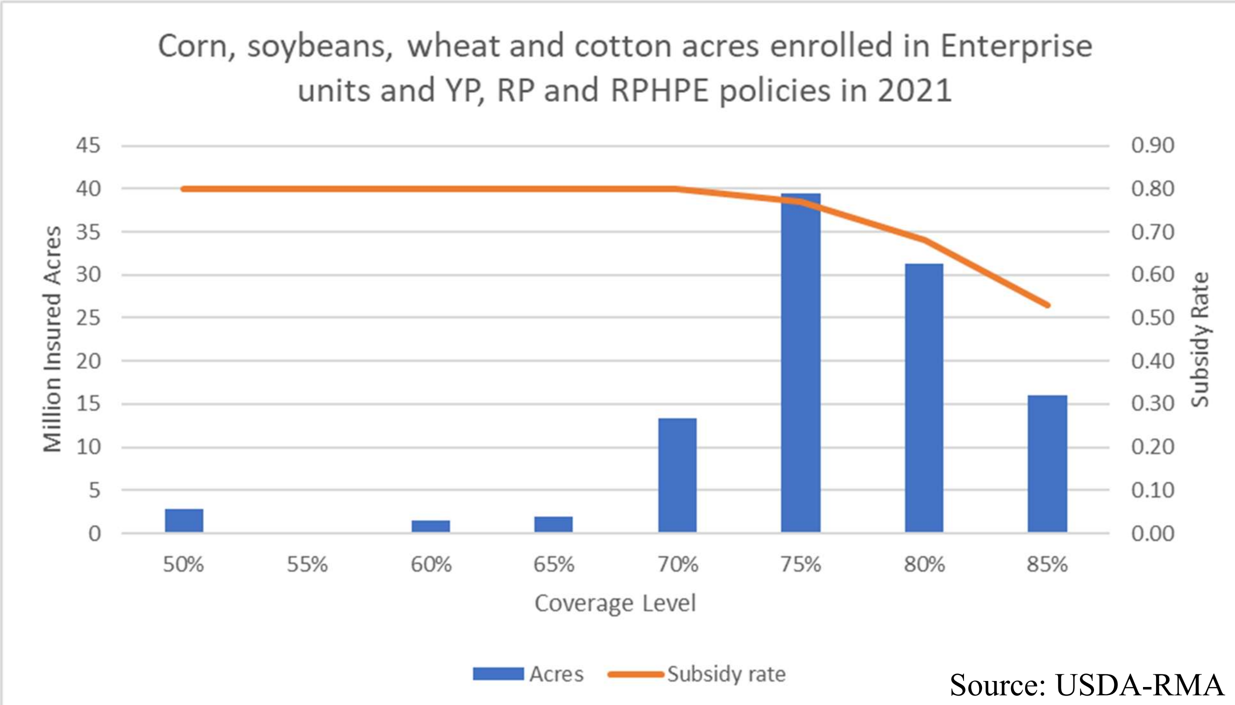
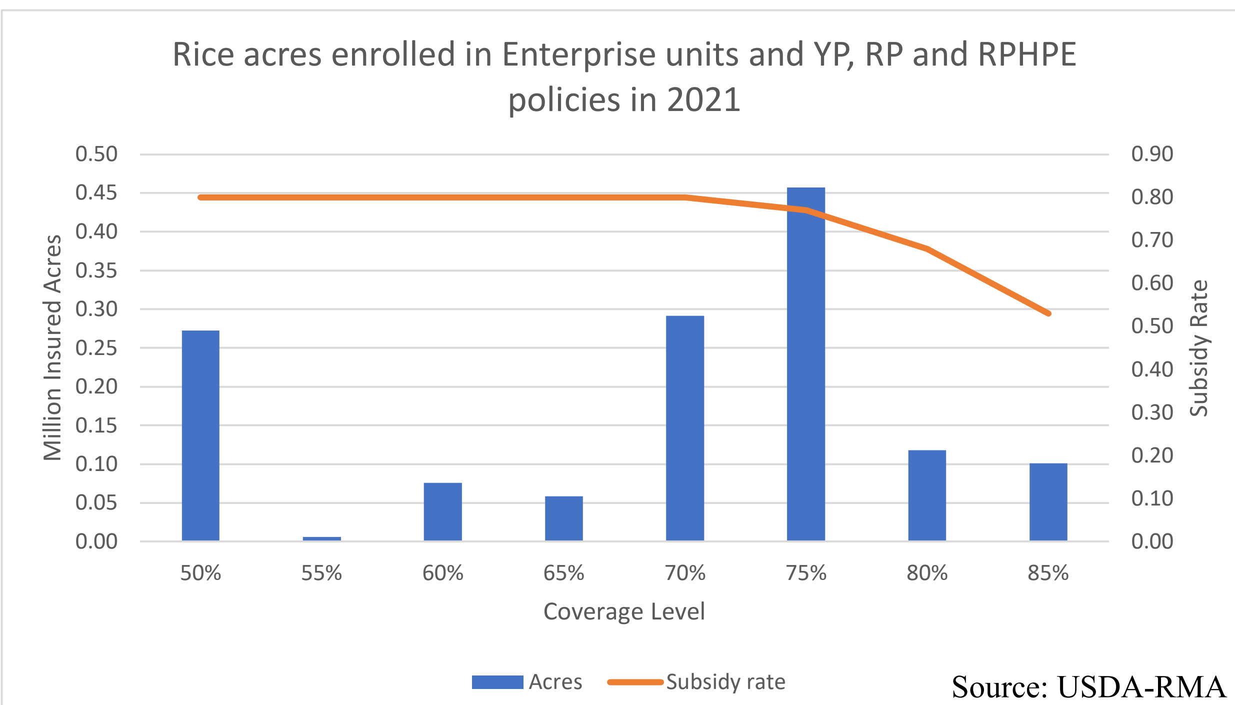


Figure 15: Rice acres enrolled in Enterprise units and YP, RP and RPHPE policies in 2021



This would call into question results based on a model that cannot reproduce historical behavior. Bulut (2018) uses a CRRA utility function but introduces a budget heuristic where producers optimize risk reduction within a budgeted amount for crop insurance. He finds that this model matches revealed preferences in several U.S. counties fairly well. Ramirez and Shonkwiler (2017) posit that information asymmetries could explain the anomalous behavior. Du et al. (2016) put forward several hypotheses including regret minimization, reluctance to insure and loss aversion when expectations are anchored around the potential yield (framing). Anything less than the potential yield would be viewed as a loss that producers will producers want to avoid, even if it increases risk. Loss aversion and framing with overestimating the probabilities of unlikely events form the backbone of prospect theory.

Cumulative prospect theory (CPT) was developed by Tversky and Kahneman in 1992. It is descended from their original work on prospect theory (Kahneman & Tversky, 1979) that was developed to help overcome the known shortcomings of expected utility theory (EUT). EUT is based upon the von Neumann-Morgenstern utility theorem which itself is based upon a set of axioms. One of the most controversial assumptions is the independence of irrelevant alternatives. The independence assumption implies $tA + (1-t)C \succcurlyeq tB + (1-t)C$ is equivalent to $tA \succcurlyeq tB$ where A, B and C are lotteries and t is a probability between zero and one. It has been found that the independence axiom doesn't hold in practice as demonstrated by the Allais' paradox. Experimental studies have shown that people will change their preference between two lotteries based upon a third, irrelevant lottery (Kahneman and Tversky, 1979).

Prospect theory allows for deviations from the independence axiom. It is a heuristic decision model that allows three unique characteristics. The first is that framing matters. Agents will choose an anchor (reference point) against which to determine whether a lottery outcome is a gain or loss. The second is that agents are risk averse in gains and risk seeking in losses (loss aversion). The third is that agents tend to overweight unlikely events. Expected utility with a discrete set of outcomes would be mathematically represented as:

(1) $$\sum_i U(x_i)p_i$$

where *U* is the utility function, p_i is the probability of event x_i. Prospect theory would be represented as

(2) $$\sum_i v(x_i - a)\pi[p_i]$$

where *a* is the reference point, *v* is the value function where *v(0)=0* and is concave for positive values and convex for negative values and *π* is the weighting probability function where *π(0)=0* and *π(1)=1*. Under CTP, the weighting function is split into two parts, one for positive outcomes (*x-a>0*) and one for negative outcomes (*x-a<0*). It is modeled as:

(3) $$\begin{gathered} \pi_n^+ = w_+(p_n) \\ \pi_i^+ = w_+(p_i + \cdots + p_n) - w_+(p_{i+1} + \cdots + p_n) \\ \pi_m^- = w_-(p_m) \\ \pi_i^- = w_-(p_{-m} + \cdots + p_i) - w_-(p_{-m} + \cdots + p_{i-1}) \end{gathered}$$

where the prospects are ordered from decreasing to increasing with n positive outcomes and m negative outcomes and *w* is an increasing weighting function with $w(0) = 0$ and $w(1) = 1$. For a positive (negative) outcome, only other positive (negative) outcomes are considered in the weighting function. The CPT weighting function considers the weights of neighboring cumulative probabilities of the same sign.

Babcock (2015) utilizes prospect theory to evaluate the insurance choices of three representative farms and finds that the theory explains the observed behavior if losses are anchored on indemnities being equal to premiums. Several studies have used different theoretical models to examine the exhibition of the prospect theory characteristics among producers. For example, Tonsor (2018) utilized choice experiments to elicit cattle farmers willingness to pay for feeder cattle and found participants tend to anchor their decisions on the best outcome experienced. Similarly, Zhao and Yue (2020) mailed a survey to commodity and specialty crop producer that asked them to choose between various lotteries. They find evidence of "reference depend[ence], diminishing sensitivity, loss aversion, and probability weighting." Feng, Du and Hennessy (2019) also used choice experiments through a survey to Iowa and Minnesota corn and soybean producers to elicit willingness to pay for insurance under different potential revenue distributions. They find that producers are generally not willing to pay the actuarially fair value of coverage, which is consistent with the potentially negatively skewed distribution of crop revenues and loss aversion along with effect of decision weights.

3.2 Conceptual framework

Consider the revenue function for a producer with insurance,

(4) $$r(y) = \begin{cases} y - s(\alpha) * p(\alpha) \text{ if } y \geq \alpha\bar{y} \\ \alpha\bar{y} - s(\alpha) * p(\alpha) \text{ otherwise} \end{cases}$$

where y is an uncertain production outcome, $\overline{y} = E[y]$, α is the insurance coverage level with range $[0, \infty)$, $p(\alpha)$ is the actuarily fair premium and $s(\alpha)$ is a loading/subsidy factor and is dependent on the coverage level. Levels of s below one correspond to subsidized insurance, and values above one correspond to a loading factor. The producer can choose any coverage level between and including no insurance to full insurance. Assume $f(y)$ is the pdf of y. In this case, the actuarially fair premium rate, p, is

(5) $$p(\alpha) = \int_{-\infty}^{\alpha\overline{y}} (\alpha\overline{y} - x) f(x) dx.$$

The expected utility equation becomes:

(6) $$E[U(r)] = \int_{\alpha\overline{y}}^{\infty} U\big(y - s(\alpha) * p(\alpha)\big) f(y) dy + \int_{-\infty}^{\alpha\overline{y}} U\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) f(y) dy.$$

Differentiating the expected utility with respect to the coverage level, α, yields:

(7a)
$$\begin{aligned}\frac{dE[U(r)]}{d\alpha} = &-\overline{y}U\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) f(\alpha\overline{y}) \\ &- [s'(\alpha) * p(\alpha) + s(\alpha) * \overline{y}F(\alpha\overline{y})] \int_{\alpha\overline{y}}^{\infty} U'\,\big(y - s(\alpha) * p(\alpha)\big) f(y) dy \\ &+ \overline{y}U\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) f(\alpha\overline{y}) \\ &+ \big(\overline{y} - s'(\alpha) * p(\alpha) - s(\alpha) \\ &* \overline{y}F(\alpha\overline{y})\big) \int_{-\infty}^{\alpha\overline{y}} U'\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) f(y) dy\end{aligned}$$

(7b)
$$\begin{aligned}= &-[s'(\alpha) * p(\alpha) + s(\alpha) * \overline{y}F(\alpha\overline{y})] \int_{\alpha\overline{y}}^{\infty} U'\,\big(y - s(\alpha) * p(\alpha)\big) f(y) dy \\ &+ [\overline{y} - s'(\alpha) * p(\alpha) - s(\alpha) * \overline{y}F(\alpha\overline{y})] U'\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) F(\alpha\overline{y})\end{aligned}$$

$s(\alpha) * p(\alpha)$ is the producer paid premium. $s'(\alpha) * p(\alpha) + s(\alpha) * \overline{y}F(\alpha\overline{y})$ is the marginal producer paid premium. If the marginal producer paid premium is decreasing or zero, Equation 7b is positive. This indicates that utility is not maximized at these rates and that the producer would not choose these coverage levels if given an option if a higher coverage is offered.

However, Equation 7b is unclear as to sign if those conditions are not met. Temporarily assume actuarially fair insurance, i.e. $s(\alpha)$=1 for all coverage levels:

(8a) $$= -\overline{y}F(\alpha\overline{y}) \int_{\alpha\overline{y}}^{\infty} U'\,\big(y - p(\alpha)\big) f(y) dy + \overline{y}\big(1 - F(\alpha\overline{y})\big) U'\big(\alpha\overline{y} - p(\alpha)\big) F(\alpha\overline{y})$$

(8b) $$= -\overline{y}F(\alpha\overline{y}) \int_{\alpha\overline{y}}^{\infty} U'\left(y - p(\alpha)\right) f(y)dy + \overline{y}F(\alpha\overline{y}) \int_{\alpha\overline{y}}^{\infty} U'\left(\alpha\overline{y} - p(\alpha)\right) f(y)dy$$

(8c) $$= \overline{y}F(\alpha\overline{y}) \int_{\alpha\overline{y}}^{\infty} \left[U'\left(\alpha\overline{y} - p(\alpha)\right) - U'\left(y - p(\alpha)\right)\right] f(y)\, dy.$$

Equation 8c is positive since $\overline{y}, F(\alpha\overline{y}), f(y) > 0$ and $U'\left(\alpha\overline{y} - p(\alpha)\right) > U'\left(y - p(\alpha)\right)$ for $y > \alpha\overline{y}$ since U is an increasing, concave function for a risk averse producer. In other words, U' is positive and $U'(x_1) > U'(x_2)$ when $x_1 < x_2$ since U'' is negative.

Due to Equation 8, we know that:

(9) $$\left|-\overline{y}F(\alpha\overline{y}) \int_{\alpha\overline{y}}^{\infty} U'\left(y - p(\alpha)\right) f(y)dy\right| < \overline{y}\left(1 - F(\alpha\overline{y})\right) U'\left(\alpha\overline{y} - p(\alpha)\right) F(\alpha\overline{y})$$

for a risk averse producer. We can now go back to assume subsidized insurance ($s(\alpha) < 1$) and also assume the subsidy level does not vary with the coverage level ($s'(\alpha) = 0$). We know in this case and with Equation (9):

(10)

$$\left|-s(\alpha) * \overline{y}F(\alpha\overline{y}) \int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y)dy\right| < \overline{y}\left(1 - s(\alpha) * F(\alpha\overline{y})\right) U'\left(\alpha\overline{y} - s(\alpha) * p(\alpha)\right) F(\alpha\overline{y})$$

This holds true for $s(\alpha) < 1$ since multiplying $s(\alpha)$ on the left hand side decreases the value, multiplying $s(\alpha)$ on the right hand side to create the term $\left(1 - s(\alpha) * F(\alpha\overline{y})\right)$ increases the value and $\frac{\partial \int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y)dy}{\partial s(\alpha)} < \frac{\partial \int_{-\infty}^{\alpha\overline{y}} U'\left(\alpha\overline{y} - s(\alpha) * p(\alpha)\right) f(y)dy}{\partial s(\alpha)}$ for an increasing, concave *U*. Equation 10 shows that a higher level is always preferred for insurance subsidized at a constant rate. If full insurance ($\alpha \rightarrow \infty$) is offered, the producer would choose that.

However, the equation becomes more complex for a nonconstant subsidy rate. For an increasing subsidy rate ($s'(\alpha) < 0$), $-s'(\alpha) * p(\alpha) > 0$ which necessitates $-s'(\alpha) *$

$p(\alpha) \int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y)dy < -s'(\alpha) * p(\alpha) \int_{-\infty}^{\alpha\overline{y}} U'\left(\alpha\overline{y} - s(\alpha) *\right.$ $\left. p(\alpha)\right) f(y)dy$ for an increasing, concave *U*. Adding this expression to Equation 10:

(11)

$$\left| -[s'(\alpha) * p(\alpha) + s(\alpha) * \overline{y}F(\alpha\overline{y})] \int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y)dy \right| < \left(\overline{y} - s'(\alpha) * p(\alpha) - s(\alpha) * \overline{y}F(\alpha\overline{y})\right) U'\left(\alpha\overline{y} - s(\alpha) * p(\alpha)\right) F(\alpha\overline{y})$$

which again indicates a higher level of crop insurance is always preferred. However, for a decreasing subsidy rate/increasing load factor, the addition of the expression would be ambiguous. From this we can conclude that, under expected utility theory, producers will never choose a coverage level where the subsidy rate is constant or increasing as long as a higher coverage level is offered.

Bulut (2018) posits that expected utility theory can explain observed behavior if a binding budget heuristic is coupled to the model. This would be represented as the following Lagrangian equation:

(12) $$L = E[U(r)] - \lambda(s(\alpha) * p(\alpha) - b)$$

where *b* is the binding budget constraint that is less than producer spending in the unconstrained optimization. There is no need to differentiate the Lagrangian to show that α will be lower in the constrained case than the unconstrained case as long as the out-of-pocket premium is increasing with the coverage level. Therefore, Bulut's hypothesis is consistent with observations that producers buy lower levels of coverage than would be expected under unconstrained EUT.

As previously mentioned, several in the literature have proposed prospect theory as potential explanation for observed coverage level decisions. While cumulative prospect theory is often utilized for discrete sets, it can also be extended to the continuous case. Equation (2) can be rewritten as:

(13)

$$\sum_{x_i>0} v(x_i - a)\left[w_+\left(1 - F(x_{i-1})\right) - w_+\left(1 - F(x_i)\right)\right] + \sum_{x_i<0} v(x_i - a)\left[w_-\left(F(x_{i-1})\right) - w_-\left(F(x_i)\right)\right]$$

where F is the cumulative distribution function. The continuous analogue is:

(14a) $E[V(w)] = -\int_a^{\infty} v_+(x-a)dw_+[1-F(x)] + \int_{-\infty}^{a} v_-(x-a)dw_-[F(x)]$

(14b) $E[V(w)] = -\int_a^{\infty} v_+(x-a)f(x)w'_+[1-F(x)]dx + \int_{-\infty}^{a} v_-(x - a)f(x)w'_-[F(x)]dx.$

While this result is known (Gurtler and Stolpe, 2017), it has not been used to examine crop insurance to our knowledge. It is worth noting that $\int_{-\infty}^{\infty} f(x)w'_+[1-F(x)]dx = \int_{-\infty}^{\infty} f(x)w'_-[F(x)]dx = 1$ and $f(x)w'_+[1-F(x)], f(x)w'_-[F(x)] > 0$. This means that the pdf transformations are themselves pdfs. Differentiating the expected cumulative prospect theory equation with respect to the coverage level yields:

(15)

$$\frac{dE[V(w)]}{d\alpha} = -\frac{da}{d\alpha}\int_a^{\infty} v'_+(x-a)\, f(x)w'_+\left(1-F(x)\right)dx - \frac{da}{d\alpha}\int_{\alpha\bar{x}}^{a} v'_-(x - a)\, f(x)w'_+\left(F(x)\right)dx + \left(\bar{x} - \frac{da}{d\alpha}\right) v'_-(\alpha\bar{x} - a)\left[1 - \int_{\alpha\bar{x}}^{\infty} f(x)w'_-\left(F(x)\right)dx\right].$$

Note that if the anchor does not depend on the coverage level, i.e. $\frac{da}{d\alpha} = 0$, the expression reduces to $\bar{x} * v'_-(\alpha\bar{x} - a)\left[1 - \int_{\alpha\bar{x}}^{\infty} f(x)w'_-\left(F(x)\right)dx\right]$ which is a strictly positive expression. This means that if the anchor does not depend on the coverage level, producers will always demand more insurance. Babcock noticed this outcome in his simulations and noted that premiums are viewed as a sunk cost in this case and expected indemnities will always rise with a higher premium level. Du et al.'s conjecture that CPT would explain the observed behavior if producers anchor with above average yields only works if the premium costs are part of the anchor formulation. If $\frac{da}{d\alpha} \neq 0$, then the sign of the expression is ambiguous, and the optimal insurance level may be less than full coverage.

As previously mentioned, Ramirez and Shonkwiler (2017) posit that information asymmetries may explain observed behavior. If a farm is less risky than RMA's ratings suggest, the premiums would be overpriced and the insurance no longer actuarially fair. A producer that knows this may purchase less than full insurance under expected utility theory. Yet, this framework can be recast the other way. While CPT says that agents overestimate the probability of unlikely events, it is possible the opposite is true, and they underestimate their likelihoods. If growing conditions have been good the last few years, recency bias would generate this outcome. In this case, the actuarial ratings may be fair but the producers perceive them to be overpriced due to their perception of the risk. Both asymmetric information and risk misperception can be represented under expected utility theory with the following equation:

(16)

$$E[U(r)] = \int_{\alpha\overline{y}}^{\infty} U\big(y - s(\alpha) * p(\alpha)\big) f(y) w'\big(1 - F(y)\big) dy$$
$$+ \int_{-\infty}^{\alpha\overline{y}} U\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) f(y) w'\big(1 - F(y)\big) dy$$

This formulation borrows the risk perception function, w, from CPT. For asymmetric information, the pdf of the true risk is $f(y)w'\big(1 - F(y)\big)$ and for risk misperception it is $f(y)$. If there is no misperception or asymmetric information, $w(x) = x$ and we are simply left with expected utility theory. Taking the derivative with respect to the coverage level yields:

(17)

$$\frac{dE[U(r)]}{d\alpha} = -[s'(\alpha) * p(\alpha) + s(\alpha) * \overline{y}F(\alpha\overline{y})] \int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y) w'\big(1 - F(y)\big) dy + [\overline{y} - s'(\alpha) * p(\alpha) - s(\alpha) * \overline{y}F(\alpha\overline{y})] \int_{-\infty}^{\alpha\overline{y}} U'\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big) f(y) w'\big(1 - F(y)\big) dy$$

which can be reduced to

(18)

$$\frac{dE[U(r)]}{d\alpha} = -[s'(\alpha) * p(\alpha) + s(\alpha) * \overline{y}F(\alpha\overline{y})] \int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y) w'\big(1 - F(y)\big) dy + [\overline{y} - s'(\alpha) * p(\alpha) - s(\alpha) * \overline{y}F(\alpha\overline{y})] U'\big(\alpha\overline{y} - s(\alpha) * p(\alpha)\big)\Big[1 - w\big(1 - F(\alpha\overline{y})\big)\Big]$$

We know in the case of a decreasing subsidy rate, the sign of the first term is negative. Whether the first term increases or decreases by reducing the variance with *w* depends on α and the shape of *w*. For instance, if $\alpha \geq 1$ and *w* reduces variance, $\int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y) w'\big(1 - F(y)\big) dy$ will increase for a Normal distribution since U' is a convex, decreasing function. Alternatively, if $\alpha \rightarrow -\infty$, $\int_{\alpha\overline{y}}^{\infty} U'\left(y - s(\alpha) * p(\alpha)\right) f(y) w'\big(1 - F(y)\big) dy$ would decrease with less variance. Since crop insurance has coverage levels between .5 and .9, it is ambiguous whether the first term increases or decreases with less variance.

On the other hand, the second term will decrease. If the marginal subsidy rate is less than the mean, i.e. $\overline{y} - s'(\alpha) * p(\alpha) - s(\alpha) * \overline{y}F(\alpha\overline{y}) > 0$, the second term is positive. Since the crop insurance coverage levels are less than the mean and w shrinks the variance, $1 - w\big(1 - F(\alpha\overline{y})\big) < F(\alpha\overline{y})$. Therefore, the second term will decrease. As a result, it is quite possible that by underestimating risk, rational producers maximizing expected utility would insure at lower coverage levels than they should.

The conceptual framework here results in several conclusions. First, under expected utility theory a risk averse producer will prefer full insurance to any alternative if the insurance is actuarially fair, subsidized at a constant rate or subsidized at an increasing rate. If full insurance is not available, he/she will always prefer a higher coverage level if the subsidy rate is constant between coverage levels.

Furthermore, a binding budget constraint can decrease the optimal coverage that would have been selected without it. Cumulative prospect theory also can lead to a selection of a lower coverage level than under EUT, but only if the premium cost is included in the anchor. Last of all, underestimating risk or possessing asymmetric information can lead to lower coverage levels.

While all of these explanations are theoretically plausible, they are not necessarily equally responsible (if at all) for the observed coverage levels. Narrowing down the options requires empirical research. To do this, we conducted a survey designed to reveal what producers believe to be the most important considerations in determining coverage levels. The next section describes the methods used in the survey to determine the drivers of coverage levels.

3.3 Survey

In order to examine the theoretically possible explanations for crop underinsurance, we conducted a survey. The survey was implemented by the agricultural analytics firm Kynetec in May through June 2019 based on their private farmer database. It was given to U.S. crop farmers through an online site. The survey consisted of 33 questions with a mean response time of five minutes and three seconds. Upon successful completion, respondents received $25 as a compensation fee. Our dataset consists of 500 completed responses that span 36 states. In order for the results to accurately represent an average insured acre, the probability of an operation being included in the survey was based upon the acres farmed. The 2017 USDA Census of Agriculture was used to develop targets for different acreage strata.

Table 4 compares the percent of respondents in some of the strata compared to the actual percent in the USDA Census of Agriculture.

Table 4: Respondents in strata

	Percent of total acres	
Cropland acres*	Census of Agriculture	This study
1-259	11%	10%
260-499	9%	10%
500-999	14%	13%
1000-1999	19%	22%
2000+	47%	45%

** USDA defines this as cropland acres in 2017 whereas this study defines it as crop acres planted in 2018*
Source: USDA-NASS (2019) and author calculations

The acreage breakouts closely match the USDA Census of Agriculture as desired. The signficance of this achievement is that the survey results represent the crop insurance demand curve. A survey that did not take this step would be representative of crop producers, not the demand curve. This could prove problematic if a particular reason for underinsurance was common among producers with few acres. The sample data may indicate that reason was a major factor, yet it may have very little impact on the overall demand for crop insurance.

Table 5 shows the demographic survey responses. Over 91% of farm respondents are the farm manager. The average number of acres planted is 2,100, but the standard deviation is almost as high indicating that there is a significant right tail to the distribution. Mean cropland acres owned exceeds 1,000, but the standard deviation is even higher. Most respondents grow corn (86.2%) and soybeans (77.2%) and are male (94.2%). The average age was 56.3 years which is just under the 57.5 years in the Census of Agriculture (USDA-NASS, 2022) for all farm operators. Annual household income was less than $100,000 for 56.4% of respondents and 47% had a four year college degree.

Respondents were asked to report on how willing they are to take risks, with 10 being very willing and 1 not willing. The mean response was 6.59. Likewise, the survey asked how much the respondent would be willing to pay for a raffle that pays $1,000 if won, $0 if not. The mean response was $133.98. Of the 500 responses, 85% were less than or equal to $250. The self-assessed willingness to take risks and lottery question both indicate the respondents have caution with regard to risk. However, the Spearman rank correlation coefficient between responses for the two questions was only .053. The raffle question was asked about halfway through the survey. Near the end, a corrolary question was posed: would the respondent accept a bet with a 50% chance they win $1,000 minus the amount of he or she was willing to pay for the raffle, and a 50% chance of losing the raffle response amount. This is an identical question to the raffle question, only posed as a potential loss instead of as only a gain. Failure to accept the bet in the corrolary is indication of framing and loss aversion. Of the respondents, 29% did not accept the corrolary bet.

Table 5: Survey demographics

Are you the farm manager:	
Yes	91.2%
No	8.8%
Crop acres planted	
Mean	2,127
Standard deviation	2,079
Cropland acres owned	
Mean	1,035
Standard deviation	1,386
Percent of respondents who planted crop in 2018	
Barley	4.4%
Corn	86.2%
Grain sorghum	6.8%
Oats	7.0%
Peanuts	1.6%
Rice	2.4%
Soybeans	77.2%
Sunflowers	2.4%
Upland cotton	9.2%
Wheat	37.4%
Gender	
Male	94.2%
Female	5.8%
Other	0.0%
Age	
Mean	56.3
Standard deviation	12.1
2018 annual household income	
Less than $30,000	5.6%
$30,000 to $39,999	4.2%
$40,000 to $49,999	5.6%
$50,000 to $59,999	9.4%
$60,000 to $69,999	8.2%
$70,000 to $79,999	10.2%
$80,000 to $89,999	6.6%
$90,000 to $99,999	6.6%
$100,000 to $149,999	19.4%
$150,000 to $199,999	6.8%
$200,000 to $249,999	5.8%
$250,000 or more	11.6%

What is the highest level of education that you have obtained?	
Some high school or less	1.2%
High school diploma	19.0%
Some college	19.8%
2 year/Associates degree	13.0%
4 year/Bachelor's degree	37.0%
Some graduate school	4.6%
Graduate school	5.4%
Number of people in household	
Mean	2.9
Standard deviation	1.4
How willing are you to take risks (1=not willing, 10=very willing)	
Mean	6.59
Standard deviation	1.75
What is the most you would be willing to pay for a raffle that pays $1,000 if won, $0 if not.	
Mean	$133.98
Median	$100.00
Would you accept a bet with a 50% chance you win ($1,000 -raffle response) and 50% chance you lose (raffle response)?	
Yes	71%
No	29%

The results of the crop insurance related questions in the survey are presented in Table 6. The first set of questions asks about the importance of various factors when deciding to purchase crop insurance. Almost 80% of responses indicate that lender requirements are very important when deciding to purchase crop insurance. In all, 98% of the responses indicate the factor was somewhat or very important. This stated preference supports the idea that producers are reluctant insurers as requirements for financing is a reason for almost everyone to obtain insurance.

Slightly less important for consideration when purchasing crop insurance than lender requirements is reducing farm risk where 88% of respondents indicated that it is somewhat or very important. This share is fairly evenly split between somewhat and very. Capturing the subsidy seems to not be a primary consideration when deciding to purchase crop insurance as over 69% rate maximizing insurance payouts relative to costs as not at all important or not very.

Likewise, respondents were asked about the importance of various factors when selecting a coverage level. Once again, lender requirements are the most important factor as 72% rate it as very important and less than 3% put it in the not important categories. Most respondents stated that a budgeted amount was important when choosing a coverage level with 78% rating it as somewhat or very important. Reducing farm risk is not stated as being a major factor when selecting a coverag level. The mode category was not at all, and over 60% put it in the not important categories. Maximizing payouts relative to costs was more important when selecting a crop insurance level than when deciding to purchase crop insurance.

Survey particpants were asked if they expected crop insurance payouts to exceed costs over time. Of those, 64% stated they did not. This is a surprising outcome since the program is designed to pay out more over time than it takes in. In fact, aggregate producer paid premiums have not exceeded indemnities since 1994. The producer loss ratio from 2011 to 2020 was 2.31[5] indicating that producers received over twice the amount in indemnities that they paid in premiums (USDA-RMA 2022). The responses could be due to several factors. First, it is possible that a small share of producers are receiving most of the indemnities. While this may not be likely, it cannot be ruled out by just looking at aggregate payment data. The other alternative is that respondents are exhibiting a biased perception of payment history. An individual producer may not receive an indemnity for several years at a time, and the perception of frequent lack of indemnities despite paying annual premiums may result in the perception that more is paid in than received over time. This view would be consistent with risk misperception.

Survey participants were asked how they would react to a 50% reduction in crop insurance premiums. Sixty-two percent would change their policy while 42% would change their crop insurance units (such as basic, optional or enterprise). Most (83%) would increase their crop insurance coverage level. Of the other 17%, about half were already at the maximum coverage level and couldn't increase further. About 2/3 of producers are already insuring all of their acres. Of the rest, most (28%) would try to purchase crop insurance for acres they are not currently insuring. The answers to these questions indicate that producers report sensitivity to crop insurance prices. Their optimal

[5] In contrast, the overall loss ratio was .87 during this time period.

policy and unit would change while those that still can would generally buy up more coverage.

Several questions about how respondents would react if premiums were halved were also asked in context of receving an extra $50,000 per year for life. More respondents would try to increase their planted area if they received the extra annual income (42%) versus if crop insurance premiums were halved (23%). While neither answer constitutes a majority of responses, the twofold difference is noticeable. This could be due to a couple of factors. First, the dollar amounts for a specific producer could be very different between the two questions. Second, crop insurance premiums are a loss whereas extra income is a gain. Loss averse producers could respond differently between the two outcomes. Most respondents would try to increase their yield if crop insurance premiums were halved (71%), but only 46% would try to do so if they received an extra $50,000 for life. In both cases, the responses were higher than the corresponding answers to the planted area questions. This is consistent with more binding land constraints than ability to alter other inputs to affect yields. The fact that more producers would want to increase yields in the face of lower premiums than with extra income is a bit more puzzling. One potential explanation is that increasing yields increases crop insurance premiums. The corrolary is that lowering premiums lowers the marginal cost of a yield increase. The most striking difference in behaviour between the crop insurance and extra income questions is in regards to crop mixes. If premiums were halved, 13.6% would alter their mix of crops while 83.3% would do so with an extra $50,000 per year. One explanation for the large difference is that crop insurance may not have the same availability for all crops. Cutting the premiums would not matter in that case. However, extra income would help cover potential liquidity issues in the absence of insurance.

Most respondents (73%) would spend the same amount of time crop farming even if they received an extra $50,000 per year for life. The rest were evenly split between more and less time. This is at least a 50% increase in household income for over half of respondents. Despite this, 86% of respondents would not cut back on time spent farming even with a significant increase in income. This seems to indicate that producers lack access to desired credit levels, interest costs are preventing the fully desired scale of the farming operation, or that producers simply derive utlity from the act of farming and will spend their marginal leisure time engaged in it.

The survey respondents were asked if they believe they had chosen the correct coverage level for the past crop year with the information they had available when making the decision. An overwhelming majority of them felt they had (96%). The number of respondents regretting their coverage level decision was less than 5%.

Table 6: Crop insurance survey results

Importance of factors when deciding to purchase crop insurance	**Not at all**	**Not very**	**Somewhat**	**Very**
Lender requirement	0.2%	1.8%	18.4%	79.6%
Reduce farm risk	3.6%	8.4%	43.0%	45.0%
Maximize insurance payouts relative to costs	42.3%	27.0%	29.5%	1.2%
Importance of factors when choosing a coverage level	**Not at all**	**Not very**	**Somewhat**	**Very**
Lender requirement	0.6%	2.2%	25.6%	71.6%
Budgeted amount	3.2%	9.0%	42.8%	45.0%
Reduce farm risk	37.2%	24.6%	25.4%	12.8%
Maximize insurance payouts relative to costs	5.0%	13.0%	55.6%	26.4%
Do you expect crop insurance payouts to exceed costs over time?				
Yes	35.8%			
No	64.2%			
If crop insurance premiums were cut in half for all policies so that you were only paying 50% of the previous amount for the same coverage:	**Yes**	**No**		
Would you change the crop insurance policy?	62.4%	37.6%		
Would you change the crop insurance units?	41.6%	58.4%		
Would you try to increase your yield?	71.4%	28.6%		
Would you alter your mix of crops?	13.6%	86.4%		
Would you try to increase your planted area?	23.2%	76.8%		
	Yes	**No**	**Already at max**	
Would you increase your crop insurance coverage level?	82.8%	8.4%	8.8%	
	Yes	**No**	**Already insure all**	
Would you purchase crop insurance for acres you are not currently insuring?	28.4%	5.4%	66.2%	
If you were to receive an extra $50,000 per year for the rest of your life, would you:	**Yes**	**No**		
Try to increase your total planted area?	42.3%	57.7%		
Alter your mix of crops?	83.3%	16.7%		
Try to increase your yield?	46.3%	53.7%		
	More	**Less**	**Same**	
Spend more, less or about or about the same amount of time crop farming?	13.1%	13.5%	73.4%	
With the knowledge you had when purchasing crop insurance in 2018, do you believe you chose the correct coverage levels?				
Yes	95.6%			
No	4.4%			

The survey revealed that lender requirements, budgeted amounts and capturing the subsidy are important stated factors in selecting a coverage level. Reducing farm risk does not appear to be an important consideration. Producers also appear to be subject to the framing effect with loss aversion and most don't expect to make money on crop insurance which is indicitive of asymetric information. Most report being sensitive to premiums when selecting a coverage level. These responses leave open the door CPT, budget heuristics, asymmetric information and reluctance to insure as possible explanations for underinsurance. However, this is based upon stated responses and may or may not be related to actual outcomes. The next section looks to test the actual explanatory power of the responses.

3.4 Empirical Analysis

Testing explanations for crop underinsurance from the survey outcomes requires classifying respondents as underinsurers or not. While seemingly simple, the categorization is anything but. A producer can have different polices and coverage levels for the same commodity grown in different locations. The subsidy rates are the same for every producer but differ by policy and coverage level. Meanwhile, the premium schedule is unique to producers. As a result, the marginal subsidy rate is unique to each policy and is not observed in aggregate data. Therefore, it is difficult to broadly classify the degree of undersinsurance without knowing the full array of premium possiblities presented to each individual which prevents the research from calculating marginal subsidies.

However, the subsidy schedule allows for some generalizations. Table 7 shows the subsidy rates by policy and coverage level with the latter by column. In the case of enterprise coverage, the subsidy rate is the same for all coverage levels between 50% and 70%. As shown in the conceptual framework, an economically rational agent would never choose a coverage level if a higher one is available that has the same subsidy rate given actuarially fair insurance. This indicates that participants selecting coverage levels of 50% to 65% are obviously undersinsuring under classical EUT. These have been denoted by a **. Likewise, the 55% and 65% coverage levels for basic and optional units would not be selected under the same assumptions and are denoted the same way.

Table 7: Crop insurance subsidy rates by policy and coverage level

Unit	**50%**	**55%**	**60%**	**65%**	**70%**	**75%**	**80%**	**85%**
Basic	*0.67	**0.64	*0.64	**0.59	*0.59	0.55	0.48	0.38
Optional	*0.67	**0.64	*0.64	**0.59	*0.59	0.55	0.48	0.38
Enterprise	**0.80	**0.80	**0.80	**0.80	*0.80	0.77	0.68	0.53

Source: USDA-RMA 2022

Table 8 shows two example subsidy per acre schedules. For McLean County, Illinois, the subsidies are maximized at the highest available coverage level, 85%, for all units. In other words, the subsidy per acre is strictly increasing. On the other hand, the subsidies for all of the Boone County, Missouri, units the subsidies are maximized at 80%. There is also a relatively modest marginal increase in the subsidies by increasing the coverage level from 75% to 85%. Without knowing the underlying premiums and subsidies offered to each producer and their utility function, it is impossible to know which unit/coverage level combinations represent underinsurance other than the ones marked with ** in Table 7. However, we create one more category that we call likely underinsured that is represented by *. These unit/coverage combinations are those one coverage level (5%) above an underinsured coverage level option. The marginal subsidy rate drop at these levels tends to be small creating little penalty for selecting yet a higher coverage level. Those options in Table 7 that are unmarked are not obviously underinsured.

Table 8: Revenue Protection premium subsidy per acre for non-irrigated commodity corn with APH yield equal to reference yield for 2019

County	Unit	50%	55%	60%	65%	70%	75%	80%	85%
McLean, IL	Basic	$1.09	$1.44	$2.05	$2.81	$4.07	$5.46	$7.00	$8.28
	Optional	$1.63	$2.09	$3.00	$3.94	$5.48	$7.19	$8.91	$10.13
	Enterprise	$1.30	$1.80	$2.46	$3.43	$4.93	$6.63	$8.55	$10.40
Boone, MO	Basic	$9.69	$11.79	$14.76	$16.71	$20.48	$23.29	$24.38	$23.90
	Optional	$15.24	$18.05	$21.93	$24.49	$29.45	$32.66	$33.41	$32.24
	Enterprise	$11.58	$14.74	$18.43	$22.66	$27.77	$32.60	$34.54	$32.35

Source: USDA-RMA 2022 and author calculations

Based on this, we classify respondents in one of three categories based upon their crop insurance decisions. For each crop on the farm, the insurance decision is rated as underinsured, likely underinsured or not obviously underinsured. This is based upon Table 7. If the crop was not insured, it was labeled as underinsured. If a crop was not insured as a COMBO policy in Revenue Protection, Revenue Protection with Harvest Price Exclusion or Yield Protection, it was not considered. The structures of other policies such as Whole Farm Revenue Protection, Catastrophic Covereage or area based policies don't allow easy comparisons with other policies. The COMBO policies represent the most common policies and only 12 resondents did not have at least one crop with one of the policies. Each producer was subsequently classified according to the lowest level of underinsurance among all of the crops on the farm. For example, if a respondent had one crop that was underinsured and another that was not obviously underinsured, the respondent would be classified as underinsured. Of the 500 respondents, only 27 did not have all of the crops in the same category.

Table 9 displays the regression variables and mean of each for the differeing categories of underinsurance. Thirty-seven observations were dropped due missing input for variables. Of the remaining 463, 378 were not obviously underinsured, 21 were potentially underinsured and 64 were underinsured.

Table 9: Mean levels for regression variables

Description	Variable	Underinsured	Potentially underinsured	Not obviously underinsured
Lender requirement is somewhat or very important in choosing coverage level	lender	0.94	0.95	0.99
Budgeted amount is somewhat or very important in choosing coverage level	budget	0.81	0.76	0.89
Reducing farm risk is somewhat or very important in choosing coverage level	farmrisk	0.31	0.43	0.39
Maximizing insurance payout relative to costs is somewhat or very important in choosing coverage level	maxpay	0.77	0.67	0.84
Crop insurance payouts expected to exceed costs over time	paycosts	0.44	0.48	0.33
Age of farmer in years	age	58.44	54.10	58.57
Respondent is female	female	0.03	0.10	0.05
Annual income in thousands of dollars (low of 15 and high of 250)	income	115.63	116.19	111.65
Percent of yearly household income that comes from crop production	perccrop	62.70	67.10	70.53
Respondent has some college but no degree	somecollege	0.17	0.14	0.19
Respondent has at least one degree	degree	0.63	0.71	0.60
Logarithm of acres planted to crops on farm	logacres	7.05	7.41	7.20
Percent of acres planted to crops that are owned	percowned	0.69	0.52	0.63
Number of different types of crops planted in 2018	no_crops	2.42	2.67	2.35
Respondent in (ND, SD, NE, KS, OK, TX)	plains	0.44	0.24	0.27
Respondent in (AR, LA, MS, AL, GA, SC, NC, TN, KY, VA)	south	0.16	0.14	0.07
Scale of willingness to take risks (1=not willing, 10=very willing)	takerisks	6.53	7.19	6.63
Does reframing lottery as a potential loss result in responding not accepting it	framing	0.27	0.33	0.29
Is the respondent the farm manager?	manager	0.91	0.95	0.90
Number of people living in household	nohousehold	2.88	3.52	2.80
Either If crop insurance premiums were cut in half, 1) would increase coverage level 2) or would not but only because already at max coverage level	half	0.86	0.76	0.95
Respondent would try to increase planted area if you received an extra $50,000 per year for life?	plantmore	0.48	0.48	0.41
Is the largest crop by area on the farm in the lowest underinsurance category?	lowacresmax	0.75	0.86	0.99
Number of observations	*n*	*64*	*21*	*378*

Many of the regression variables are from Table 5 and Table 6. Variables that had responses of Very Important, Somewhat Important, Not Very Important and Not At All Important were reduced to a binary variable of Important=1 and Unimportant=0. The natural logarithm of acres planted on the farm was used to deal with the right tail of the variable. A similar adjustment was not made for income since respondents selected a category instead of reporting the amount. This effectively Winsorized the data.

Categorical dependent variables with a natural order are a good candidate for the ordinal logistic regression model. This model estimates the following set of equations in the case of three categories:

(19)
$$y^* = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$
$$y = \begin{cases} y_1 \; if \; y^* < \alpha_1 \\ y_2 \; if \; \alpha_1 < y^* < \alpha_2 \\ \vdots \\ y_m \; if \; \alpha_{m-1} < y^* \end{cases}$$

where *y* is an ordinal variable with possible values of $y_1, y_2, \ldots y_m$, x_i is an independent variable, β_i is a parameter and ε is a random variable with a standard logistic distribution. This is simply the multivariate, ordered version of the logistic regression. The ordinal regression model can predict probabilites of being at a level given a set of independent variables. The α's provide breakpoints that determine which category the result will fall into. The constant β's for all values of *y* is a key assumption known as parallel slopes or proportional odds. The Brant test checks the model specification to ensure the assumption is not violated. Table 10 shows the result of the test for our model where the null hypothesis is parallel slopes. The omnibus is a test of the overall model and is not significant which indicates the model does not violate the parallel slopes assumption[6]. The table also reports the results for individual variables. *Plains* falls below the .05 significance level, but that shouldn't be viewed as a failure of the overall model. For instance, using the .05 significance level with a Bonferroni correct for the 23 variables

[6] The Brant test was not initially able to be performed due to the test difficulties inverting the covariance matrix of the estimators. After dropping the variable related to whether respondents believe they chose the correct coverage level in 2018, the test was able to be performed. All of the results are based upon the model that excludes the correct coverage level variable.

yields a value of .002. No p-value falls below that threshold. The Brant test shows that we cannot reject the parallel assumption requirement for our model.

Table 10: Brant Test for Parallel Slopes

	Chi^2	**Degrees of Freedom**	**P-Value**
Omnibus	24.24	23	0.390
lender	0.03	1	0.870
budget	0.84	1	0.360
farmrisk	1.50	1	0.220
maxpay	1.99	1	0.160
paycosts	0.05	1	0.820
age	0.26	1	0.610
female	0.61	1	0.430
income	0.23	1	0.630
perccrop	0.13	1	0.720
somecollege	0.02	1	0.890
degreeTRUE	0.11	1	0.740
logacres	0.85	1	0.360
percowned	0.08	1	0.780
no_crops	0.32	1	0.570
plains	**4.84**	**1**	**0.030**
south	0.71	1	0.400
takerisks	3.01	1	0.080
framing	1.57	1	0.210
manager	1.62	1	0.200
nohousehold	0.45	1	0.500
half	1.51	1	0.220
plantmore	0.06	1	0.800
lowacresmax	0.81	1	0.370

The results of the subsequent logistic regression are in Table 11 and Table 12. The regression coeffecients can be interpreted as the log of the odds ratios. The p-value for the overall regression is less than .0001 indicating that at least one variable is significant.The predicted probability is in Table 12 is for the average respondent and indicates that he/she belongs with 85% probability in the not obviously underinsured category. All variables showed a change of sign in the marginal probabilities between likely underinsured and not obviously underinsured. The first two variables (α_1 and α_1) in Table 11 are the breakpoints between underinsured and likely undersinsured, and likely underinsured and not obviously underinsured, respectively. Interestingly, the stated importance of factors when choosing coverage levels does not generally have a statistically significant effect on underinsurance. Lender requirements, budgeted amount, reducing farm risk and maximizing payouts relative to costs (subsidy capture) are not significant at any meaningful level, although all have a positive sign. The idea of a budget heuristic for crop insurance is not supported by the regression results. It should be noted these results are based on stated levels of importance. Unperceived motivations would not be captured.

Table 11: Ordered logistic regression results

	Coefficient	S.E.	Wald Z.	P-Value
α_1	**-4.253**	**1.820**	**-2.340**	**0.019**
α_2	**-4.692**	**1.825**	**-2.570**	**0.010**
lender	1.182	0.757	1.560	0.119
budget	0.600	0.381	1.580	0.115
farmrisk	0.103	0.306	0.340	0.735
maxpay	0.393	0.363	1.080	0.279
paycosts	-0.533	0.281	-1.890	0.058
age	-0.015	0.014	-1.070	0.283
female	-0.301	0.632	-0.480	0.634
income	-0.001	0.002	-0.300	0.763
perccrop	0.007	0.005	1.290	0.197
somecollege	-0.089	0.458	-0.190	0.847
degree	-0.222	0.368	-0.600	0.547
logacres	0.172	0.153	1.130	0.259
percowned	0.020	0.187	0.110	0.915
no_crops	0.148	0.159	0.930	0.351
south	**-0.961**	**0.456**	**-2.110**	**0.035**
plains	**-0.857**	**0.321**	**-2.670**	**0.008**
takerisks	-0.034	0.082	-0.420	0.678
framing	0.205	0.322	0.640	0.523
manager	0.422	0.468	0.900	0.368
nohousehold	-0.176	0.103	-1.720	0.086
half	**1.151**	**0.415**	**2.770**	**0.006**
plantmore	0.022	0.287	0.080	0.938
lowacresmax	**3.356**	**0.556**	**6.040**	**<0.0001**
Likelihood ratio Chi^2		89.5		
Degrees of freedom		23		
Pr(>Chi^2)		<.0001		

Table 12: Predicted probabilities and marginal effects

	Underinsured	Likely underinsured	Not obviously underinsured
Predicted probability	0.099	0.047	0.854
Marginal effects			
lender	-0.163	-0.047	0.209
budget	-0.064	-0.023	0.087
farmrisk	-0.009	-0.004	0.013
maxpay	-0.039	-0.015	0.054
paycosts	0.051	0.019	-0.070
age	0.001	0.001	-0.002
female	0.030	0.011	-0.041
income	0.000	0.000	0.000
perccrop	-0.001	0.000	0.001
somecollege	0.008	0.003	-0.011
degree	0.019	0.008	-0.027
logacres	-0.015	-0.006	0.021
percowned	-0.002	-0.001	0.002
no_crops	-0.013	-0.005	0.018
plains	0.089	0.032	-0.121
south	0.118	0.038	-0.156
takerisks	0.003	0.001	-0.004
framing	-0.018	-0.007	0.025
manager	-0.043	-0.016	0.059
nohousehold	0.016	0.006	-0.022
half	-0.151	-0.046	0.196
plantmore	-0.002	-0.001	0.003
lowacresmax	-0.644	-0.036	0.680

Paycosts has a negative coefficient and is significant at the 10% level. This is contrary to what might be expected as those who expect to make money on crop insurance might be expected to buy up coverage to maximize the subsidy capture. It might be explained by the higher subsidy rate at lower levels which make it more likely for indemnities to surpass premiums.

The variables that control for demographics and the size of the operation were not significant. Age, gender, income, percent of income from crops, college education, operation size and percent of land owned were not significant. In other words, we fail to find evidence that the size of the operation or operator characteristics explain underinsurance.

One potential explanation for crop underinsurance is that farms with many crops have difficulty getting good premium rates. With the crop rotation, they may not have production history for all years for a particular crop. As a result, the producer may have to use transition yields, or fractions thereof, which may result in a low APH yield. This results in higher premium rates due to asymmetric information. However, the regression finds no relationship between the number of crops grown on the farm and the level of underinsurance.

In contrast, the regional variables, *south* and *plains*, are both significant and have negative coefficients. This indicates that farmers in these regions are more likely to underinsure, even with other factors taken into account. This could be due to regional beliefs about the effectiveness of crop insurance. It also could be due to the differences in crops grown in the regions. Figure 16 shows the correlation between the regional dummies and crops grown (not the number of acres). Tetrachoric correlation was used since all of the variables were binary with the ‘psych’ pacakge in R. In four instances, a value of zero was corrected with .5 in the underlying pairwise tables used for the calculation. The resulting correlation matrix was also not positive semi-definite, so smoothing was used.

Figure 16: Tetrachoric correlation of regions and crops

	Plains	South	Barley	Corn	Grain sorghum	Oats	Peanuts	Rice	Soybeans	Sunflowers	Upland cotton	Wheat
Plains	1.00	-0.56	0.00	-0.06	0.61	-0.10	-0.01	-0.32	-0.17	0.11	0.31	0.31
South	-0.56	1.00	0.03	-0.14	-0.10	-0.17	0.52	0.62	0.12	0.08	0.42	-0.20
Barley	0.00	0.03	1.00	-0.35	-0.09	0.12	0.46	-0.02	-0.37	0.38	0.03	0.31
Corn	-0.06	-0.14	-0.35	1.00	-0.31	0.17	-0.33	-0.25	0.70	0.02	-0.49	-0.41
Grain sorghum	0.61	-0.10	-0.09	-0.31	1.00	0.09	0.13	0.18	-0.36	0.27	0.54	0.51
Oats	-0.10	-0.17	0.12	0.17	0.09	1.00	0.20	0.07	-0.08	0.53	0.02	0.03
Peanuts	-0.01	0.52	0.46	-0.33	0.13	0.20	1.00	0.22	-0.49	0.33	0.80	-0.05
Rice	-0.32	0.62	-0.02	-0.25	0.18	0.07	0.22	1.00	-0.05	0.41	0.27	-0.09
Soybeans	-0.17	0.12	-0.37	0.70	-0.36	-0.08	-0.49	-0.05	1.00	-0.12	-0.52	-0.26
Sunflowers	0.11	0.08	0.38	0.02	0.27	0.53	0.33	0.41	-0.12	1.00	0.19	0.48
Upland cotton	0.31	0.42	0.03	-0.49	0.54	0.02	0.80	0.27	-0.52	0.19	1.00	0.10
Wheat	0.31	-0.20	0.31	-0.41	0.51	0.03	-0.05	-0.09	-0.26	0.48	0.10	1.00

Respondents in the Plains tend to be more likely to grow grain sorghum, upland cotton and wheat and less likely to grow rice. In the South, the respondents are more likely to grow peanuts, rice and upland cotton. The crops tend to get higher farm bill Title I payments per base acre. While a base acres is tied to historical plantings and not current, that link also means the producer is more likely to currently be growing the crop. As a result, the ARC-CO and PLC programs in the farm bill should provide some level of risk protection for producers currently growing the crop. Figure 17 shows the amounts for payments from ARC-CO and PLC per base. The figures were calculated by taking the higher of the national average of each payment type since a producer can only be in one program and averaging the past two marketing years along with the almost complete marketing year payment at the time when the survey was taken. The crops correlated with South tend to have some of the highest payment rates, especially peanuts and rice. The crops correlated with Plains aren’t quite as lucrative, but still tend to be on the higher side as grain sorghum received the third highest payment level. Many of the Plains crops such as sunflowers, wheat and sorghum tend to have lower variable costs which means the payments tend to be on the higher end relative to variable costs[7]. For example, although

[7] ARC and PLC are made on base acres, not planted acres, so care should be made with interpretation.

corn and wheat have similar absolute payment levels, those levels are about three times greater for wheat than corn as a share of their respective variable costs. Growers in the South and Plains may view crop insurance as less important as they receive more aid from other programs. In fact, Bulut (2018) includes the farm bill Title I programs in addition to crop insurance when calculating revenues to producers to account for this. As aforementioned, his work found that farmers are generally maximizing utility for a given budget which is consistent with using ARC-CO and PLC in place of crop insurance for the South and Plains.

Figure 17: 2016/17 through 2018/19 average[8] of the higher of national PLC or ARC-CO payments, dollars per base acre

	Absolute	Divided by avg variable costs
Barley	$13.66	7.9%
Corn	$23.62	7.0%
Grain sorghum	$42.77	33.5%
Oats	$9.64	7.7%
Peanuts	$179.36	35.2%
Rice	$146.90	27.2%
Soybeans	$3.68	2.1%
Sunflowers	$27.92	19.4%
Upland cotton	$30.10	7.0%
Wheat	$27.02	22.1%

Source: FAPRI March 2021 Baseline and author calculations

Although a dummy for individual crops in place of the regions could add more informative results, the high degree of correlation between some crops makes this approach problematic. For instance, peanuts and upland cotton have a correlation of .8 and upland cotton and sorghum have a correlation of .54. Given this, it would be hard to

[8] Upland cotton is for seed cotton and is for 2018/19 only as it was not eligible for ARC-CO and PLC in the prior years.

distentangle the various crops. Instead, using regions captures the differing crop mixes and any area based attitudes regarding crop insurance.

Several other variables seemed to have no significant effect on the extent of underinsurance. *Takerisks*, *framing*, *manager* and *plantmore* all failed to achieve any meaningful level of significance. This translates to lack of relationship between the level of underinsurance and the self-described willingness to take risks. Additionally, there doesn't appear to be a clear relationship between framing and the coverage. This is a core concept of prospect theory, but the regression is based on a survey question and could suffer from cheap talk. We also didn't find that the coverage level was tied to regret from the previous crop year. The lack of significance also indicates the inability to conclude a relationship between underinsurance and liquidity constraints as *plantmore* lacked significance. *Nohousehold* was significant at the 10% level with a negative sign. A clear explanation for this escapes us as liquidity issues that might be affected by a larger household are accounted for in other variables.

Half was signifcant with a p value of .006 and had a positive sign. This indicates that those more sensitive to crop insurance premiums are better insured. This seems counter-intiutive at first as price sensitive consumers might be expected to purchase less. However, it might be in the case of crop insurance that those paying attention to the price recognize the potential returns to crop insurance and are more carefully considering the potential indemnities compared to premiums. Those with a bias against crop insurance might be less likely to optimize coverage at any premium.

Likewise, *lowacresmax* had a positive sign and was highly significant. This means that if the largest crop by area of the farm was in the lowest underinsurance category for the farm, the respondent was likely better insured. This could simply be the result of more consistent coverage across the farm for those producers. In this case, they wouldn't be trying to cut total premium cost for an expensive crop, but would be trying to optimize coverage regardless of the premium.

3.5 Conclusion

This research seeks to help understand the reasons for crop underinsurance. Given that actuarial fairness requirements with the premium subsidies, crop insurance should be very appealing. Yet, the uptake hasn't always matched what would be optimal under expected utility maximization. We examine some of the potential explanations posited in the literature. These include prospect theory, a budget heuristic, reluctance to insure, asymmetric information/risk underestimation, regret minimization. Several of these were examined in a theoretical framework. It was determined that the following would explain the lower the coverage level: a binding budget constraint, prospect theory if the premium is in the anchor and asymmetric information in the form of the producer believing the risk is lower than RMA does. Under classical expected utility theory a risk averse producer would select the maximum coverage level if the premium were actuarialy fair and the subsidy rate was non-decreasing. A decreasing subsidy rate leaves open the possibility of an interior solution.

We further examine some of these potential explanations through a survey sent to crop producers. The survey sampling was weighted by the farm size in order to be representative of the insurance demand curve. The responses indicate that lender requirements, budgeted amount and capturing the subsidy are important factors that farmers consider when selecting a coverage level. Producer responses indicate asymmetric information about crop insurance as well as some evidence of the framing effect. Cumulative prospect theory, budget heuristics, asymmetric information and reluctance to insure could all be consistent with the responses.

The survey results are tested against the insurance decisions that were actually made. In general, the factors that were stated as important failed to have a statistically meaningful relationship to actual levels of underinsurance. Instead, the farm region and price sensitivity appear to be highly related to underinsurance. This could be due to a combination of regional attitudes and the crops grown in different parts of the U.S. The areas that relate to lower coverage tend to grow more crops with higher farm bill Title I payments. These could be substituting for crop insurance in those areas.

With regards to premium price sensitivity, producers that indicate they are more sensitive to premiums tend to more fully insure. This result may be counter-intuitive at first. One possible explanation is that these producers are more thoroughly investigating the tradeoffs and therefore likely selecting more optimal coverage levels.

This work refines possible reasons for crop underinsurance that have been posited. We find that some of the results are plausible but don't necessarily have strong evidence. The results do indicate that analysis of crop insurance decisions need to account for the role of farm bill programs and regional perceptions of the programs.

Further work on this subject could consider the role of incomplete yield histories on a farm either due to crop rotations or lack of tenure. In these cases, farmers must substitute yields that are oftentimes low for the missing data which can change the premium rates. The substitution could cause the premium rates to be less than actuarially fair.

Our result that respondents accounting for nearly 2/3's of the demand curve for crop insurance believe that the program loses money is surprising but doesn't seem to be correlated with underinsurance. However, this result has very large implications for crop insurance research and the effect of crop insurance subsidies on planted acreage. Theoreritcal underpinnings for crop insurance research often implicitly assume that producers understand the actuarials of crop insurance. Our evidence indicates this is not true. Research that is based on this assumption seems to fail to grasp agents' actual perceptions when making formulations.

Furthermore, crop insurance returns seem to be viewed differently than other income streams. Not only do producers perceive the returns from crop insurance to be much smaller than they actually are, more producers indicate they would try to increase their planted area if they received a fixed annual payment than if crop insurance premiums were reduced. While the payment levels between the two options are not necessarily the same and the incremental cost of increasing acreage may be a step function with certain thresholds required to expand, this demonstrates that farmers don't view crop insurance returns the same as other income. Any model that treats crop insurance premium costs the same as negative income should be called into question.

This work is based upon a survey. It is always possible that respondents didn't adequately understand the questions or didn't consider them with the same level of rigor they would demonstrate in making farm decisions. Further work is needed to investigate our findings as it would reshape much of the crop insurance demand literature. If this result is confirmed, theoretical work on crop insurance should incorporate the producers belief about ratings. The additional research is warranted as it addresses the underlying principles that are used to derive the crop supply curve assumptions critical to much of the work in the field.

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3.7 Appendix: Producer Survey

1. Are you the farm manager?
    1. Yes
    2. No

2. How many acres planted to crops do you currently farm? _______ (To qualify, must be > 1)

3. How many acres of cropland do you currently own? _______

4. How many acres of the following crops did you plant in 2018?

Crop	Acres
Barley	{0-99999}
Corn	{0-99999}
Grain Sorghum	{0-99999}
Oats	{0-99999}
Peanuts	{0-99999}
Rice	{0-99999}
Soybeans	{0-99999}
Sunflowers	{0-99999}
Upland Cotton	{0-99999}
Wheat	{0-99999}
Other [specify]	{0-99999}
Other [specify]	{0-99999}
Other [specify]	{0-99999}

5. Did you purchase crop insurance for the following crops in 2018?

[Pipe in crops with acres > 0]		
Crop	**Yes**	**No**
[crop 1]	o	O
[crop 2]	O	O
[crop 3]	O	O
Etc	O	O

[Ask Q6a, Q6b, and Q6c for the 2 crops with the most acres AND crop insurance purchased] [Repeat questions 6a, 6b, and 6c for each crop]

6a. What policy did you insure the [crop] with? If you have more than one crop insurance policy for [crop], please report that policy that covers the most acres planted for the crop in 2018.

1. Revenue Protection (RP)
2. Revenue Protection with Harvest Price Exclusion (RPHPE)
3. Yield Protection (YP) (Not catastrophic coverage)
4. Catastrophic coverage (Cat)
5. Area based policy
6. Other [specify]

6b. What was the insurance unit?

1. Enterprise
2. Optional
3. Basic
4. N/A

6c. What was the coverage level?

1. 50%
2. 55%
3. 60%
4. 65%
5. 70%
6. 75%
7. 80%
8. 85%
9. Other [specify]

7. When considering purchasing crop insurance, how important are the following factors to you:

[Randomize List]	Not important at all	Not very important	Somewhat important	Very important
a. Reduce farm risk				
b. Maximize insurance payouts relative to costs				
c. Lender requirement				

[Force one answer per row]

8. When choosing a coverage level, how important are the following factors to you:

[Randomize List]	Not important at all	Not very important	Somewhat important	Very important
a. Reduce farm risk				
b. Maximize insurance payouts relative to costs				
c. Lender requirement				
d. Budgeted amount				

[Force one answer per row]

9. Did you receive or do you expect to receive crop insurance payments for the 2018 crop?
    1. Yes
    2. No

10. With the knowledge you had when purchasing crop insurance in 2018, do you believe you chose the correct coverage levels?
    1. Yes
    2. No

11. Do you expect crop insurance payouts to exceed premium costs over time?
    1. Yes
    2. No

12. If crop insurance premium costs were cut in half for all policies so that you were only paying 50% of the previous amount for the same coverage:

[Randomize list]	**Yes**	**No**	**Already at maximum level**	**Already insure all**
Would you change the crop insurance policy?	O	O		
Would you purchase crop insurance for acres you are not currently insuring?	O	O		O

Would you change the crop insurance units?	O	O		
Would you increase your crop insurance coverage level?	O	O	O	
Would you alter your mix of crops?	O	O		
Would you try to increase your yield?	O	O		
Would you try to increase your area planted?	O	O		

[Force one answer per row]

13. Suppose there is a raffle that pays $1,000 if won, $0 if not. You have a 50% chance of winning the raffle. What is the highest amount you would be willing to pay for a ticket?

The following questions are regarding Price Loss Coverage (PLC) and Agriculture Risk Coverage (ARC) payments.

14. Do you own or rent land with base acres?
    1. Yes
    2. No [skip to Q25]

15. Which of your program crops has the most base area?

	Crop
O	Barley
O	Corn
O	Grain Sorghum
O	Oats
O	Peanuts
O	Rice
O	Soybeans
O	Sunflowers
O	Upland Cotton

O	Wheat
O	Other [specify]
O	Other [specify]
O	Other [specify]

[Force answer]

16. Is most of this [answer to 15] base area in:

1. ARC
2. PLC

[Display Q17a and 17b on the same screen]

17a. Assume in five years base area will be updated. What you plant in the next four years will determine the new allocation. Knowing this, would you plant more or less acres to **[Q15 crop]** next year?

1. I would plant **more** [Q15 crop] acres next year
2. I would plant **less** [Q15 crop] acres next year
3. I would plant the **same** amount of [Q15 crop] acres next year.

[Ask if 'more' or 'less' acres will be planted in Q17a]

17b. Approximately, how many [more/fewer] acres of **[Q15 crop]** would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q18a and 18b on the same screen]

18a. If you knew with certainty that you would receive $25 more per base acre in **[Q15 crop]** ARC or PLC payments because of changes in the programs but all other crop payments remain unchanged, would you plant more or less acres to **[Q15 crop]** next year?

1. I would plant **more** [Q15 crop] acres next year
2. I would plant **less** [Q15 crop] acres next year
3. I would plant the **same** amount of [Q15 crop] acres next year.

[Ask if 'more' or 'less' acres will be planted in Q18a]

18b. Approximately, how many [more/fewer] acres of **[Q15 crop]** would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q19a and 19b on the same screen]
[Ask if more than one crop has acres planted]

19a. If you knew with certainty that you would receive $25 more per base acre in **[Q15 crop]** ARC or PLC payments because of changes in the programs but all other crop payments remain unchanged, would you plant more or less acres to **your next largest crop by area** next year?

1. I would plant **<u>more</u>** acres next year
2. I would plant **<u>less</u>** acres next year
3. I would plant the **<u>same</u>** amount of acres next year.

[Ask if 'more' or 'less' acres will be planted in Q19a]

19b. Approximately, how many [more/fewer] acres would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q20a and 20b on the same screen]

20a. If you knew with certainty that you would receive $25 more per acre in **[Q15 crop]** market receipts because of an increase in the price but all other market receipts remain the same, would you plant more or less acres to **[Q15 crop]** next year?

1. I would plant **<u>more</u>** [Q15 crop] acres next year
2. I would plant **<u>less</u>** [Q15 crop] acres next year
3. I would plant the **<u>same</u>** amount of [Q15 crop] acres next year.

[Ask if 'more' or 'less' acres will be planted in Q20a]

20b. Approximately, how many [more/fewer] acres of **[Q15 crop]** would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q21a and 21b on the same screen]
[Ask if more than one crop has acres planted]

21a. If you knew with certainty that you would receive $25 more per acre in **[Q15 crop]** market receipts because of an increase in the price but all other market receipts remain the same, would you plant more or less acres to **your next largest crop by area** next year?

1. I would plant **<u>more</u>** acres next year
2. I would plant **<u>less</u>** acres next year
3. I would plant the **<u>same</u>** amount of acres next year.

[Ask if 'more' or 'less' acres will be planted in Q21a]

21b. Approximately, how many [more/fewer] acres would you plant next year?

__________ acres **[answer must be > 1]**

22. If you knew with certainty that you would receive $25 more per acre in **[Q15 crop]** ARC or PLC payments because of changes in the programs but all other crop payments remain unchanged, would you try to increase your yields of **[Q15 crop]**?
    1. Yes
    2. No

23. Have you ever made a planting decision based upon expected base area or program yield updates?
    a. Yes
    b. No

24. If you were to receive a gift of $50,000 per year for the rest of your life, would you:

[Randomize] **[one question per screen]**				
a.	alter your mix of crops?	o Yes	o No	
b.	try to increase your yield?	o Yes	o No	
c.	try to increase your total area planted?	o Yes	o No	
d.	spend more, less, or about the same amount of time crop farming?	o More time	o Less time	o Same amount of time

25. Suppose you are offered a bet. There is a 50% chance that you win $[1000 minus Q13 answer] and a 50% chance you lose $[Q13 answer]. Would you take the bet?
    a. Yes
    b. No

Demographic questions

26. For demographic purposes, in what year were you born?

27. What is your gender?
    a. Male
    b. Female
    c. Other

28. What was your 2018 household income?
    a. Less than $30,000
    b. $30,000 - $39,999
    c. $40,000 - $49,999
    d. $50,000 - $59,999
    e. $60,000 - $69,999
    f. $70,000 - $79,999
    g. $80,000 - $89,999
    h. $90,000 - $99,999
    i. 100,000 - $149,999
    j. $150,000 - $199,999
    k. $200,000 - $249,999
    l. $250,000 or more

29. What percentage of your yearly household income comes from
    a. Crop Production: _______
    b. Off-farm labor: _______
    c. All other: _______

[Must sum to 100]

30. What is the highest level of education that you obtained?
    a. Some high school or less
    b. High School diploma
    c. Some college
    d. 2 year/Associates degree
    e. 4 year/Bachelor's degree
    f. Some graduate school
    g. Graduate school

31. Including yourself, how many people live in your household? _______

32. In what state do you produce most of your crops?

33. On a scale from 1 to 10, where 1 is not at all willing to take a risk and 10 is very willing to take risks, how would you rate yourself?

Not all willing to take risks **Very willing to take risks**

1	2	3	4	5	6	7	8	9	10

4. PRODUCER PERCEPTIONS OF CROP INSURANCE RETURNS

Crop insurance is a fundamental program in the farm safety net, yet producer views on the program largely remain unsolicited. We distributed a survey that found that respondents representing 64% of the crop insurance demand curve believes they lose money on the program, despite historical program performance and intentions. This response is related to whether an indemnity was received in the prior year indicating recency bias. A respondent's view on actuarial fairness did not correspond to crop insurance choices in the prior year. However, increasing self-reported price sensitivity related to higher coverage levels.

4.1 Introduction

Crop insurance is a fundamental feature of the U.S. farm safety net and a natural draw to researchers given the availability of extensive public data. Participation in the program has grown to the point that almost 500 million acres were insured in 2022 (RMA, 2023). This has occurred after increased subsidy rates encouraged participation after a slow start to the program (Glauber, 2013). Despite farmers clearly perceiving benefits from participating in the crop insurance program as evidenced by the high participation rate, the effect of farmer perceptions on their decisions has not been thoroughly studied. This research investigates how the views of producers about crop insurance returns affect their crop insurance decisions.

The Federal Crop Insurance Reform Act of 1994 and subsequent legislation increased the subsidized portion of crop insurance premiums. At the same time, crop insurance is legislatively required to operate in an actuarially fair manner, defined in terms of the expected loss ratio of indemnity payments to total premiums, including the subsidized portion. (Du, Feng, and Hennessy, 2016). As a result, producers as a group have received more in indemnities than they have paid in premiums over time. However, knowledge about producer views on the relationship between what the program costs them and what they expect to get in return is lacking.

In setting premiums, USDA's Risk Management Agency (RMA) uses a loading factor of 0.12 which translates into a targeted loss ratio of 0.88 in practice (Coble, Knight, Goodwin, Miller and Rejesus, 2010). The subsidy rate that a producer receives depends upon the policy, units and coverage levels selected. Over the past 10 years (2012 to 2021), the loss ratio has averaged 0.84 and the subsidy rate has averaged 63%[9] (RMA, 2023). This has corresponded to a producer loss ratio of 2.26. In other words, on average a producer gets back $2.26 in indemnities for each dollar of premiums paid. The subsidy rate more than covers the loading factor which has resulted in large net transfers to producers.

Producers as a group are getting more in crop insurance indemnities than they are paying in premiums. In an effort to determine whether farmer views concurred with this aggregate observed experience, a survey was conducted that directly asked producers their view on this as well as other crop insurance and demographic questions. While literature has consistently identified that producers are underinsuring under classical economic assumptions (as examined in the second paper of this dissertation), we are not aware of any prior attempts to solicit producer views on this subject.

[9] This excludes the 2021 pandemic cover crop program which was in addition to the base subsidy amounts.

4.2 Survey

The survey was conducted by the agricultural analytics firm Kynetec in May through June 2019 based on their private farmer database. The survey was administered to U.S. crop farmers through an online site. The survey consisted of 33 questions with a mean response time of five minutes and three seconds. Upon successful completion, respondents received $25 as a compensation fee. Our dataset consists of 500 completed responses that span 36 states. In order for the results to accurately represent an average insured acre, the probability of an operation being included in the survey was based upon the acres farmed. The 2017 USDA Census of Agriculture was used to develop targets for different acreage strata. Table 13 compares the percent of respondents in some of the strata compared to the actual percent in the USDA Census of Agriculture.

Table 13: Respondents in strata

	Percent of total acres	
Cropland acres*	Census of Agriculture	This study
1-259	11%	10%
260-499	9%	10%
500-999	14%	13%
1000-1999	19%	22%
2000+	47%	45%

** USDA defines this as cropland acres in 2017 whereas this study defines it as crop acres planted in 2018*
Source: USDA-NASS (2019) and author calculations

The acreage breakouts closely match the USDA Census of Agriculture as desired, so it is plausible that the survey results can be used to estimate the crop insurance demand curve. A survey that did not take this step would be representative of producers, not the demand curve. This would bias the results if responses were correlated with the number of acres in the operation. The sample data could lead to incorrect conclusions about important factors. For exampe, suppose producers with less than 100 acres all say *X* and those with more than 100 acres all say *Y*. We might mistakingly concude that *X* has a major impact on the overall demand for crop insurance, even though only a small portion of acreage would be affected.

Table 14 shows the results of the crop insurance survey questions. One of the questions asks, “Do you expect crop insurance payouts to exceed costs over time?” The respondents answered “No” at a rate of 64%. The equates to almost 2/3’s of acre-weighted farmers believing they are losing money in the long-run on crop insurance. By coincidence, this response rate corresponds very closely to the 64% of respondents who reported receiving an indemnity for the prior year’s crops. Most respondents (96%) felt they chose the right coverage level for the prior crop year with the knowledge they had at the time, indicating little regret.

Table 14: Crop insurance survey results

Importance of factors when deciding to purchase crop insurance	**Not at all**	**Not very**	**Somewhat**	**Very**
Lender requirement	0.2%	1.8%	18.4%	79.6%
Reduce farm risk	3.6%	8.4%	43.0%	45.0%
Maximize insurance payouts relative to costs	42.3%	27.0%	29.5%	1.2%
Importance of factors when choosing a coverage level	**Not at all**	**Not very**	**Somewhat**	**Very**
Lender requirement	0.6%	2.2%	25.6%	71.6%
Budgeted amount	3.2%	9.0%	42.8%	45.0%
Reduce farm risk	37.2%	24.6%	25.4%	12.8%
Maximize insurance payouts relative to costs	5.0%	13.0%	55.6%	26.4%
Do you expect crop insurance payouts to exceed costs over time?				
Yes	35.8%			
No	64.2%			
If crop insurance premiums were cut in half for all policies so that you were only paying 50% of the previous amount for the same coverage:	**Yes**	**No**		
Would you change the crop insurance policy?	62.4%	37.6%		
Would you change the crop insurance units?	41.6%	58.4%		
Would you try to increase your yield?	71.4%	28.6%		
Would you alter your mix of crops?	13.6%	86.4%		
Would you try to increase your planted area?	23.2%	76.8%		
	Yes	**No**	**Already at max**	
Would you increase your crop insurance coverage level?	82.8%	8.4%	8.8%	
	Yes	**No**	**Already insure all**	
Would you purchase crop insurance for acres you are not currently insuring?	28.4%	5.4%	66.2%	
If you were to receive an extra $50,000 per year for the rest of your life, would you:	**Yes**	**No**		
Try to increase your total planted area?	42.3%	57.7%		
Alter your mix of crops?	83.3%	16.7%		
Try to increase your yield?	46.3%	53.7%		
	More	**Less**	**Same**	
Spend more, less or about or about the same amount of time crop farming?	13.1%	13.5%	73.4%	
With the knowledge you had when purchasing crop insurance in 2018, do you believe you chose the correct coverage levels?				
Yes	95.6%			
No	4.4%			
Did you receive or do you expect to receive crop insurance payments for the 2018 crop?				
Yes	36.4%			
No	63.6%			

The survey also asked a series of questions about the importance of various factors in making crop insurance decisions. When deciding to purchase crop insurance, lender requirements and reducing farm risk were stated to be consequential with 98% and 88%, respectively, rating them them as somewhat or very important. Only 31% stated that maximizing payouts relative to costs was a somewhat or very important factor when deciding to purchase insurance. In other words, respondents don't report subsidy capture as a reason for purchasing the insurance.

Lender requirement was also reported to be a significant factor when choosing the coverage level, with about 97% stating it was somewhat or very important. This is indicative of a reluctance to insure among producers and the importance of agricultural credit to operations. A budgeted amount was also reported to be somewhat or very important (88%), with the split fairly even between the two responses. Surprisingly, reducing farm risk was not that important, as only 38% stated it was somewhat or very important. Reducing farm risk seems to be important when deciding to purchase crop insurance, but not in selecting the coverage level. This would consistent with the idea that producers are taking care of their risk by purchasing crop insurance, and the marginal coverage level selection is less about risk than other factors. While maximizing payouts relative to costs was not very important when deciding to purchase crop insurance, the same is not true when selecting a coverage level (82% indicated it was somewhat or very important). Instead of minimizing risk when selecting a coverage level, producers seem to be shopping for the best deal.

Respondents were asked how they would respond to a 50% reduction in premiums. Most (62%) were interested in changing their crop insurance policy but not in changing their units (42%). Units define the level of aggregation of fields for a crop. Increasing aggregation can lead to a higher subsidy rate but reduces the expected indemnities due to the imperfect correlation among fields. Most (83%) would try to increase their coverage level. Respondents would generally try to increase their yields due to lower premiums (71%), but most did not indicate a desire to alter their crop mix (14%) nor increase their area planted (23%).

Survey participants were also asked how they would respond to a gift of $50,000 per year. This series of questions were designed to shed information on liquidity constraints and wealth effects. Most respondents would not try to increase planted area (58%) with the increased income, but would alter mix of crops (83%), would not try to increase yields (54%) and would spend about the same amount of time farming (73%). Other than altering the mix of crops, the extra income would cause changes in less than half of respondents.

Survey respondents were also asked demographic questions (Table 15). Ninety-one percent of farm respondents are the farm manager. The average responders plants 2,100 of crops, but the standard deviation is almost as showing a skewness to the distribution. The mean responder owns over 1,000 acres, but the standard deviation exceeds this amount. Most respondents grow corn (86%) and soybeans (77%) and are male (94%). The average age was 56.3 years which is just under the 57.5 years in the Census of Agriculture (USDA-NASS, 2022) for all farm operators. Annual household income was less than $100,000 for 56.4% of respondents and 47% had at least a four year college degree.

Respondents were asked to report on how willing they are to take risks, with 10 being very willing and 1 not willing. The mean response was 6.59. Likewise, the survey asked how much the respondent would be willing to pay for a raffle that pays $1,000 if won, $0 if not, with each option equally likely. The mean response was $133.98. Of the 500 responses, 85% were less than or equal to $250. The self-assessed willingness to take risks and lottery question both indicate the respondents have caution with regard to risk. However, the Spearman rank correlation coefficient between responses for the two questions was only .053. The raffle question was asked about halfway through the survey. Near the end of the survey, a corrollary question was posed: would the respondent accept a bet with a 50% chance they win $1,000 minus the amount he or she was willing to pay for the raffle in response to the earlier question, and a 50% chance of losing the raffle response amount. This is the same question to the raffle question, only posed as a potential loss instead of as only a gain. Failure to accept the bet in the corrolary is indication of framing and loss aversion. Of the respondents, 29% did not accept the corrollary bet.

Table 15: Survey demographics

Are you the farm manager:		**What is the highest level of education that you**	
Yes	91.2%	**have obtained?**	
No	8.8%	Some high school or less	1.2%
Crop acres planted		High school diploma	19.0%
Mean	2,127	Some college	19.8%
Standard deviation	2,079	2 year/Associates degree	13.0%
Cropland acres owned		4 year/Bachelor's degree	37.0%
Mean	1,035	Some graduate school	4.6%
Standard deviation	1,386	Graduate school	5.4%
Percent of respondents who planted crop in 2018		**Number of people in household**	
Barley	4.4%	Mean	2.9
Corn	86.2%	Standard deviation	1.4
Grain sorghum	6.8%	**How willing are you to take risks (1=not willing,**	
Oats	7.0%	**10=very willing)**	
Peanuts	1.6%	Mean	6.59
Rice	2.4%	Standard deviation	1.75
Soybeans	77.2%	**What is the most you would be willing to pay for a**	
Sunflowers	2.4%	**raffle that pays $1,000 if won, $0 if not.**	
Upland cotton	9.2%	Mean	$133.98
Wheat	37.4%	Median	$100.00
Gender		**Would you accept a bet with a 50% chance you**	
Male	94.2%	**win ($1,000 -raffle response) and 50% chance you lose**	
Female	5.8%	**(raffle response)?**	
Other	0.0%	Yes	71%
Age		No	29%
Mean	56.3		
Standard deviation	12.1		
2018 annual household income			
Less than $30,000	5.6%		
$30,000 to $39,999	4.2%		
$40,000 to $49,999	5.6%		
$50,000 to $59,999	9.4%		
$60,000 to $69,999	8.2%		
$70,000 to $79,999	10.2%		
$80,000 to $89,999	6.6%		
$90,000 to $99,999	6.6%		
$100,000 to $149,999	19.4%		
$150,000 to $199,999	6.8%		
$200,000 to $249,999	5.8%		
$250,000 or more	11.6%		

The survey results indicate that producers do not believe that crop insurance is actuarially fair, even with the subsidy. Given the program and historical performance, this result is surprising. It is possible that outcomes are skewed such that a subset of producers receive most of the indemnities. In such a case, most producers might get less back from the program than they pay in, even though producers as a group might receive more indemnity payments than they pay in premiums.

Alternatively, it could also reveal a perception bias among producers. Biswal and Bahinipati (2022) posit multiple biases that can affect crop insurance purchases. Loss aversion occurs when participants are more sensitive to losses than gains. While generally used in the context of prospect theory for valuing options, the pattern of thinking could explain a greater emphasis on losses in memory than gains. Producers might overweight the years they paid premiums but received no indemnity payments but might discount the years when the reverse was true. The certainty effect is when agents overvalue certainty relative to probabilistic outcomes and present bias or hyperbolic discounting is when gains and losses in the present are much more meaningful than in the future. However, these latter two biases are largely irrelevant in the case of U.S. crop insurance as premiums are not paid until the harvest. At that point, the premium is subtracted from the indemnity and producers settle the remainder with USDA. As a result, there is no difference in timing between premiums or indemnities. Furthermore, there is no constant outlay separated from probabilistic indemnities. Instead, they are all combined into one probabilistic outcome. Another potential explanation is overconfidence gain where producers expect above average outcomes. However, given the large subsidy rates for crop insurance, a producer would have to expect well above average outcomes before crop insurance would be expected to generate an average net loss.

One type in particular, recency bias, has been noticed among insurance participants. Recency bias occurs when participants overweight the experience of recent events. This could be viewed as historical hyperbolic discounting. In the crop insurance case, a producer's view on actuarial fairness would be strongly influenced by recent indemnities. For instance, a recent indemnity payment could influence the producer to increase insurance coverage while a lack of recent indemnities might have the opposite outcome.

Several studies have examined recency bias in insurance markets other than U.S. crop insurance. Bjerge and Trifkovic (2018) found that excess rainfall during the previous harvest increased rainfall index insurance demand for Indian farmers. Likewise, Stein (2016) also studied rainfall index insurance in India and found that the likelihood of purchasing the insurance increases by 9 to 20% the year after an indemnity. A similar pattern was noticed by Cai, Janvry and Sadoulet (2020) in China. They studied producers for two years. Those who received insurance payouts in the first-year increased crop insurance participation in the second year. Gallagher's (2014) work showed that flood insurance take-up jumps the year after a flood, both for victims and others in the area. Kousky (2017) also observed this phenomenon with flood insurance after a hurricane. However, disaster aid may require purchasing insurance in the future as a condition for benefits. Once this is accounted for, Kousky (2017) found that voluntary insurance participation still increased but at a much more muted level.

A couple of studies have examined recency bias in the U.S. crop insurance market. Chong and Ifft (2016) examined county level RMA and NASS data. They found that the share of the crop insured increased the year after a negative yield shock. A positive yield shock tended to decrease insurance participation, but the result was generally statistically weaker and smaller in absolute magnitude.

Che, Feng and Hennessy (2020) also examined recency effects and participation in the U.S. crop insurance program. They utilize RMA and NASS data at the county level to analyze the effect of recent events on the intensive (coverage level) and extensive (acres) margin of crop insurance coverage. The authors examine the effect of both recent indemnities and weather events. The found that indemnities affected both intensive and extensive participation but failed to find the same relationship for weather.

While expected utility theory with Bayesian updating would conclude that recency bias should not be expected in crop insurance participation (Chong and Ifft, 2016), the literature to date indicates that the opposite has been observed. If producers are basing crop insurance decisions on recent experiences, it seems natural that their view of crop insurance would be flavored by that experience. In the next section, we test that hypothesis. Additionally, we test to test to see whether the producers' views on crop insurance, which is an intermediate step in decision making, relates to their final coverage decisions.

4.3 Empirical Analysis

Producer perceptions about crop insurance skew toward the belief that participants lose money over time, despite program design and historical performance. The survey allows for the testing of potential factors influencing that belief. In order to do this, a number of variables were constructed to regress the belief on demographic, production and other answers to ascertain the factors that relate to the belief. Table 16 shows the regression variables and their mean levels. Twenty-nine observations were dropped due to missing values.

Many of the regression variables are from Table 14 and Table 15. Variables that had responses of Very Important, Somewhat Important, Not Very Important and Not At

All Important were reduced to a binary variable, with the first two labeled as Important with a value of 1 and the latter two labeled as Unimportant with a value of 0. The natural logarithm of acres planted on the farm was used to deal with the right tail of the variable. A similar adjustment was not made for income since respondents selected a category instead of reporting the amount. This effectively Winsorized the data. The midpoint of each range option was used to create a continuous variable. The lowest range option was averaged between $0 and $30,000 and the highest range was set to $250,000.

Table 16: Mean levels for regression variables

Description	**Variable**	**Mean**
Crop insurance payouts expected to exceed costs over time	paycosts	0.35
Lender requirement is somewhat or very important in choosing coverage level	lender	0.98
Budgeted amount is somewhat or very important in choosing coverage level	budget	0.88
Reducing farm risk is somewhat or very important in choosing coverage level	farmrisk	0.38
Maximizing insurance payout relative to costs is somewhat or very important in choosing coverage level	maxpay	0.82
Did the respondent receive or expect to receive payments for the 2018 crop	indem2018	0.37
Age of farmer in years	age	58.37
Respondent is female	female	0.05
Annual income in thousands of dollars (low of 15 and high of 250)	income	112.44
Percent of yearly household income that comes from crop production	perccrop	69.00
Respondent has some college but no degree	somecollege	0.18
Respondent has at least one degree	degree	0.61
Logarithm of acres planted to crops on farm	logacres	7.18
Percent of acres planted to crops that are owned	percowned	0.63
Number of different types of crops planted in 2018	no_crops	2.37
Respondent in (ND, SD, NE, KS, OK, TX)	plains	0.29
Respondent in (AR, LA, MS, AL, GA, SC, NC, TN, KY, VA)	south	0.09
Scale of willingness to take risks (1=not willing, 10=very willing)	takerisks	6.63
Does reframing lottery as a potential loss result in responding not accepting it	framing	0.29
Is the respondent the farm manager?	manager	0.91
Number of people living in household	nohousehold	2.83
Does the respondent believe he or she selected the correct coverage levels for the 2018 crops given the knowledge at the time	correctcovg	0.96
Either If crop insurance premiums were cut in half, 1) would increase coverage level 2) or would not but only because already at max coverage level	half	0.93
Respondent would try to increase planted area if you received an extra $50,000 per year for life?	plantmore	0.42
Number of observations	*n*	*471*

A logistic regression model was employed to test the potential explanatory variables correlation with producer beliefs about crop insurance returns (Table 17). Only one variable was significant at the 5% level, *indem2018*. This is consistent with previous research that finds recency bias in crop insurance. Producer views about the returns relative to costs are related to the outcome from the most recent year. The average marginal effect is .094. This translates to almost a 10% increase in the probability of believing that crop insurance payouts exceed costs if an indemnity was received in the most recent crop year.

Table 17: Logistic regression of paycosts

	Coefficient	S.E.	Z Value	P-Value	Marginal
Intercept	-1.057	1.522	-0.694	0.487	
lender	-0.805	0.747	-1.078	0.281	-0.173
budget	0.694	0.360	1.931	0.053	0.149
farmrisk	0.010	0.222	0.044	0.965	0.002
maxpay	0.014	0.291	0.047	0.962	0.003
indem2018	**0.436**	**0.209**	**2.081**	**0.037**	**0.094**
age	-0.003	0.011	-0.314	0.753	-0.001
female	0.718	0.448	1.602	0.109	0.154
income	0.002	0.001	1.665	0.096	0.001
perccrop	0.001	0.004	0.231	0.818	0.000
somecollege	-0.074	0.318	-0.232	0.817	-0.016
degree	-0.355	0.260	-1.363	0.173	-0.077
logacres	-0.001	0.116	-0.006	0.995	0.000
percowned	0.067	0.125	0.540	0.589	0.014
no_crops	-0.060	0.121	-0.494	0.621	-0.013
plains	-0.228	0.246	-0.928	0.354	-0.049
south	0.274	0.361	0.757	0.449	0.059
takerisks	0.018	0.062	0.296	0.768	0.004
framing	-0.136	0.233	-0.583	0.560	-0.029
manager	0.234	0.365	0.641	0.522	0.050
nohousehold	0.119	0.081	1.475	0.140	0.026
correctcovg	0.163	0.516	0.315	0.753	0.035
half	-0.278	0.386	-0.719	0.472	-0.060
plantmore	0.159	0.209	0.759	0.448	0.034

Null deviance 610.08 on 470 degrees of freedom
Residual deviance 584.01 on 447 degrees of freedom

A couple of variables are significant at the 10% level, *budget* and *income*. If a budgeted amount was important in choosing the coverage level, the producer was more likely, by almost 15%, to believe that crop insurance is a good deal. If liquidity is not a constraint for a farmer, he or she may potentially maximize gains by choosing the highest coverage level. However, given practical liquidity constraints and the opportunity cost of capital and the relative risks, returns may not be maximized with the highest coverage level in the constrained optimization. It appears that producers who are budgeting, at least for crop insurance, are more closely evaluating the long-term returns from crop insurance. Perhaps financial analysis helps provide the awareness of crop insurance performance.

The other variable that is significant at the 10% level, *income*, shows a positive relationship between income and the belief that crop insurance is a net financial gain. This could be due to several factors such as larger farms spending more time evaluating their costs and returns or that higher incomes may be less reliant on crop insurance to offset risk. The marginal value of 0.001, indicates that a $100,000 increase in income raises the probability of thinking crop insurance is a good deal by 10%.

While the belief about crop insurance actuarial fairness implies skepticism among producers, the translation of that skepticism into insurance decisions is an important step. Just because a producer believes that crop insurance does not make him or her money in the long run doesn't mean that the producer wouldn't make decisions based on other reasons such as risk protection or lender requirements. This next set of regressions examine potential linkages.

The crop insurance decisions investigated here are for the 2018 crop, which is the same year in which the survey has information about if an indemnity was received. As such, the regressions are not directly examining if a recent indemnity affected subsequent decisions. The marginal impact of *indem2018* was less than 10% while about 64% of respondents believe that indemnities don't exceed costs over time. As such, *paycosts* is more than just a function of recent indemnities. The following regressions relating it to insurance elections are making use of that information, even if the timing of the indemnities prevents a test of recency bias in decision making.

A crop insurance participant must make several decisions. The first is whether to insure a crop. Only five respondents in the survey did not insure any crop which prevents any meaningful analysis for the initial decision. After that step, producers must decide on the deductible (coverage level), type of policy and aggregation level for the crop. The sample sizes are large enough for these subsequent decisions to support analysis.

Most types of crop insurance are on a per crop basis. While the farmer can potentially make different elections for the same crop in different areas, the survey asked for the predominant policy for the crop. To further simplify the regression, respondents who were not consistent across crops were not included. Different policies and aggregation levels cannot be combined in any meaningful way. While coverage level potentially could, it would be inconsistent of the necessary treatment of the other variables. However, producers in the survey showed a strong consistency across crops which resulted in very few observations discarded.

The first evaluation was the effect of actuarial fairness perception on the coverage level decision (Table 18). The coverage level is coded as an integer with values of one through eight that correspond to 50% to 85% coverage levels in increments of 5%. Only individual insurance plans were included. The *indem2018* variable was excluded while the *paycosts* variable was added relative to the previous regression to minimize the chance of multicollinearity issues affecting the interpretation of *paycosts* which is the variable of interest.

The OLS regression did not find a significant relationship between the coverage level and perceptions of crop insurance actuarial fairness as the p-value was .609. *Budget*, *plains*, *south* and *half* were the only variables significant at the 5% level. Surprisingly, the importance of budgeting in choosing a coverage level correlates to a higher coverage level. This appears to be somewhat at odds with a budget heuristic where farmers try to maximize coverage without spending more than a specified amount. As in the previous regression, this is consistent with the hypothesis that producers who prioritize financial performance are the ones with a more positive view of crop insurance and are therefore selecting higher coverage levels.

The regional variables, *south* and *plains*, are both significant and negative indicating that growers in those areas tend to select lower crop insurance coverage. These locations tend to grow crops that receive higher farm bill Title I payments as indicated in the second essay. Producers could be relying more on those programs for risk reduction. Some of the crops in those regions are also more likely to be irrigated which also reduces the need for yield protection in crop insurance. Perceptions of crop insurance weren't affected by the regions in the previous regression, so that explanation is unlikely to be the explanatory factor.

Table 18: OLS regression of coverage level

	Coefficient	S.E.	T Value	P-Value
Intercept	**4.308**	**1.307**	**3.296**	**0.001**
paycosts	-0.095	0.184	-0.513	0.609
lender	1.114	0.671	1.658	0.098
budget	**0.779**	**0.272**	**2.867**	**0.004**
farmrisk	-0.187	0.195	-0.959	0.338
maxpay	0.396	0.248	1.600	0.111
age	-0.004	0.009	-0.461	0.645
female	-0.154	0.375	-0.409	0.683
income	0.000	0.001	-0.210	0.834
perccrop	0.004	0.003	1.078	0.282
somecollege	-0.114	0.278	-0.410	0.682
degree	-0.121	0.229	-0.530	0.597
logacres	0.033	0.098	0.340	0.734
percowned	-0.170	0.103	-1.655	0.099
no_crops	-0.057	0.100	-0.569	0.570
plains	**-0.837**	**0.212**	**-3.954**	**0.000**
south	**-1.213**	**0.320**	**-3.793**	**0.000**
takerisks	-0.031	0.055	-0.570	0.569
framing	-0.286	0.196	-1.461	0.145
manager	-0.106	0.295	-0.360	0.719
nohousehold	-0.137	0.076	-1.807	0.072
correctcovg	0.065	0.433	0.151	0.880
half	**0.926**	**0.341**	**2.718**	**0.007**
plantmore	-0.123	0.181	-0.678	0.498

Residual standard error: 1.651 on 350 degrees of freedom
R-squared: 0.1841 Adjusted R-squared: 0.1305
F-statistic: 3.435 on 23 and 350 DF p-value: <0.001

Half was significant with a p value of .005 and had a positive sign. This indicates that those more sensitive to crop insurance premiums are better insured. This seems counter-intuitive at first as price sensitive consumers might be expected to purchase less. However, as with the case of *budget*, it might be in the case of crop insurance that those paying attention to the price recognize the potential returns to crop insurance and are more carefully considering the potential indemnities compared to premiums.

The next set of regressions are multinomial logistic regressions for the type of policy (Table 19 and Table 20). The policies considered are individual common crop insurance policies which include Revenue Protection (RP), Revenue Protection with Harvest Price Exclusion (RPHPE), Yield Protection (YP) and Catastrophic Coverage (Cat) (Plastina and Drollette, 2021). Revenue Protection establishes a guarantee before planting based upon the product of the coverage level, expected yield and established price. If the price is higher at harvest, the harvest price replaces the established price from before planting in the guarantee. Indemnities are equal to the guarantee minus the harvest price times the harvest yield. RPHPE operates the same except that the guarantee cannot increase if the harvest price is higher than the planting price. YP is similar to RPHPE, only it insures the yield instead of revenue. The guarantee is the coverage level multiplied by the expected yield. If the harvest yield is less than the guarantee, the indemnity is the difference of the two multiplied by the projected price established before planting. Cat coverage is just a special case of YP. The coverage level for the product is 50% and the projected price is multiplied by 55% when calculating indemnities. However, the product is fully subsidized, other than a $655 administrative fee for each crop in a county (USDA-RMA, 2019).

Table 19: Multinomial logistic regression for policy (base RP)

	RPHPE	YP	Cat
Intercept	**-6.397*****	1.166	**26.564*****
	(2.330)	(2.639)	**(1.020)**
paycosts	0.248	0.082	-0.073
	(0.292)	(0.410)	(0.548)
lender	-1.065	-2.137	-1.006
	(0.959)	(1.399)	(1.334)
budget	0.375	1.183	-0.786
	(0.482)	(0.784)	(0.709)
farmrisk	0.092	0.044	0.713
	(0.310)	(0.429)	(0.609)
maxpay	0.430	1.258	-1.059
	(0.415)	(0.793)	(0.676)
age	0.027*	0.007	-0.019
	(0.015)	(0.020)	(0.027)
female	-0.233	0.416	1.750*
	(0.718)	(0.901)	(0.963)
income	-0.001	-0.0004	0.004
	(0.002)	(0.003)	(0.004)
perccrop	-0.009	0.015*	-0.012
	(0.005)	(0.008)	(0.010)
somecollege	-0.427	-0.793	-0.486
	(0.447)	(0.715)	(0.831)
degree	-0.315	-0.316	-0.783
	(0.354)	(0.525)	(0.705)
logacres	0.266	-0.159	0.504
	(0.166)	(0.227)	(0.320)
percowned	-0.345	0.312*	-1.012
	(0.308)	(0.170)	(0.802)
no_crops	**0.454*****	-0.470*	-0.352
	(0.160)	(0.269)	(0.343)
plains	-0.070	0.083	**-1.821****
	(0.318)	(0.485)	**(0.835)**
south	-0.452	**1.371****	1.036
	(0.701)	**(0.622)**	(0.806)
takerisks	-0.012	-0.193*	-0.137
	(0.085)	(0.117)	(0.158)
framing	0.242	-0.117	0.283
	(0.321)	(0.473)	(0.585)
manager	0.080	0.170	**13.392*****
	(0.532)	(0.726)	**(1.020)**
nohousehold	0.018	**0.331****	0.204
	(0.111)	**(0.141)**	(0.165)
correctcovg	0.705	-1.196	**13.494*****
	(0.816)	(0.763)	**(1.020)**
half	0.900	**-2.098*****	-0.674
	(0.784)	**(0.564)**	(0.945)
plantmore	0.507*	0.815*	-0.389
	(0.299)	(0.421)	(0.562)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 20: Predicted probabilities and marginal effects for policy

	RP	RPHPE	YP	Cat
Predicted probability	0.772	0.164	0.058	0.006
Marginal effects				
paycosts	-0.035	0.033	0.002	-0.001
lender	0.235	-0.125	-0.106	-0.004
budget	-0.097	0.041	0.061	-0.005
farmrisk	-0.017	0.011	0.001	0.004
maxpay	-0.106	0.048	0.065	-0.007
age	-0.004	0.004	0.000	0.000
female	0.003	-0.038	0.024	0.010
income	0.000	0.000	0.000	0.000
perccrop	0.000	-0.001	0.001	0.000
somecollege	0.092	-0.051	-0.039	-0.002
degree	0.058	-0.039	-0.014	-0.004
logacres	-0.029	0.038	-0.011	0.003
percowned	0.034	-0.049	0.021	-0.006
no_crops	-0.035	0.067	-0.030	-0.002
plains	0.013	-0.009	0.006	-0.011
south	-0.009	-0.076	0.079	0.006
takerisks	0.011	0.000	-0.010	-0.001
framing	-0.027	0.034	-0.009	0.001
manager	-0.078	-0.003	0.004	0.077
nohousehold	-0.018	-0.001	0.018	0.001
correctcovg	-0.097	0.095	-0.077	0.078
half	-0.017	0.144	-0.123	-0.004
plantmore	-0.099	0.062	0.040	-0.003

There is no natural ranking or order between the crop insurance policies. They are discrete, unordered choices. As such, a multinomial logistic regression model was employed. This regressor is the logistic regression model extended beyond two discrete outcomes. Like the logistic regression model, there is a base against which other outcomes are compared. The regressions use RP as the base. Under the restriction that all crop insurance policies across crops must be the same for the respondent, there are 290 observations for RP, 74 for RPHPE, 37 for YP and 24 for Cat. The average producer was predicted to have a 77% probability of selecting RP, 16% of selecting RPHPE, 6% of YP and only 1% probability of selecting Cat.

The only variable that is significantly different at the 5% level for RPHPE from RP is *no_crops* (Table 19). The positive coefficient indicates that increasing the number of crops on a farm increases the likelihood that the producer chooses RPHPE. For YP, only three variables were significant at the 5% level. The first is *south* which indicates that producers in the Southern U.S. are more likely to purchase yield-based insurance. This is consistent with the idea that crops grown in this region tend to receive more benefits from Title I of the farm bill as was highlighted in the second paper. Thus, there is less need for price protection from crop insurance. The second is *nohousehold* which corresponds to more people in the household corresponding to an increased likelihood of purchasing YP. The last is *half*, which has a negative coefficient. Those that would be willing to purchase more insurance if premiums were reduced are less likely to purchase yield-based insurance.

Likewise, Cat has three coefficients significant at the 5% level. The first is *plains* which has a negative coefficient indicating that producers in that area are less likely to purchase Cat coverage. The second is *manager*. Respondents who identified as the manager are more likely to enroll in catastrophic coverage. Last of all, those would believe they chose the correct coverage level last year are more likely to enroll in cat. While unlikely to pay out, the lack of premium prevents situations where the producers pay premiums but receive no indemnities.

Interestingly, *paycosts* was not significant for any of the policies. Producer views on actuarial fairness do not translate into the type of policy they purchase. While RP is more likely to trigger than RPHPE due to the ability to increase the price used in the guarantee, the increased likelihood of an indemnity recently doesn't seem to be related to producer views.

Another major decision a producer makes when purchasing crop insurance is the unit level. Optional units are an aggregation of fields by township section and ownership for a crop. Owned and cash rented land would be one unit and each share rent with a different landowner would add another. Basic units are the same as optional units only aggregated to the county level. Enterprise units combine all units into one for a crop within a county, regardless of ownership structure (Schnitkey, 2009). In other words, going from optional to basic to enterprise units increases the level of aggregation and thereby reduces the probability that a producer will receive an indemnity on a given field. While optional and basic units have the same subsidy rate, enterprise always has a higher subsidy rate. Given the level of aggregation and the subsidy structure, enterprise should be the cheapest unit for a producer.

Table 21: Crop insurance subsidy rates by policy and coverage level

Unit	**50%**	**55%**	**60%**	**65%**	**70%**	**75%**	**80%**	**85%**
Optional	0.67	0.64	0.64	0.59	0.59	0.55	0.48	0.38
Basic	0.67	0.64	0.64	0.59	0.59	0.55	0.48	0.38
Enterprise	0.80	0.80	0.80	0.80	0.80	0.77	0.68	0.53

Source: USDA-RMA 2022

Unlike crop insurance policies, the crop insurance units have a natural order. Categorical dependent variables with a natural order are a good candidate for the ordinal logistic regression model. This model estimates the following set of equations in the case of three categories:

$$y^* = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

(1)
$$y = \begin{cases} y_1 \; if \; y^* < \alpha_1 \\ y_2 \; if \; \alpha_1 < y^* < \alpha_2 \\ \vdots \\ y_m \; if \; \alpha_{m-1} < y^* \end{cases}$$

where y is an ordinal variable with possible values of y_1, y_2, … y_m, x_i is an independent variable, β_i is a parameter and ε is a random variable with a standard logistic distribution. This is simply the multivariate, ordered version of the logistic regression. The ordinal regression model can predict probabilites of being at a level for each level given a set of independent variables. The α's provide breakpoints that determine which category the result will fall into. The constant β's for all values of y is a key assumption known as parallel slopes or proportional odds. The Brant test checks the model specification to ensure the assumption is not violated. Table 22 shows the result of the test for our model where the null hypothesis is parallel slopes. The omnibus is a test of the overall model and is not significant which indicates the model does not violate the parallel slopes assumption. The table also reports the results for individual variables. Several fall below the .05 significance level, but that shouldn't be viewed as a failure of the overall model. For instance, using the .05 significance level with a Bonferroni correct for the 23 variables yields a value of .002. No p-value falls below that threshold. The Brant test shows that we cannot reject the parallel assumption requirement for our model.

Table 22: Brant test for parallel slopes for units

	Chi^2	Degrees of Freedom	P-Value
Omnibus	32.73	23	0.090
paycosts	0.04	1	0.830
lender	**4.35**	**1**	**0.040**
budget	3.32	1	0.070
farmrisk	3.24	1	0.070
maxpay	1.42	1	0.230
age	0.76	1	0.380
female	0.08	1	0.780
income	0.10	1	0.750
perccrop	0.16	1	0.690
somecollege	1.34	1	0.250
degreeTRUE	0.43	1	0.510
logacres	2.37	1	0.120
percowned	0.00	1	0.980
no_crops	1.60	1	0.210
plains	1.25	1	0.260
south	0.00	1	1.000
takerisks	0.00	1	0.990
framing	1.37	1	0.240
manager	1.09	1	0.300
nohousehold	0.03	1	0.860
correctcovg	**6.56**	**1**	**0.010**
half	0.40	1	0.530
plantmore	0.46	1	0.500

The results of the subsequent logistic regression are in Table 23 and Table 24. The p-value for the overall regression is less than .0001 indicating that at least one variable is significant. The model predicts a 25%, 14% and 61% probabilities of the respondent selecting optional, basic and enterprise units, respectively. The first two variables (α_1 and α_1) are the breakpoints between optional and basic, and basic and not enterprise, respectively.

Table 23: Ordered logistic regression for units

	Coefficient	S.E.	Z Value	P-Value
α_1	**-4.737**	**1.547**	**-3.060**	**0.002**
α_2	**-5.388**	**1.553**	**-3.470**	**0.001**
paycosts	-0.134	0.218	-0.610	0.540
lender	-0.680	0.713	-0.950	0.340
budget	**0.678**	**0.341**	**1.990**	**0.047**
farmrisk	-0.432	0.231	-1.870	0.061
maxpay	0.375	0.293	1.280	0.200
age	**0.024**	**0.011**	**2.220**	**0.026**
female	-0.714	0.457	-1.560	0.118
income	0.002	0.002	0.920	0.356
perccrop	0.003	0.004	0.690	0.491
somecollege	0.546	0.328	1.660	0.096
degree	**0.547**	**0.263**	**2.080**	**0.038**
logacres	0.143	0.119	1.200	0.231
percowned	-0.075	0.127	-0.600	0.552
no_crops	**0.297**	**0.130**	**2.280**	**0.023**
plains	-0.139	0.246	-0.560	0.572
south	-0.156	0.381	-0.410	0.683
takerisks	-0.029	0.066	-0.440	0.658
framing	0.069	0.244	0.280	0.779
manager	-0.222	0.355	-0.630	0.532
nohousehold	0.177	0.092	1.930	0.054
correctcovg	**1.250**	**0.534**	**2.340**	**0.019**
half	**0.746**	**0.380**	**1.960**	**0.050**
plantmore	0.052	0.215	0.240	0.808
Likelihood ratio Chi^2		41.110		
Degrees of freedom		23.000		
Pr(>Chi^2)		0.012		

Table 24: Predicted probabilities and marginal effects for units

	Optional	Basic	Enterprise
Predicted probability	0.247	0.139	0.614
Marginal effects			
paycosts	0.025	0.007	-0.032
lender	0.104	0.040	-0.144
budget	-0.140	-0.026	0.166
farmrisk	0.082	0.021	-0.103
maxpay	-0.073	-0.017	0.090
age	-0.004	-0.001	0.006
female	0.151	0.025	-0.176
income	0.000	0.000	0.000
perccrop	0.000	0.000	0.001
somecollege	-0.091	-0.031	0.122
degree	-0.103	-0.027	0.130
logacres	-0.026	-0.007	0.034
percowned	0.014	0.004	-0.018
no_crops	-0.055	-0.015	0.070
plains	0.026	0.007	-0.033
south	0.030	0.008	-0.037
takerisks	0.005	0.002	-0.007
framing	-0.012	-0.004	0.016
manager	0.039	0.012	-0.051
nohousehold	-0.033	-0.009	0.042
correctcovg	-0.282	-0.020	0.302
half	-0.158	-0.026	0.183
plantmore	-0.010	-0.003	0.012

Several variables reach significance at the 5% threshold. The first is *budget* which has been discussed before. This variable, along with *half* which is also significant, shows that producers carefully engaged with farm financials tend to take advantage of crop insurance provisions that provide more expected returns. *Degree* and *age* were both positively correlated with more aggregated units. Last of all, *correctcovg* was significant. This variable could be highly sensitive to 2018 results, so an interpretation could easily overfit the one year of data. As with policies and coverage levels, *paycosts* was not found to influence the choice of units.

4.4 Conclusions

Crop insurance is a major pillar of the safety net for U.S. farmers. The program is designed to pay more in indemnities than farmers pay in premiums over time. The historical performance of the program largely follows the program intentions. We designed a survey that solicited crop insurance participation information, views on crop insurance and demographic information from 500 producers. Approximately two-thirds of the respondents believed they are paying more in premiums than they are collecting in indemnities over time. This outcome is related to whether they received indemnities in the prior year which is consistent with recency bias found in prior literature.

However, the producer view on the actuarial fairness of crop insurance does not translate into actual crop insurance decisions. Regressions on coverage level, policy and unit failed to find any relationship. This is not at odds with prior literature as the survey collects information on the prior year so we cannot observe how future elections change. Studies using time series have found changes in subsequent years.

Our study does find that many crop insurance decisions are related to the price sensitivity of producers. Surprisingly, the more price sensitive a producer reports himself or herself to be, the more likely he or she increases coverage. We hypothesize that given the favorable returns of crop insurance, these producers are looking more closely at the program and determining that the increase in coverage is a good investment.

Future research should investigate how producer views affect crop insurance decisions in subsequent years. Given the linkages found in other literature between indemnities and participation in the subsequent years, we would expect that producer views would also follow a similar pattern. Confirming this would help in educational efforts for producers. If recency effects are leading to suboptimal decisions, then educational efforts using informational nudges to overcome hyperbolic discounting could help lead to more optimal decisions.

Additionally, future research could also ask for producer views on this topic on a Likert scale instead of a binary variable. Producers could also be asked to estimate their return on investment for crop insurance. This would help provide the intensity of the belief which help better identify the factors affecting the belief and how the belief affects crop insurance decisions.

Nevertheless, our research provides an important finding that subject to recent outcomes, most producers don't believe crop insurance to be actuarially fair. The only explanatory factor we find is recent experience with the program. This view alone likely leads to suboptimal decisions among producers eligible for the program. While we fail to find a statistically significant relationship between decisions and producer views, failing to reject the null is not the same as accepting it. Efforts to address this viewpoint could lead to a more effective safety net for U.S. producers.

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4.6 Appendix: Producer Survey

5. Are you the farm manager?
    1. Yes
    2. No

6. How many acres planted to crops do you currently farm? ________ (To qualify, must be > 1)

7. How many acres of cropland do you currently own? ________

8. How many acres of the following crops did you plant in 2018?

Crop	Acres
Barley	{0-99999}
Corn	{0-99999}
Grain Sorghum	{0-99999}
Oats	{0-99999}
Peanuts	{0-99999}
Rice	{0-99999}
Soybeans	{0-99999}
Sunflowers	{0-99999}
Upland Cotton	{0-99999}
Wheat	{0-99999}
Other [specify]	{0-99999}
Other [specify]	{0-99999}
Other [specify]	{0-99999}

6. Did you purchase crop insurance for the following crops in 2018?

[Pipe in crops with acres > 0]		
Crop	**Yes**	**No**
[crop 1]	o	O
[crop 2]	O	O
[crop 3]	O	O
Etc	O	O

[Ask Q6a, Q6b, and Q6c for the 2 crops with the most acres AND crop insurance purchased] [Repeat questions 6a, 6b, and 6c for each crop]

6a. What policy did you insure the [crop] with? If you have more than one crop insurance policy for [crop], please report that policy that covers the most acres planted for the crop in 2018.

17. Revenue Protection (RP)
18. Revenue Protection with Harvest Price Exclusion (RPHPE)
19. Yield Protection (YP) (Not catastrophic coverage)
20. Catastrophic coverage (Cat)
21. Area based policy
22. Other [specify]

6b. What was the insurance unit?

5. Enterprise
6. Optional
7. Basic
8. N/A

6c. What was the coverage level?

10. 50%
11. 55%
12. 60%
13. 65%
14. 70%
15. 75%
16. 80%
17. 85%
18. Other [specify]

23. When considering purchasing crop insurance, how important are the following factors to you:

[Randomize List]	Not important at all	Not very important	Somewhat important	Very important
d. Reduce farm risk				
e. Maximize insurance payouts relative to costs				
f. Lender requirement				

[Force one answer per row]

24. When choosing a coverage level, how important are the following factors to you:

[Randomize List]	Not important at all	Not very important	Somewhat important	Very important
e. Reduce farm risk				
f. Maximize insurance payouts relative to costs				
g. Lender requirement				
h. Budgeted amount				

[Force one answer per row]

25. Did you receive or do you expect to receive crop insurance payments for the 2018 crop?
    1. Yes
    2. No

26. With the knowledge you had when purchasing crop insurance in 2018, do you believe you chose the correct coverage levels?
    3. Yes
    4. No

27. Do you expect crop insurance payouts to exceed premium costs over time?
    3. Yes
    4. No

28. If crop insurance premium costs were cut in half for all policies so that you were only paying 50% of the previous amount for the same coverage:

[Randomize list]	**Yes**	**No**	**Already at maximum level**	**Already insure all**
Would you change the crop insurance policy?	O	O		
Would you purchase crop insurance for acres you are not currently insuring?	O	O		O

Would you change the crop insurance units?	O	O		
Would you increase your crop insurance coverage level?	O	O	O	
Would you alter your mix of crops?	O	O		
Would you try to increase your yield?	O	O		
Would you try to increase your area planted?	O	O		

[Force one answer per row]

29. Suppose there is a raffle that pays $1,000 if won, $0 if not. You have a 50% chance of winning the raffle. What is the highest amount you would be willing to pay for a ticket?

The following questions are regarding Price Loss Coverage (PLC) and Agriculture Risk Coverage (ARC) payments.

30. Do you own or rent land with base acres?
    1. Yes
    2. No [skip to Q25]

31. Which of your program crops has the most base area?

	Crop
O	Barley
O	Corn
O	Grain Sorghum
O	Oats
O	Peanuts
O	Rice
O	Soybeans
O	Sunflowers

O	Upland Cotton
O	Wheat
O	Other [specify]
O	Other [specify]
O	Other [specify]

[Force answer]

32. Is most of this [answer to 15] base area in:
    3. ARC
    4. PLC

[Display Q17a and 17b on the same screen]

17a. Assume in five years base area will be updated. What you plant in the next four years will determine the new allocation. Knowing this, would you plant more or less acres to **[Q15 crop]** next year?
    4. I would plant **more** [Q15 crop] acres next year
    5. I would plant **less** [Q15 crop] acres next year
    6. I would plant the **same** amount of [Q15 crop] acres next year.

[Ask if 'more' or 'less' acres will be planted in Q17a]

17b. Approximately, how many [more/fewer] acres of **[Q15 crop]** would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q18a and 18b on the same screen]

18a. If you knew with certainty that you would receive $25 more per base acre in **[Q15 crop]** ARC or PLC payments because of changes in the programs but all other crop payments remain unchanged, would you plant more or less acres to **[Q15 crop]** next year?

    4. I would plant **more** [Q15 crop] acres next year
    5. I would plant **less** [Q15 crop] acres next year
    6. I would plant the **same** amount of [Q15 crop] acres next year.

[Ask if 'more' or 'less' acres will be planted in Q18a]

18b. Approximately, how many [more/fewer] acres of **[Q15 crop]** would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q19a and 19b on the same screen]
[Ask if more than one crop has acres planted]

19a. If you knew with certainty that you would receive $25 more per base acre in **[Q15 crop]** ARC or PLC payments because of changes in the programs but all other crop payments remain unchanged, would you plant more or less acres to **your next largest crop by area** next year?

4. I would plant <u>**more**</u> acres next year
5. I would plant <u>**less**</u> acres next year
6. I would plant the <u>**same**</u> amount of acres next year.

[Ask if 'more' or 'less' acres will be planted in Q19a]

19b. Approximately, how many [more/fewer] acres would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q20a and 20b on the same screen]

20a. If you knew with certainty that you would receive $25 more per acre in **[Q15 crop]** market receipts because of an increase in the price but all other market receipts remain the same, would you plant more or less acres to **[Q15 crop]** next year?

4. I would plant <u>**more**</u> [Q15 crop] acres next year
5. I would plant <u>**less**</u> [Q15 crop] acres next year
6. I would plant the <u>**same**</u> amount of [Q15 crop] acres next year.

[Ask if 'more' or 'less' acres will be planted in Q20a]

20b. Approximately, how many [more/fewer] acres of **[Q15 crop]** would you plant next year?

__________ acres **[answer must be > 1]**

[Display Q21a and 21b on the same screen]
[Ask if more than one crop has acres planted]

21a. If you knew with certainty that you would receive $25 more per acre in **[Q15 crop]** market receipts because of an increase in the price but all other market receipts remain the same, would you plant more or less acres to **your next largest crop by area** next year?

4. I would plant <u>**more**</u> acres next year

5. I would plant **less** acres next year
6. I would plant the **same** amount of acres next year.

[Ask if ‘more’ or ‘less’ acres will be planted in Q21a]

21b. Approximately, how many [more/fewer] acres would you plant next year?

__________ acres **[answer must be > 1]**

34. If you knew with certainty that you would receive $25 more per acre in **[Q15 crop]** ARC or PLC payments because of changes in the programs but all other crop payments remain unchanged, would you try to increase your yields of **[Q15 crop]**?
    1. Yes
    2. No

35. Have you ever made a planting decision based upon expected base area or program yield updates?
    a. Yes
    b. No

36. If you were to receive a gift of $50,000 per year for the rest of your life, would you:

[Randomize] [one question per screen]				
a.	alter your mix of crops?	o Yes	o No	
b.	try to increase your yield?	o Yes	o No	
c.	try to increase your total area planted?	o Yes	o No	
d.	spend more, less, or about the same amount of time crop farming?	o More time	o Less time	o Same amount of time

37. Suppose you are offered a bet. There is a 50% chance that you win $[1000 minus Q13 answer] and a 50% chance you lose $[Q13 answer]. Would you take the bet?
    a. Yes
    b. No

Demographic questions

38. For demographic purposes, in what year were you born?

39.

40. What is your gender?
    a. Male
    b. Female

c. Other

41. What was your 2018 household income?
m. Less than $30,000
n. $30,000 - $39,999
o. $40,000 - $49,999
p. $50,000 - $59,999
q. $60,000 - $69,999
r. $70,000 - $79,999
s. $80,000 - $89,999
t. $90,000 - $99,999
u. 100,000 - $149,999
v. $150,000 - $199,999
w. $200,000 - $249,999
x. $250,000 or more

42. What percentage of your yearly household income comes from
a. Crop Production: _______
b. Off-farm labor: _______
c. All other: _______
[Must sum to 100]

43. What is the highest level of education that you obtained?
a. Some high school or less
b. High School diploma
c. Some college
d. 2 year/Associates degree
e. 4 year/Bachelor's degree
f. Some graduate school
g. Graduate school

44. Including yourself, how many people live in your household? _______

45. In what state do you produce most of your crops?

46. On a scale from 1 to 10, where 1 is not at all willing to take a risk and 10 is very willing to take risks, how would you rate yourself?

Not all willing to take risks									**Very willing to take risks**
1	2	3	4	5	6	7	8	9	10

5. CONCLUSION

Agricultural policy is an important component of risk management in U.S. agriculture. Crop production is an inherently uncertain process as environmental and market factors can have large effects and are beyond the control of an individual producer. This research examines three areas that relate to agricultural policy and risk management. The first essay (Chapter 2) examines whether baselines generated as part of the policy-making process have forecasting value. The second and third essay (Chapters 3 and 4) examine particular aspects of crop insurance decisions and perceptions among producers.

The first essay examined whether FAPRI and USDA baselines have forecasting value. Each organization has generated an annual baseline for many years against to which to compare scenarios. Although caveats from the organizations warn that the baselines are not forecasts, that has not prevented their use as such. Assumptions such as constant policy distinguish the baselines from forecasts. Given this hindrance, would the public be better served by a simpler forecasting procedure to generate forecasts?

This was tested by creating several alternatives for predicting future corn and soybean prices. The first was a time-series model that used recent history to forecast. The other alternative was a futures-based forecast. Since FAPRI and USDA report the marketing-year average farm price, the futures prices had to be adjusted for timing and basis. Due to lack of trades beyond the near-term, futures data could only be used to predict the average farm price for one year out.

We found that results were mixed between FAPRI and USDA in the short-term, but in the long-term USDA had a slight edge. Both generally outperformed the alternative forecasts. Statistical tests failed to confirm that the alternatives performed better or contained all of the information already in the baselines. The futures forecasts suffered from several large errors and the time-series forecast could not incorporate new information known to FAPRI and USDA when the baselines were created. Those in need of forecasts generally shouldn't discount FAPRI and USDA baselines.

The second and third essays both used a survey distributed to crop producers in 2019. The second essay examines why some producers choose crop insurance coverage levels that are less than optimal under expected utility theory (EUT). We show that under EUT a producer will always seek to select a higher coverage level when faced with a non-decreasing subsidy rate. Multiple reasons have been posited in the literature to explain gap between theory and observations exists. This work examines the theoretical justifications for these reasons and determines that several are justified. In particular, a binding budget constraint would lead to lower coverage levels than the unconstrained case. Asymmetric information would also lead to the same outcome. This encompasses the case where producers believe that their risk is less than the actuaries believe, whether that belief is true or not. This misinformed case would include recency bias. Last of all, cumulative prospect theory was found to be a plausible explanation if the anchor includes the premium. If this condition were not met, the producer would always demand more crop insurance.

While these explanations were found to be plausible, they are not necessarily correct. The producer survey allowed us to further test different explanations. While producers claimed that budgets were important in selecting coverage levels, our regression analysis failed to find a relationship between underinsuring and this answer. We also failed to find evidence that a producer's sensitivity to framing was related to underinsurance or that producer views about crop insurance affected underinsurance. Instead, the geographic region and sensitivity to premiums were the factors that were found to be significant in explaining underinsurance. Specifically, producers in the South and Plains were more likely to be underinsured. Surprisingly, producers who reported being more sensitive to premiums were less likely to be underinsured. We hypothesize that more price-sensitive buyers may be more closely examining their options to determine the optimal policy.

The third essay further dives into data from the survey. Sixty-four percent of the respondents indicated they believe that they lose money on crop insurance over time. This result is surprising given program design and historical performance. Regressing this variable against many others that serve as potential explanations reveals that an indemnity received from the most current crop has a significant effect on this perception. The marginal change was a 9% increase in the belief that crop insurance payouts exceeds costs over time if an indemnity was just received or was expected to be received.

The third essay further examined whether producer perception of the returns from crop insurance affected their crop insurance decisions. Examining coverage levels, units and policies found no relationship between views and decisions. As in the second paper, we find that that self-reported sensitivity to premiums is a significant variable in explaining crop insurance selections.

This research adds to the existing knowledge in several important areas. First, it affirms that baselines can be used to forecast season-average farm prices. The research did not investigate whether they are appropriate for forecasting futures prices. Second, we find a relationship between price sensitivity and more rational crop insurance decisions. It appears that budgets are less likely to be a determinant of crop insurance decisions than an individual's scrutiny of their options. Last of all, we find that most producers view crop insurance as a net loss of income. This result has the potential to rewrite the theoretical crop insurance models to account for asymmetric information.

VITA

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