Recency Effect and Crop Insurance in Oklahoma (draft of research paper)

Introduction

The yield of agricultural production is unknown with absolute certainty. The unfavorable weather, flood, drought, insect infestations and diseases are all adverse to the profit of farmers. Crop insurance is vital to manage those risk. The government may choose to cover economic losses in agriculture due to unexpected events. As the economy of Oklahoma state bases on agriculture, investigating recency effect of crop insurance plays an important role in economic development, so farther policy could incite individuals to purchase it.

We need to know how recent experience affects people's choice. To answer this question, some previous scientists have done several researches. We argue that recency effect not only enables decisions, but also distorts perceptions. In our memory, episodes play a small role in the evaluations of prior affective experiences, but the affect at the end of experiences matters. In other word, when making decisions, the preference is evidently determined by the psychology at the end and it shows duration neglection (Fredrickson and Kahneman 1993). Although Schreiber and Kahneman concluded that the effect of duration was significant and strictly additive, peak and end are both good predictor of remembered utility (2000). What's more, some researchers found when decision makers face salient negative events, their behaviors are inconsistent with Bayesian model. After knowing abnormal, different, unusual, or more readily available news, both tyros and highly experienced person overreact (Chong and Ifft, 2016). Especially, some stock markets who experienced low market tended to leave the stock market (Malmendier and Nagel, 2011), and a number of experienced agents temporarily increased cash holdings after hurricanes (Chong and Ifft, 2016).

Researchers in different area have also studied the influence of recency bias on insurance purchasing, which reflects how farmers respond to the risk. They found insurance purchases increase after losses for terrorism, travel, flood, rice and rainfall. However, the reasons for increasing insurances are disparate. Stein noticed farmers' behavior depends on psychological effects of receiving payout, which is the actual money from insurance company (2016). Nevertheless, Kousky thought individuals are bad decision makers (2017). They focus on the potential loss as opposed to the probability and they largely underestimate the damage a flood would cause, despite the survey being conducted the year following massive flooding. Cai and Song hold the position that low take-up rate of weather insurance is due to the lack of education and information, so after changes in experience of disasters, the insurance purchases increase (2012).

There are limited researches about the recency effect on insurance choices in a certain region. Moore has researched the effect of recency bias on crop insurance purchases in the Mississippi Delta Region (2018). The researcher uses liability acre and policies earning premium to measure insurance participation and understand loss history from the data of indemnity per acre, prior year loss ratio and categorical measure of disaster in prior year. By modeling the regression relationship between crop insurance participation and loss history, they took attempt to find a significant, positive relationship as prevailing literature suggested. Whereas they found the relationship is nonexistent in Delta. In another study, people investigated how recent experience affects insurance choices with the U.S. Federal crop insurance program (FCIP) (Yuyuan; Hongli; David, 2019). They analyze the relationship between weather variable, indemnity ratio and participation ratio for different type of insurance and found that Participation increases after a large loss or a natural disaster except CAT.

This paper seeks to understand whether and how recent experience affects insurance choices with the crop insurance in Oklahoma. We use indemnity amount to quantify previous experience since big events like unfavorable weather, flood, drought, insect infestations and diseases always destroy crop yield and cause higher indemnity amount in the next year. The indemnity will be caused when actual yield is less than historical average yield or actual yield times the harvest price is less than historical average yield time projected price or harvest price (Jisang; Aaron; Daniel, 2016). We also use policies sold to account for participation. Thus, according to literature review, we hypothesize that in Oklahoma, the policy sold count will increase and farmers will purchase more insurance after a large loss due to a disaster, so the previous year's indemnity amount positively affects the current year's policy sold count. To better understand recency effect, we also seek to discover factors influencing and responding to indemnity amount.

Statistical analysis

To gain our data, we download the ZIP files of state/ county/crop summary business from Summary of Business and spreadsheets of crop prices and yields form the Risk Management Agency in USDA.

We decide to consider nine variables for nine crops in Oklahoma from the year 2011 to 2019. Our variables are year, area, policy types (as defined in ***Table 1.*** they are APH, RP, YP and RI), policies indemnified amount, coverage level (includes 0.5, 0.55,0.6, 0.65, 0.7, 0.75, 0.85 and 0.9), loss ratio, producer payment per ten thousand dollars (gained by dividing producer payment by ten thousand), crop price, and crop yield lagged. Nine crops are corn, wheat, peanut, rye, canola, soybeans, oats, sorghum, and cotton.

Table 1. Descriptive Name of Policy Types

The List of symbols	
APH	historic actual production
RP	revenue protection
YP	yield protection
RI	rainfall index
IM	indemnified amount
Cov	coverage level
LR	loss ratio
pp	producer payment per ten thousand dollars
yieldlagged	lagged crop yield (previous year's yield)
NoIMLagged	lagged indemnity (in previous year, 0: indemnity; 1: no indemnity)
IMLagged	lagged indemnified amount (previous year's indemnity amount)
producerpayment	producer payment

In order to take the influence of country in account, we divide more than 60 countries/regions into 9 parts according to Oklahoma Agricultural Statistics Districts (***Figure 1.***).

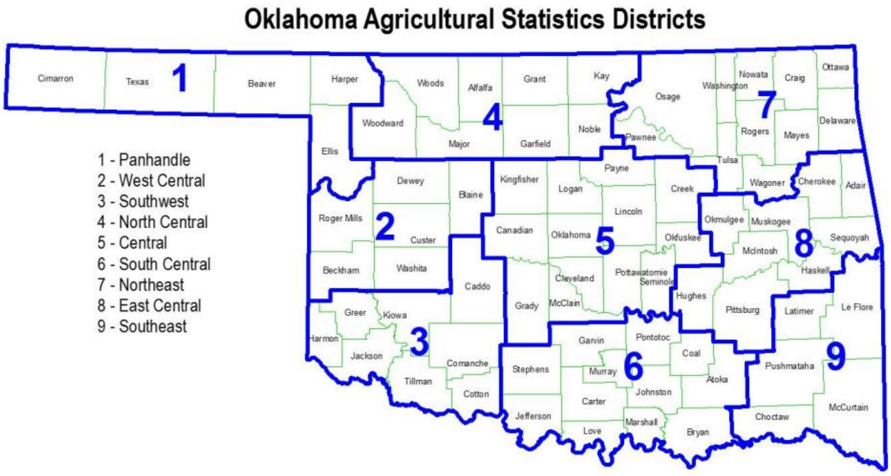

Figure 1. Oklahoma Agricultural Statistics Districts in 2017

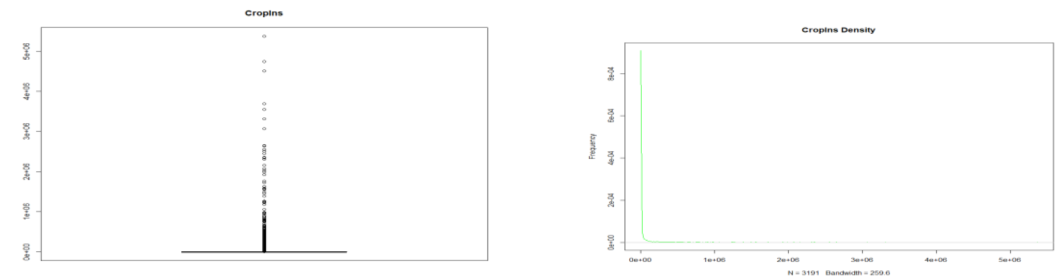

Figure 2. Box Plot of IM and Density Plot of IM

In our analysis, dependent variable is indemnity amount (IM), and we intended to discover the relationship between IM and other variables: year, area, policy type (APH, RP, YP and RI), coverage level (0.5, 0.55,0.6, 0.65, 0.7, 0.75, 0.85 and 0.9), loss ratio (LR), price, yield lagged (yieldlagged) and producer payment per ten thousand dollars (pp).

In order to choose the most proper model, we started from some data views. Almost 2/3 values of our dependent variable, IM, are zeros, which will be a problem for normal regression. By using IM as our dependent variable, we have a count data model. As box plot of IM and density plot of IM (***Figure 2.***) showing, most values of IM concentrate on zero, and the data is quite skewed because of all of zeros.

For corn, since the values of policy sold in APH and RI are all zero, which means the policies were either unavailable, or there were not policies sold, we dropped APH and RI variables in corn data. Then, we test correlations between all remained variables. There are no interactions and multicollinearity between variables, except YP and RP. Due to their negative relationship, we dropped YP. When modeling, the values of AIC (Akaike information criterion) before and after dropping are quite close, which means we still catch information of YP although dropping it. So do wheat, peanut, canola, soybean, sorghum, cotton. Whereas we discovered for oats and rye no one purchase policies except APH, which means there is no variety for policy type, so we dropped all policy types of variables for oats and rye. To summary all needed variables for all crops, we applied the multi functions of Excel to calculate, combine, sort and analyze data to summarize the policies sold, loss ratio, insurance plan type, coverage level, policies indemnified count, liability amount, total subsidy, producer payment, crop price and crop yields for each crop for nine years. IM variable tells which crop had the highest payout levels. The RP and YP variables tell whether yield risk or yield and price risk (revenue) were more commonly protected by commodity. Cov tells what the most common coverage level was by commodity. (***Table 2.***)

Table 2. Summary Statistics for Crop Insurance Data

	Corn		**Wheat**		**Peanut**	
	Mean(Std.Dev)	***Min,Max***	***Mean(Std.Dev)***	***Min,Max***	***Mean(Std.Dev)***	***Min,Max***
IM	52682(2.794674e+05)	0,5.371154e+06	167989(7.3701e+05)		6608(3.7673e+04)	0，727703
Area	4.46(2.1970)	1,9	4.019(2.1070)	1,9	3.352(1.4376)	2,8
RP	0.5694(4.9524e-01)	0,1	0.4628(4.9866e-01)	0,1	0.2146(0.4109)	0,1

YP	0.3833(4.8626e-01)	0,1	0.3915(4.8813e-01)	0,1	0.4155(0.4932)	0,1
APH	N/A	N/A	N/A	N/A	N/A	N/A
Cov	0.6387(9.6472e-02)	0.50,0.85	0.6438(1.0211e-01)	0.50,0.85	0.6298(8.4606e-02)	0.50,0.85
price	4.526(1.1593)	3.390,7.040	5.324(1.387)	3.44,7.45	0.2597(4.8651e-02)	0.211,0.369
yieldlagged	126.3(1.5788e+01)	92,147	29.12(1.3869)	17,39	3500(4.0582e+02)	2600, 4000
LR	0.7364(2.4948)	0,59.2800	0.7534(1.1984)	0,20.01	0.4761(1.8944）	0,16.78
pp	7.755(69.5288)	0,1764.204	17.7382(8.1977e+01)	0,1484.6879	1.0294（3.6967）	0,40.378
	Rye		**Canola**		**Soybean**	
	Mean(Std.Dev)	***Min,Max***	***Mean(Std.Dev)***	***Min,Max***	***Mean(Std.Dev)***	***Min,Max***
IM	4448(1.4674e+04)	0，155306	63041(1.7950e+05)	0,2153759	22258(1.0081e+05)	0,2264039
Area	3.983(1.0329)	2,5	3.506(1.0178)	1,7	4.922(2.099)	1,9
RP	N/A	N/A	0.6302(0.4829)	0,1	0.5574(4.9676e-01)	0,1
YP	N/A	N/A	0.3409(4.7422e-01)	0,1	0.4238(4.9422e-01)	0,1
APH	1(0)	1,1	N/A	N/A	N/A	N/A
Cov	0.6259(9.1306e-02)	0.5,0.75	0.6607(7.5505e-02)	0.5,0.8	0.6323(9.3378e-02)	0.5,0.85
price	8.184(1.722)	5.05,11.8	15.91(5.0769)	10.6,25.2	10.43(2.1584)	7.89,14.4
yieldlagged	20.66(5.3263)	9,26	1155(2.8330e+02)	570, 1550	24.89(6.3667)	13,30.5
LR	0.6124(1.5954)	0,13.45	1.232(1.6852)	0,7.88	0.5314(1.1680)	0,15.94
pp	1.1882(3.5367)	0,38.1445	2.4989(7.9063)	0,117.45	2.7561(14.6669)	0,370.1032
	Oats		**Sorghum**		**Cotton**	
	Mean(Std.Dev)	***Min,Max***	***Mean(Std.Dev)***	***Min,Max***	***Mean(Std.Dev)***	***Min,Max***
IM	267.3(2.6235e+03)	0,62355	19266(1.2819e+05)	0,3864908	201004(1.4808e+06)	0,41256366
Area	3.577(1.6831)	1,8	4.041(2.1239)	1,9	3.036(1.2185）	1,9
RP	N/A	N/A	0.5096(4.9997e-01)	0,1	0.5588(4.9665e-01)	0,1
YP	N/A	N/A	0.4503(4.9758e-01)	0,1	0.385(4.8672e-01)	0,1
APH	1(0)	1,1	N/A	N/A	N/A	N/A
Cov	0.6341(8.2781e-02)	0.5,0.8	0.6279(9.1727e-02)	0.5,0.85	0.6495(1.0401e-01)	0.5,0.9
price	3.461(9.5733e-01)	2.3,5.1	7.202(2.2547)	4.82,12	0.6715(8.5597e-02)	0.553,0.819

yieldlagged	41.46(3.2423)	38,48	47.06(1.2303e+01)	21,56	726.6(1.6317e+02)	531.0,1021.0
LR	0.08(0.4294)	0,6.03	0.4547(1.0775)	0,11.69	0.8198(1.7735)	0,17.8
pp	0.0224(0.1615)	0,2.6686	1.8236(11.2091)	0,264.0226	9.932(58.5185)	0,1480.1974

Footnote: summary across counties in years 2011 to 2019. Not all policy types were sold for every crop.'N/A' indicates the absence of data for that policy type.

Multiple Linear Regression Model

1 Multiple Linear Regression Model

To model linear relationship between policy sold count (response variable) and various explanatory variables, we used regression analysis in Excel to build a multiple linear regression model. In this model, dependent variables is policy sold count, while independent variables are previous year's indemnity amount (IMLagged), previous year's yield (yieldlagged), price, year, producer payment (producerpayment), and a dummy variable: previous year's indemnity (NolIMLagged, 0 for indemnity; 1 for no indemnity).

Considering the use of previous year's data, we used data of IMLagged, NolIMLagged and yieldlagged from 2011 to 2018, and information of price, year, producerpayment and policy sold count between 2012 to 2019.

2 Results

After regression analysis in Excel, we gained results in ***Table 3***. To identify significance of each variable, we set 95% significant level and 80% moderately significant level. For all crops, NoIMLagged play a negatively role on policy sold amount due to negative coefficients and less than 0.05 p-value. For corn, IMLagged, yieldlagged, and producerpayment positively affect policy sold cont and price negatively affects it, although yieldlagged and price are moderately significant, and year is highly insignificant. For wheat and canola, all independent variables are statistically significant and have positive relationship with policy sold count. As for peanut, yieldlagged, price, and producerpayment are highly insignificant, but other variables positively influence policy sold count except year with moderate significant level. Rye's IMLagged and yieldlagged do not have any influence on previous year's policy sold amount, but positively respond to price and producerpayment and negatively respond to year. Except yieldlagged and year, other explanatory variables of soybean and sorghum have positive relationship with policy sold amount. For oats, all variables are not significant, and the model does not work. In terms of cotton, IMLagged, price, and producerpayment positively affect policy sold cont and yieldlagged negatively affects it.

Table 3. Multiple Linear Regression Results for Crop Insurance Data

	Corn		**Wheat**		**Peanut**	
	coefficient	***p-value***	***coefficient***	***p-value***	***coefficient***	***p-value***
Intercept	56.98685	0.911403	-7932.94	1.94E-17	1299.633	0.198135
NoIMLagged	-12.9927	2.13E-39	-13.4603	7.42E-21	-5.28861	0.046924
IMLagged	0.0000192	9.17E-38	0.0000138	2.15E-79	0.0000568	0.010222
yieldlagged	0.048335	0.206696	6.812144	9.88E-24	19.88109	0.600271
price	-0.88563	0.23849	1.054559	2.01E-33	0.001817	0.434701
Year	-0.01977	0.937581	3.914425	2.48E-17	-0.64364	0.194607
producerpayment	0.000004	1.63E-12	0.0000287	1.1E-282	0.00000597	0.781771

	Rye		Canola		Soybean	
	coefficient	***p-value***	***coefficient***	***p-value***	***coefficient***	***p-value***
Intercept	723.0233	0.032377	-9980.8	2.26E-08	-180.197	0.827363
NoIMLagged	-3.22187	0.0000137	-14.5349	1.27E-19	-6.76128	4.99E-14
IMLagged	0.0000137	0.648943	0.0000241	0.000118	0.0000821	1.42E-73
yieldlagged	0.101136	0.602223	1.418638	0.000935	-0.03047	0.969901
price	0.185765	0.012602	0.024618	1.38E-15	0.293996	0.126183
Year	-0.3578	0.032945	4.935627	0.000000022	0.092457	0.819739
producerpayment	0.0000547	0.00000423	0.000199	7.06E-44	0.0000451	2.69E-59
	Oats		**Sorghum**		**Cotton**	
	coefficient	***p-value***	***coefficient***	***p-value***	***coefficient***	***p-value***
Intercept	25.34475	0.932439	-352.147	0.487192	187.0944	0.71478
NoIMLagged	-1.84025	0.034592	-16.616	1.98E-75	-16.2054	1.73E-53
IMLagged	-0.0000016	0.986367	0.0000805	3.6E-140	0.00000548	8.18E-69
yieldlagged	0.047016	0.894029	0.075637	0.835259	-10.2018	0.155711
price	-0.00313	0.956316	0.076286	0.169971	0.014453	0.0000316
Year	-0.00982	0.947229	0.184058	0.464	-0.08415	0.739984
producerpayment	0.000154	0.264317	0.000105	1.5E-176	0.0000207	3.1E-137

Footnote: summary across counties in years 2012 to 2019

Zero-inflated Binomial Regression Model

1 Zero-inflated Binomial Regression Model

As mentioned, we have a count model with excessive zeros, and dependent variable (IM) is over-dispersal. As a result, we need to build a zero-inflated negative binomial model. According to model theory, excessive zeros in IM are due to two separated processes. One is a negative binomial model that models count process, the other is a logit model to model zero-inflation process. In our research, we are going to let area to model logit process, and the other variables are used to model IM in negative binomial part.

The excepted value is expressed as following:

$$E(IM=k)=P(Area1)*E(y=k\mid Area1)+P(Area2)*E(y=k\mid Area2)+\ldots$$
$$\ldots+P(Area9)*E(y=k\mid Area9)$$

In negative binomial model, the negative binomial probability density function is :

$$PDF(y;p,r)=\frac{(y_i+r-1)!}{y_i!(r-1)!}p_i^r(1-p_i)^{yi}$$

where (p) is the probability of (r) successes. Then, we gain likelihood function of expected value:

$$L(\mu;y,\alpha)=\prod_{i=1}^{n}\exp(y_i\ln(\frac{\partial\mu_i}{1+\partial\mu_i})-\frac{\ln(1+\partial\mu_i)}{\partial}+\ln\Gamma(y_i+\frac{1}{\partial})-\ln\Gamma(y_i+1)-\ln\Gamma(\frac{1}{\partial}))$$

where μ given the data and α which allows for dispersion. It could be presented as log likelihood:

$$L(\mu;y,\alpha)=\sum_{i=1}^{n}y_i\ln(\frac{\partial\mu_i}{1+\partial\mu_i})-\frac{\ln(1+\partial\mu_i)}{\partial}+\ln\Gamma(y_i+\frac{1}{\partial})-\ln\Gamma(y_i+1)-\ln\Gamma(\frac{1}{\partial})$$

In zero-inflated negative binomial model, likelihood function depends on whether IM is zero ($y_i=0$) or greater than zero ($y_i>0$):

$$L=\begin{cases}\sum_{i=1}^{n}[\ln(p_i)+(1-p_i)(\frac{1}{1+\partial\mu_i})^{\frac{1}{\partial}}],y_i=0\\ \sum_{i=1}^{n}[\ln(p_i)+\ln\Gamma(\frac{1}{\partial}+y_i)-\ln\Gamma(y_i+1)-\ln\Gamma(\frac{1}{\partial})+(\frac{1}{\partial})\ln(\frac{1}{1+\partial\mu_i})+y_i\ln(1-\frac{1}{1+\partial\mu_i})],y_i>0\end{cases}$$

where $p=\frac{1}{1+e^{-x_i'\beta}}$, and $1-p=\frac{1}{1+e^{x_i'\beta}}$.

2 Results

After modeling in R, in model call, we gain the relationship between indemnity amount (IM) and all independent variables in ***Table 4***: For corn, wheat, and soybean, all independent variables have positive influence on indemnity amount: revenue protection (RP), coverage level (Cov), loss ratio (LR), price, yield lagged (yieldlagged) and producer payment per ten thousand dollars (pp), and they are all significant at 95% level because P-values are greater than 0.05. Peanut's Cov, LR, price, pp positively affect IM,but p-value is NA, which means regression model does not work. As for rye, yieldlagged and pp are insignificant, which means indemnity amount cannot efficiently respond the previous yield and current producer payment. The previous yield of sorghum, and cotton also cannot effectively affect their indemnity amount, while that of canola is moderately significant since its p-value is less than 0.20. For oats, the current price is also moderately significant and reflects its indemnity amount.

We also draw Q-Q (quantile-quantile) plot, and the linearity of the points suggests there is a normality in the data. Overall, our model works efficiently.

Table 4. Zero-inflated Binomial Regression Results for Crop Insurance Data

	Corn		**Wheat**		**Peanut**	
	coefficients	***p-value***	***coefficients***	***p-value***	***coefficients***	***p-value***
count model						
Intercept	2.7101	0.0014	1.7571	4.01E-14	-1.9493	0.1676
price	0.3342	5.53E-13	0.3895	<2E-16	9.6764	1.24E-06
yieldlagged	0.0087	0.0372	0.0409	<2E-16	0.0005	N/A
pp	0.0024	0.0096	0.011	<2E-16	0.0473	0.0813
RP	1.2450	<2E-16	1.522	<2E-16	N/A	N/A

Cov	6.8533	<2E-16	6.4324	<2E-16	11.1977	3.67E-08
LR	0.2329	<2E-16	0.6428	<2E-16	0.0863	0.0213
Log(theta)	-0.7462	<2E-16	-0.5642	<2E-16	-0.0381	0.6572
zero-inflation model						
intercept	1.1636	<2E-16	-1.2794	<2E-16	0.7878	0.0374
Area	-0.0406	0.0247	0.2377	<2E-16	0.3532	0.0038
	Rye		**Canola**		**Soybean**	
	coefficients	***p-value***	***coefficients***	***p-value***	***coefficients***	***p-value***
count model						
Intercept	3.8285	0.0092	0.6014	0.326	3.5908	4.93E-06
price	0.2038	0.001	0.0247	0.0067	0.22	73.63E-09
yieldlagged	0.011	0.73	0.0008	0.1825	0.033	0.0161
pp	0.034	0.2586	0.1015	7.83E-13	0.0441	<2E-16
RP	N/A	N/A	0.9009	<2E-16	0.6985	9.13E-15
Cov	3.9038	0.0157	9.8628	<2E-16	3.6441	2.52E-15
LR	0.3758	0.0007	0.5125	<2E-16	0.4697	<2E-16
Log(theta)	-0.1882	0.1878	-0.1306	0.4413	-0.4646	<2E-16
zero-inflation model						
intercept	3.5288	2.70E-06	-0.0718	0.736	2.4069	<2E-16
Area	-0.6857	7.77E-05	-0.0178	0.76	-0.3662	<2E-16
	Oats		**Sorghum**		**Cotton**	
	coefficients	***p-value***	***coefficients***	***p-value***	***coefficients***	***p-value***
count model						
Intercept	-2.6115	0.3788	3.7191	<2E-16	6.016	<2E-16
price	0.2873	0.1905	0.233	<2E-16	1.379	0.0376
yieldlagged	0.1552	0.0035	0.0009	0.804	9.36E-05	0.7849
pp	0.9737	0.019	0.0711	<2E-16	0.0233	<2E-16
RP	N/A	N/A	0.9342	<2E-16	0.7899	5.67E-13

Cov	3.7435	0.0776	4.8102	<2E-16	5.03	<2E-16
LR	0.4516	0.01	0.3424	<2E-16	0.3929	<2E-16
Log(theta)	0.2339	0.2873	0.4723	<2E-16	-0.6635	<2E-16
zero-inflation model						
intercept	3.6772	<2E-16	-0.0016	0.983	-0.1828	0.348
Area	-0.1899	0.0563	0.2309	<2E-16	0.2322	2.30E-03

Footnote: summary across counties in years 2011 to 2019. Not all policy types were sold for every crop.'N/A' indicates the absence of data for that policy type.

Discussion and Conclusion

According to multiple linear model, we discovered that most crop insurance purchase in Oklahoma are influenced by recency affect. For 7 crops (apart from rye and oats), current year's policy sold count positively responds to previous year's indemnity amount, which mean in Oklahoma, the huger destroy on crops, the higher indemnity amount farmers got, the more policy bought by them in the next year. It coincides with weather events' influence on crop insurance in literature review. Furthermore, for corn, wheat, canola, the higher last year's yield is, the more policy purchased by farmers in the next year; but the higher last year's cotton yield is, the less policy purchased in the second year.

We used zero-inflated negative binomial model to get the relationship between indemnity amount (IM) and all independent variables for 9 crops. For all crops, revenue protection (RP) offers different coverage to protect farmers against loss brought by recent big events, so buying RP leads higher IM. Buying YP (yield protection) also leads higher IM due to the correlation between RP and YP. When purchasing insurance policy like RP, choosing higher coverage level means higher IM after loss of revenue. Loss ratio (LR) is the ratio of the sum of indemnities paid to the sum of total premiums, so there is a positive relationship between LR and IM. Besides, the price of corn also positively influences IM, because higher corn price brings higher loss of revenue, which means a higher indemnity paid. Producer payment is gained by total premium amount minus total subsidy, and these three variables are positively related normally, so higher producer payment per ten thousand dollars (pp) causes higher IM in our model for most crops except rye. The most struggled is the previous yield. Only yields lagged of corn, wheat, soybean, canola and oats are positively related to indemnity amount, but for sorghum and cotton, it does not influence current indemnity amount.

It is noticeable that multiple linear regression model does not work for oats because of all insignificant variables and zero-inflated negative binomial model also does not work for peanut due to NA p-value. Both oats and peanut are minor crop in Oklahoma, and farmers do not rely on them to make a living. This suggests future researches including minor crops. To study how recency effect influences crop insurance for these crops needs more data and expands counties or states. These results can be used by crop insurance agents, extension educators and USDA to inform future crop insurance demand expectations.

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