The Geography and Psychology of Participation in U.S. Federal Crop Insurance Programs

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Yuyuan Che
Department of Agricultural, Food, and Resource Economics
Michigan State University
Email: cheyuyua@msu.edu

Hongli Feng
Department of Agricultural, Food, and Resource Economics
Michigan State University, and
Department of Economics and Center for Agricultural and Rural Development
Iowa State University
Email: hennes65@anr.msu.edu

David A. Hennessy
Department of Agricultural, Food, and Resource Economics
Michigan State University, and
Department of Economics and Center for Agricultural and Rural Development
Iowa State University
Email: hennes64@anr.msu.edu

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Abstract

The U.S. Federal crop insurance program has changed from a tangential minor program in the 1980s to become a central plank of agricultural policy. Participation in crop insurance has increased since 2001, but there are clear spatial and temporal variations. The participation rates in recent years averaged over 90% for corn and soybeans acres in the Dakotas and about 75% for Michigan. Many locations saw strong increases in participation after the 2012 drought year but declines in 2014. Many previous literatures have studied the influence factors of crop insurance participation such as premium prices, adverse selection, premium rates or subsidies, but research about the effect of recency biases is much more limited. Traditional economic theory assumes that insurance participation decision is based on expected net payouts, however, recent findings in behavioral economics suggest that it is not entirely convincing. This study focuses on recency biases related to risks that motivate the decisions to participate in crop insurance. Using crop insurance and weather data during the period of 2001-2015, we specify two channels through which recent experience can affect crop insurance participation. First, we apply past weather variables to instrument the main explanatory variable of indemnity ratio. After controlling for the direct effects of past adverse weather conditions, we find that indemnity payouts in the previous year has a positive effect on the current year's crop insurance participation for corn. The positive effects for soybeans are not statistically significant. Second, we employ nonparametric estimation to test the lasting effects on participation of large indemnities based on a flexible event study model. The results show that the effect of large indemnity on participation is strongest in the first year after large loss, then begins to steadily decline.

Keywords: recency biases; participation rates; uncertain risks; crop insurance program.

1. Introduction

The U.S. Federal crop insurance program has changed from a tangential minor program in the 1980s to become a central plank of agricultural policy. The program had a long history of outcomes that revealed actuarially unsound products as well as questionable and often noisy payouts. In addition, when widespread crop failure occurred then the uninsured often lobbied successfully for obtaining disaster payments. Broad agreement emerged among policymakers that higher participation was required in order to reduce information asymmetry concerns and to mitigate the need for large disaster payments. Commencing about 1990, subsidies were expanded while coverage had been extended to all major agricultural land uses. Although the government sets rates with intent to approximate objectively fair rates and underwrites many of the riskiest contracts, participation remains incomplete while chosen coverage levels would not appear to be optimal from the standard view of growers' objectives (Pétraud et al. 2015; Du et al. 2017).

Participation rates have increased since 2001, and the average participation rates of corn and soybeans have similar increasing trends. Figure 1 provides trend lines of average participation rates for corn and soybean from 2001 to 2015. For both corn and soybeans acres, average participation rate increased from about 70% in 2001 to 86% in 2015, the trend lines are almost identical to each other. However, participation did not increase evenly during the time. Compared with Figure 2, which provides trend lines of indemnity ratio for corn and soybeans, it is clear that indemnity ratio had a strong increase between 2007 and 2008, then participation had an increase between 2008 and 2009; while indemnity ratio increased largely between 2011 and the drought year 2012, then participation had a little stronger increase just after the year 2012.

However, the spatial variation in participation is noticeable. For example, regarding corn acres in Figure 3: in South Dakota participation increased from 91% in 2001 to 97% in 2015; in Illinois participation increased from 67% in 2001 to 87% in 2015; and in Michigan participation increased from 56% in 2001 to 73% in 2015. Noteworthy is that participation did not increase uniformly over the period, where many locations saw strong increases in participation between the 2012 drought year and 2013, but declines between 2013 and 2014. At the same time, Figure 4 shows that average indemnity ratio increased sharply between 2011 and 2012 for South Dakota, Illinois, Michigan, Iowa, Indiana. That is, participation increased strongly after the year with increasing indemnity ratio which indicated negative weather conditions, and declined in the year after that.

Average coverage levels demonstrate somewhat similar patterns. Figure 5 provides two maps of the fraction of corn acres in a county that took out coverage levels (in yield insurance and/or revenue insurance) of at least 75% in 2001 and 2015. For a given year, it is clear that coverage levels are higher in the Western Corn Belt but low in fringe areas that include the Great Plains, Wisconsin, Michigan and Eastern Ohio. Comparing the two years, the participation rates in 2015 were much higher than that of 2001 in most districts. Average participation has increased surely but unevenly over time, increasing sharply in the year after adverse growing conditions, and stalling or declining in the year after that. Given the clear policy intent of expanding coverage and the attractive terms, the main purpose of this paper is to provide a better understanding of how recency biases can affect the spatial and temporal variations of participation in crop insurance program.

Many previous studies have developed the conceptual and empirical foundations for how crop insurance participation can be affected by some influence factors. Some of these studies have examined the effect of premium subsidies on participation. O'Donoghue (2014) tests the effect of premium subsidies on the demand for crop insurance across major crops such as corn, soybeans and wheat. Based on county-level data from 1989 through 2012, the findings show that increases in subsidies can induce more enrollment of land, and encourage more participation in higher levels of coverage. Goodwin et al. (2004) focus on corn and soybeans in the Corn Belt and wheat and barley in the Upper Great Plains, using the data from 1985 to 1993, their results confirm that premium subsidies can increase crop insurance participation. Du et al. (2017) employ unit-level insurance record data for corn and soybeans and apply the mixed logit framework. They find that the probability of choosing an insurance product would decline with the increases in premium expenditures.

There is limited research on the spatial and temporal variations of participation in the U.S. crop insurance program. Du et al. (2013) focus on spatial variations in coverage levels rather than participation that we are interested in here. To own best knowledge, we have not found any literature which studies effect of recency bias on participation in U.S. crop insurance program.

However, many studies have applied recency bias to different types of insurance and other situations beyond insurance. Stein (2014) analyzes the dynamic nature of rainfall insurance purchasing decisions. Based on the customer data from the Indian micro-finance institution BASIX from 2005 to 2007, the paper examines the effect of past year insurance payout on the purchasing decision for the following year. The results show that the past year insurance payout is associated with a 9 to 22 percentage points increased participation in insurance for the following year. The study also discusses the direct effect of rainfall shocks on insurance payouts that further driving increased take-up next year. For flood insurance, Gallagher (2014) applies a flexible event study framework to have shown that insurance take-up spikes the year after a flood and then steadily declines to baseline, based on a nation-wide panel dataset of large regional floods and flood insurance policies. Kousky (2017) uses flood insurance policy dataset for all states on the Atlantic and Gulf coasts between 2001 and 2010 and applies fixed effects model to test the effect of hurricanes and tropical storms' occurrence on take-up rates for flood insurance. The results show that occurrence of hurricane in the previous year increases net flood insurance purchases and this effect dies out by three years after the storm. Cai et al. (2016) use data from a two-year field experiment in rural China and apply dynamic model to show that recent experience can affect insurance demand.

Traditional economic theory assumes that decision making is based on expected net payouts in the crop insurance program, however, recent findings in behavioral economics suggest that it is not entirely convincing. For example, recency biases may play a role on decision making when facing uncertain risks. Our main interest in this paper is to study how recency biases related to risks that motivate decisions of participating in crop insurance program. We take corn and soybeans as examples and employ crop insurance and weather data during the period of 2001-2015, to estimate the effect of recency biases on crop insurance participation. In our study, we specify two channels through which recent experience can affect crop insurance participation: (1) we apply parametric estimation approach to examine the causal effect of past year indemnity payouts on crop insurance participation, working directly with weather data; (2) we employ nonparametric estimation to test the lasting effects on participation of large indemnities based on a flexible event study model. The results show that, first, indemnity payouts in the previous year has a positive effect on the current year's crop insurance participation for corn with controlling for the direct effects of past adverse weather conditions. The positive effects for soybeans are not statistically significant. Second, the effect of large indemnities on participation is strongest in the first year after large loss, then begins to steadily decline. Besides, larger levels of indemnities have more significant influence on participation.

The paper proceeds as following. In section 2, we introduce the U.S. federal crop insurance program and market setting. In section 3, we develop our theoretical framework. In section 4, we clarify our employed data and variable construction. In section 5, we construct the empirical analysis. Section 6 reports our estimation results. In section 7, we come up our conclusions.

2. Market Setting

In this section, we briefly explain the history and structure of the U.S. federal crop insurance program with a focus on participation. Federal crop insurance was first authorized by Congress in 1938, but during the initial decades the program remained relatively low participation. Firstly, the producers faced low farm income due to the Great depression and the drought and dust storms; Secondly, the crop insurance program was a minor program at that time, often completing with other free disaster coverage implemented in various Farm Acts. Federal Crop Insurance Act of 1980 expanded to cover more crops and regions, and introduced premium subsidies. Then the participation rates grew during the 1980s. But the participation rates did not reach the policymakers' expectation despite offering subsidies which covered up to 30 percent of the total premium. Federal Crop Insurance Reform Act of 1994 further increased the premium subsidies and added a new insurance policy which was Catastrophic Risk Protection Endorsement (CAT) that covered severe losses. Participation rates jumped after the 1994 Reform Act, and grew further in the late 1990s. Agricultural Risk Protection Act of 2000 wrote the previous ad hoc premium subsidies into law, and introduced 25 percent reduction in premiums, especially on higher levels of coverage. This further increased the participation rates of the crop insurance program, particularly at higher coverage levels. The 2008 Farm Bill created new average crop revenue election program and established a new disaster assistance program. The 2014 Farm Act helped producers cover some of their crop insurance deductibles.

Recalling the history of federal crop insurance program, we find that participation rates were closely related to the development of policies and subsidy rates. But this is not the entire story about the farmers' decision. In this paper, we focus on participation rates during the period of 2001-2015, studying how recency biases that are caused by adverse weather conditions affect participation, also confirming that past indemnity payouts provide a different channel though which the actions of taking out insurance are influenced. Moreover, we go into our questions respectively with different coverage levels and different policies.

Taking corn as an example, from Figure 3 and Figure 6-9, participation rates of the representative states have increasing trends during the period of 2001-2015. Comparing with coverage levels, the participation rates at coverage levels of at least 75% have a larger growth range than that of 65%; while comparing with Buy-up and CAT policies, participation rates for Buy-up are always much higher than that for CAT, and participation rates of CAT have a slightly downward trend. Moreover, geographical and temporal variations appear among these five different states, we will study these differences and motives behind them in the later sections.

3. Theoretical framework

For a given farm, write crop revenue in year t as R_t. It is held to be random with year-invariant probability density function $f(R_t)$ and mean value $\bar{R}$. Farm costs are given as C. Revenue insurance is available at coverage level ψ so that the actuarially fair premium is $p(\psi) = \int_0^{\psi\bar{R}} (\psi\bar{R} - R_t) f(R_t) dR_t$. With increasing and concave utility function $U(\cdot)$ and premium subsidy rate $s > 0$, expected utility of profit is

$$\max\left[\int_0^{\infty} U\left(R_t - C\right) f(R_t) dR_t, \int_0^{\infty} U\left(\max[\psi\bar{R}, R_t] - C - (1-s)p(\psi)\right) f(R_t) dR_t\right]. \quad (1)$$

If the farmer's goal is to choose whether to participate (i.e., which branch of the outer max statement) and what coverage level any participant should take out, then the expected utility maximizing grower will both participate and take out the highest coverage level available. As pointed out in Du et al. (2017), this is true even if the subsidy rate declines with coverage level according to the schedule that has been in place for many years.

Based on traditional economic theory, farmers will make their participation to maximize expected utility. However, this is not entirely true according to recent findings in behavioral economics. For example, recency biases can play a role in farmers' decision, which is not included in the classical economic theory. In this paper, we examine how crop insurance participation decisions are affected by past experience with a simple model of temporal difference reinforcement learning, including recency biases which is introduced by Sutton and Barto (1998) and applied by Cai et al. (2016).

In this model, farmers' expected utility from crop insurance has two components: the expected monetary gain and the psychological gain or loss based on past experience. The latter component will be updated based recent experience. Let V denote the net psychological gain or loss of participating in crop insurance, the expected net psychological value of having insurance in time t including recency biases is:

$$EV_t = EV_{t-1} + \delta_t (V_{t-1}^* - EV_{t-1}) \quad (2)$$

where V_{t-1}^* denotes the realized benefit in time t-1, here we do not specify the functional form of V_{t-1}^* further. $V_{t-1}^* - EV_{t-1}$ represents the difference between the realized value and expected value of having insurance, where recency biases arise. δ_t denotes the discount rate of information from past experience. The range of δ_t is [0, 1]. If $\delta_t = 0$, then $EV_t = EV_{t-1}$, the expected values are same in year t and t-1, that is, no updating valuation of insurance from the past experience; If $\delta_t = 1$, then $EV_t = V_{t-1}^*$, the expected value in year t is the realized value in year t-1, that is , the valuation in year t is totally dependent on the past year's experience. Therefore, the value of δ_t measures the effect of recent realizations. The larger is the value of δ_t, the stronger is the effect of past experience on current valuation. More specifically, farmers' belief is based on the expected valuation of having insurance, which influenced by past realization. This also means that past indemnity payout experience has an effect on the subsequent participation decision in the crop insurance, and the past indemnity payout realization is also influenced by the weather events.

Equation (2) provides an alternative aspect to study the spatial and temporal variations of participation in crop insurance program, creating a recency bias in insurance demand. We have two channels to study the effect of recency bias. First, the biases from past year's weather shock and indemnity payouts have direct effect on farmers' participation in the following year. For the insured farmers, suppose they experience some weather event and get indemnity payout, then $V_{t-1}^* - EV_{t-1}$ is positive and the expected valuation of crop insurance in year t is greater than that in year t-1. This will lead to more favorable view of crop insurance and so higher participation rates. Second, the biases from recent multi-year weather events and indemnity payouts also play a role on insurance's participation. From equation (2), considering δ_t have the value of (0, 1), we can also expect that the earlier historical experiences have weaker power than most recent realization to affect farmers' current participation decisions.

4. Data Description and Variable Construction

In this study, we employ the crop insurance participation data from the Summary of Business (SOB) Reports and Data and Cause of Loss Historical Data Files by the Risk Management Agency (RMA). The SOB dataset contains county-level crop insurance participation information, including net reported acreage, policies earning premium count, policies indemnified count under different coverage categories and coverage levels for major crops all over the United States.[1] The Cause of Loss dataset includes the determined acreage data at different stages.[2] The county-level planted acreage data for corn and soybeans are obtained from the survey of National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture.[3] However, in this paper, we focus on two primary crops (corn and soybeans) in the counties of 12 states in the Midwest and Great Plains regions (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI) during the year from 2001 to 2015. We also study the difference between the two policy categories (CAT vs Buy-up), and find out the results in specific coverage levels.

The participation rate is calculated by dividing net reported acres by the sum of planted acres and prevented planting acres for each county-crop observation. Since prevented planting acres indicate the number of acres that are lost due to damage, which are included in net reported acres but not in planted acres. We compute prevented planting acres by adding determined acres with the stage codes of P2, PF and PT which are from Cause of Loss Historical Data Files. We obtain net reported acres from the SOB dataset and planted acres from NASS. Since NASS combines

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[1] Detailed dataset variable lists are at http://www.rma.usda.gov/data/sob/sccc/sobsccc_1989-2010.pdf and http://www.rma.usda.gov/data/sob/scc/sobscc_coverage2011forward.pdf.
[2] Detailed dataset variable lists are at http://www.rma.usda.gov/data/col/indemnity/colindemnitiesonly_2001-2010.pdf and http://www.rma.usda.gov/data/col/indemnity/colindemnitiesonly_2011-2015.pdf.
[3] Detailed data are available at https://quickstats.nass.usda.gov/.

counties with small planted acres into one county-crop observation for each state in each year and the combined observations change over the years, so we do not consider the combined observations.

To consider the effect of prior year indemnity payouts on participation rates, we define indemnity ratio as the ratio of policies indemnified count to policies earing premium count. Taking corn as an example, the time trend of average indemnity ratio in five representative states are shown in Figure 4. They did not have uniform variation, but we can notice that the indemnity ratio of five representative states all took a jump in 2012, during which the U.S. experienced a severe drought.

Weather shocks are fundamental basis for the growth of crops, so we work directly with weather data to identify the effect of weather variables on indemnity payouts and participation of crop insurance. We use growing degree days (GDD) and stress degree days (SDD) to measure the heat stress as well as Palmer Z index to measure moisture stress.

GDD is defined as the sum of degrees between lower (T^l) and upper (T^h) thresholds during growing season, while SDD is a way of tracking the temperature stress for specific crop within its growing season. May-August is the assumed growing season for corn and soybeans. The calculation formulas for GDD and SDD is as following:

$$\text{GDD}_{i,t} = \sum_{d \in M_t} [0.5(\min(\max(T_{id}^{\max}, T^l), T^h) + \min(\max(T_{id}^{\min}, T^l), T^h)) - T^l]; \tag{3a}$$

$$\text{SDD}_{i,t} = \sum_{d \in M_t} [0.5(\max(T_{id}^{\max}, T^k) + \max(T_{id}^{\min}, T^k)) - T^k]; \tag{3b}$$

where i indicates county, t indicates year, d indicates day, M is the set of days during the growing season for year t, and for corn and soybeans, $T^l = 10$, $T^h = 30$, $T^k = 32.2$.

We use daily temperature to calculate yearly GDD and SDD at county level. Station-level daily maximum and minimum temperatures are obtained from the Global Historical Climatology

Network (GHCN-D) dataset by National Oceanic and Atmospheric Administration (NOAA).[4] First, we transfer station-level maximum and minimum temperatures into county-level data, that is, average the maximum temperatures of the stations in each county, and it is same as minimum temperatures. Then, we use county-level maximum and minimum temperatures and the above calculation formulas to get the county-level yearly GDD and SDD.

Consider recent weather bias, a measure of a county's heat stress bias is to be constructed as deviation from past ten-years' average, the terms are given as following:

$$GDDdeviation_{it} = (GDD_{it} - \frac{1}{10}\sum_{n=1990}^{1999} GDD_{in}) \Big/ (\frac{1}{10}\sum_{n=1990}^{1999} GDD_{in}); \tag{4a}$$

$$SDDdeviation_{it} = (SDD_{it} - \frac{1}{10}\sum_{n=1990}^{1999} SDD_{in}) \Big/ (\frac{1}{10}\sum_{n=1990}^{1999} SDD_{in}). \tag{4b}$$

These two constructions represent the temperature variation compared with historical weather conditions.

Moisture stress is measured by the Palmer Z index. Monthly Palmer Z for climate divisions in the conterminous U.S. data are obtained directly from the website of National Oceanic and Atmospheric Administration (NOAA).[5] Data from NOAA are for climate divisions, so we employ the area-weighted function to transfer the climate division data into county-level. And we select the average monthly Palmer Z of May-August to represent water pressure for the growing season of corn and soybeans. Since the value of 0 is to be expected and -2 or less represents droughts, while the value equals to 5 or more represents flood, so to consider dry and wet weather condition separately, we apply the following transformation for Palmer Z index:

$$PZdry_{it} = -\min(0, PZ_{it}); \tag{5a}$$

$$PZwet_{it} = \max(0, PZ_{it}). \tag{5b}$$

[4] Detailed data are available at ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/.
[5] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/, accessed on 04 April 2017

Therefore, the larger is the value of $PZdry$, the drier is the weather condition. Similarly, the larger is the value of $PZwet$, the wetter is the weather condition. The expected weather condition for crop growth is neither too dry nor too wet.

We construct the county-year panel from NASS, RMA, NOAA data. The County-year panel is unbalanced since NASS combines counties with small planted acreage into one combined county observation for each state in each year. Besides, some counties do not have GDD and SDD data, since county-level GDD and SDD is calculated from station-level data but some counties do not contain a station. Therefore, we do not include the combined observation from NASS and the missing counties from NOAA. The issue of unbalanced panel is discussed in later sections.

Table 2-5 show the descriptive statistics of variables for corn and soybeans both with full sample and balanced panel. Taking corn as example, the overall average participation rate is about 79%, which is similar to participation rate for Buy-up policy, that is 73%. The average participation rate for CAT is much lower, which is about 6%. For coverage levels of at least 65% and 75%, the average participation rates are respectively about 67% and 41%.

Participation rates in balance panel that are available in all datasets tends to be larger than the average participation rates for full sample in the categories of all levels, Buy-up policy, coverage levels of at least 65% and 75%, while it is smaller than that in the full sample for CAT. The average indemnity ratio is smaller than the full-sample average for all the categories except CAT.

5. Model Specification

In this section, we construct models to examine crop insurance participation response from recency biases in which farmers can update their belief of insurance's benefit with their recent experience. We specify two recognized channels through which recent experience can affect crop insurance participation: (1) we apply parametric estimation approach to examine the causal effect of past year indemnity payouts on crop insurance participation, working directly with weather data;

(2) we employ nonparametric estimation to test the lasting effects on participation of large indemnities based on a flexible event study model.

5.1 Parametric estimation of participation based on indemnity payouts

In this section, we employ two-stage least squares (2L2S) approach to test the effects of past indemnity payouts on participation in crop insurance, using recent weather variables as instruments. Then we also work on estimations for corn and soybeans based on different policies (Buy-up vs CAT) and different coverage levels (we consider the coverage levels greater than 65% and 75% respectively).

We specify the dependent variable as the logit transformation of participation rate, which is $\ln[r_{it}/(1-r_{it})]$. The main explanatory variable is indemnity ratio, which is denoted as $indemnityratio_{it}$ for county i in year t, recalling the definition in prior section, it is the ratio of policies indemnified count to policies earing premium count.

The time-fixed regression equation is

$$\ln[r_{it}/(1-r_{it})] = \sigma_0 + \sigma_1 indemnityratio_{it-1} + \omega_3 T_{2003} + \ldots + \omega_{15} T_{2015} + u_{it} \tag{6}$$

where u_{it} denotes the error item.

The coefficient is interpreted to describe the relationship between the prior indemnified payouts and participation rate.

We apply the logit transformation on participation rate r_{it} for county i and year t within their true domain [0, 1], that is, the dependent variable is $\ln[r_{it}/(1-r_{it})]$, and then we estimate the parameters. For the zero values of participation rates, the values are replaced with 0.0001 before transformation; while for the one values of participation rates, the values are replaced with 0.9999 before transformation. The results in the logit transformation with or without the replacements of ones provide similar outcomes.

The main variable $indemnityratio_{it-1}$ is endogenous to the dependent variable $\ln[r_{it} / (1-r_{it})]$. The ratio of the number of policies that are indemnified to the number of policies earning premium is correlated with the error term, resulting in biased coefficient estimates. Furthermore, it is not clear from this specification how the causation relationship runs.

To mitigate this concern, we adopt the instrumental variable approach. First, using the fixed effect regression can mitigate the bias from time-invariant omitted variables. Then instrumenting $indemnityratio$ with the weather variables including *GDDdeviation, SDDdeviation, PZdry, PZwet.* Table 6 shows the results of the first stage regression. As expected, the instruments weather variables are strongly correlated with the variable of $indemnityratio$.

For the estimation, we take two-stage least squares (2L2S) approach. The instruments are then used in the first stage of the regression to create instrumental variable $indemnityratio^{\mathrm{IV}}$ which is used in the second stage:

$$\ln[r_{it} / (1-r_{it})] = \sigma_0 + \sigma_1 indemnityratio_{it-1}^{IV} + \omega_3 T_{2003} + \ldots + \omega_{15} T_{2015} + u_{it} \tag{7}$$

5.2 Non-parametric estimation of the lasting effects on participation of large indemnities

In this section, we use a flexible event study framework to estimate the causal effect of large indemnity ratio on participation in crop insurance. Equation (8) is the main estimation equation.

$$\ln[r_{it} / (1-r_{it})] = \sum_{\tau=-T}^{T} \beta_\tau \mathrm{W}_{i\tau} + \alpha_2 T_{2002} + \ldots + \alpha_{15} T_{2015} + \varepsilon_{it} \tag{8}$$

The dependent variable, $\ln[r_{it} / (1-r_{it})]$, logit transformation of participation rate for county i in year t. The independent variables are the event time indicator variables, $W_{i\tau}$, which track the year of large indemnity ratio and the years before and after a large loss. Here we define a large loss occurs in one county when the county's indemnity ratio is greater than a specific cutoff point such as 10%, 20%, 30%, 40%, 50%. The value of cutoff point can denote the magnitude of a large loss.

For a calendar year t, the indicator variable W_{i0} equals to 1 if a large loss appears in county i in that year t; the indicator variable $W_{i\tau}$ equals to 1 if a large loss appears in county i in year $t-\tau$. Some counties may have more than one large loss during the event study, then each loss is coded with its own indicator variable. For example, county i has a large loss in year 2006 and 2012, then for the calendar year 2010, the indicator W_{i4} equals 1 since it is 4 years after the loss year 2006 and the indicator W_{i-2} equals 1 since it is 2 years before the loss year 2012. We take $\tau \in [-5, 5]$ in the equation (8), since we are interested in the participation response in the recent years around a large loss. We use fixed-effect regression in equation (8) to control the unobservable factors. The value of coefficients can represent the magnitude of participation change.

6. Estimation Results

6.1 The effects on participation of indemnity payouts

Table 6 shows the estimated results of the first stage for equation (7) taking crop insurance of corn as example. As expected, the coefficients of the weather variables suggest that the adverse weather conditions significantly encourage indemnified payouts. For variables of heat stress, the deviation of the past average growing degree days has a significantly negative effect on indemnity payouts; while the deviation of the past average stress degree days has a significantly positive effect on indemnity payouts. In other words, the insufficient heat accumulation and excessive heat stress will increase indemnity payouts. For the variables of PZdry and PZwet, they are the transformation of the index of Palmer Z. Recalling the meaning of these two variables, the value of PZdry is response to dryness, that is, the larger of PZdry, the drier is the weather condition; while the value of PZwet is response to wetness, that is, the larger of PZwet, the wetter is the weather condition. If PZdry or PZwet are large enough, they represent the extreme weather conditions such as drought or flood. Back to the coefficients of PZdry and PZwet, the positive values mean that negative weather conditions with too much moisture or too little water will increase indemnity payouts.

Note that these effects are statistically significant.

Comparing the coefficients among the regressions on indemnity ratio for the policies of Buy-up and CAT and for the coverage levels of at least 65% and 75%. Under all these groups, the values and signs of the coefficients of four weather variables are consistent. The absolute values of the coefficients in CAT group are smaller than that of other groups. This may be caused by the characteristic of CAT, which is a crop insurance product with equal total premium and subsidy, that is, 100% subsidy rate. Besides, the absolute values of coefficients at coverage levels of at least 75% are slightly higher than that of 65%. This can explain that the effects of adverse weather condition on the indemnity payouts are larger with higher coverage levels.

Therefore, the results from Table 6 identify the relationship between the adverse weather biases and indemnity payouts of crop insurance. Under different insurance policies and coverage levels, the results are consistent that recency biases with adverse weather conditions are more likely to induce indemnity payouts responses.

Table 7 shows that the effects of past year indemnity payouts on participation of crop insurance. We can observe that past year indemnity payouts play a positive significant role in the action of taking out insurance except for CAT. The effects of past year indemnity payouts on participation are greater for coverage levels of at least 75% than that of 65%.

Combining the results of Table 6 and Table 7, the estimation results are consistent with our expectation. The matrix of weather variables allows for the identification of recency and availability biases in regard to risks posed, then past indemnity payouts provide a positive channel through which biases can arise, where the payouts provide positive effect on the action of taking out crop insurance. In other words, recency biases caused by past adverse weather conditions encourage indemnity payouts, and past indemnity payouts further positively promote participation of crop insurance.

Table 10 and Table 11 respectively report the regression results in the first and second stage for soybeans. The results for soybeans have some difference from that for corn. In the first stage, the effects of heat stress variables, that is, the deviation of past average growing degree days and stress degree days are not significant. The estimation results of water stress variables are consistent with the results for corn. In the second stage, the effect of past indemnity payouts on participation is not statistically significant with overall data. For Buy-up, coverage levels of at least 65% and 75%, the results for soybeans are consistent with that for corn. We can also observe that past indemnity payouts have a larger influence on participation with higher coverage levels. Therefore, the basic regression results for soybeans are consistent with corn, but some coefficients are not statistically significant.

Recalling the data section, we introduce that the panel data is unbalanced because the combined counties in NASS and the missing county data from the calculation of growing degree days and stress degree days. If the dropping observations are correlated with error term, the unbalanced panel can lead to attribution bias. We take balanced panel to do robustness check.

Table 8 and Table 9 show the regression results with balanced panel for corn, which are similar with Table 6 and 7. The absolute values of estimated coefficients of four weather variables in the first stage are larger than that in the unbalanced panel. In the second stage, there is no such comparison relations. Table 12 and 13 report the results with balanced panel for soybeans, which are similar with Table 10 and 11. There is no such comparison relations as for corn. The regression results with balanced panel are consistent with the results with unbalanced panel. So, the observations with missing years do not influence the regression results.

6.2 The lasting effects on participation of large indemnities

Figure 10-14 plot the coefficients of event time indicator, β_τ, which come from the estimation of equation (8) on the 2001-2015 county-year panel among different policy categories and coverage levels for corn and soybeans. Event times are plotted on the x-axis. Year 0 means that a large loss occurs in that calendar year, while years -1,..., -5 are the years before a large loss, and years 1,..., 5 are years after a large loss. The bands represent the 95 percent confidence interval.

Figure 10 plots the point estimates with overall crop insurance data for corn and soybeans respectively. Taking corn as example in Figure 10a, there is no noticeable trend in participation in the years before a large loss. The effect of a future large loss is economically small and not statistically significant for all the years before a large loss. In the year of a large loss, it has similar results as the years before it. For the first year after loss year, there is a largest significant increase in the participation of crop insurance relative to the loss year. Participation after the large loss keeps positive and statistically significant for four years, but the increasing effect tapers year by year. After four years, participation is not statistically significant, which is similar as the years before a large loss. This trend is consistent for all our definition of a large loss with the indemnity ratio greater than 10%, 20%, 30%, 40%, 50% respectively. As the value of this cutoff point increases, the severity of loss increases. The figure also shows that participation has greater increases after event year when facing a more severer loss, which is defined with a larger cutoff point. Figure 10b shows similar findings of participation in crop insurance for soybeans, and the average increase magnitude after a large loss is a little smaller than that of corn.

Figure 11-12 plot the coefficients of event time indicator for categories "Buy-up" and "CAT". For "Buy-up", we can find that it has the similar trend of participation as overall crop insurance for both corn and soybeans. The values of coefficients after event year are a bit larger for "Buy-up", that is, the participation increases more after a large loss. However, participation for "CAT" has an opposite trend after the event year, which experiences a largest decline in the first year after a large loss and this effect tapers off in the following four years.

Figure 13-14 plot estimates of crop insurance participation for higher coverage levels of at least 65% and 75% for corn and soybeans. They have similar participation trends as overall crop insurance situation. However, it is evident that their participation increases after event year are larger than that of overall insurance. For the higher coverage levels of at least 75%, increasing magnitude after a large loss is greater than that for lower coverage levels of at least 65%.

7. Conclusion

The U.S. Federal crop insurance program has a long history of growing from a minor program into a central agricultural policy. The participation of crop insurance program has increased significantly. This study focuses on recency biases related to risks that motivate the decisions of participating in crop insurance program. We specify two recognized channels through which recent experience can affect crop insurance participation in this paper.

First, we apply parametric estimation approach to examine the causal effect of past year indemnity payouts on crop insurance participation, working directly with weather data. We estimate the effect of past weather biases on past indemnity payouts, then confirm that past year indemnity payouts provide a district channel through which the biases further influence the action of taking out crop insurance program. To identify the motivation behind participation, we apply past weather variables to instrument the main explanatory variable of indemnity scale. This approach can mitigate the endogeneity concerns and confirm the action mechanism. Our estimation results regarding to corn acreage show that the past reverse weather conditions have a significantly positive effect on past indemnity payouts, and the past indemnity payouts further significantly increase the possibility of crop insurance participation. Facing the crop insurance choices, the decision makers are influenced by the recency biases in regard to risks.

Second, we employ nonparametric estimation to test the lasting effects on participation of large indemnities based on a flexible event study model. We construct a simple model to examine crop insurance participation response from recency biases in which farmers can update their belief of insurance's benefit with their recent experience. The results show that the effect of large indemnities on participation is strongest in the first year after large loss, then begins to steadily decline. Larger levels of indemnities have more significant influence on participation.

In summary, we find some motivates behind the crop insurance decision makers facing the uncertain risks and examine the effect of recency biases on participation. Our study provides a mechanism of crop insurance participation that prior adverse weather can increase past indemnity payouts though which recency biases arise, where the past payouts further promote future possibility of participation. Further, we have studied the lasting effects on participation of large indemnities.

It is by now widely recognized that typical decision makers encounter at least some difficulties with making decisions about how to manage uncertain future outcomes. These facts have been established through experimental studies, and also through limited use of market outcome studies (Kunreuther et al. 2013). As with many other choice contexts (e.g., personal health, recreational and labor choices, and financial investment choices), many readily documented crop insurance choices are prima facie inconsistent with standard economic theory. Given their well-specified and rigid contractual structure, ample public information allowing for objective measures of risk exposure and public reporting of uptake (albeit at the county level), crop insurance markets are an ideal 'laboratory' in which to inquire into behavioral biases in the face of risks.

References

Babcock, B. A. (2015). Using cumulative prospect theory to explain anomalous crop insurance coverage choice. *American Journal of Agricultural Economics*, 97(5), 1371-1384.

Baicker, K., Congdon, W. J., and Mullainathan, S. (2012). Health Insurance Coverage and Take-Up: Lessons from Behavioral Economics. *Milbank Quarterly*, 90(1), 107-134.

Cai, J., De Janvry, A., & Sadoulet, E. (2016). Subsidy policies and insurance demand (No. w22702). National Bureau of Economic Research.

Chong, H., J. Ifft. (Undated). (Over)reacting to Bad Luck: Low Yields Increase Crop Insurance Participation. Dyson School of Management powerpoint presentation, Cornell University.

Du, X., Feng, H., and Hennessy, D. A. (2017). Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics*, 99(3), 732-756.

Du, X., Hennessy, D. A., and Feng, H. (2014). A natural resource theory of US crop insurance contract choice. *American Journal of Agricultural Economics*, 96(1), 232-252.

Gallagher, J. (2014). Learning about an infrequent event: evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*, 6(3), 206-233.

Glauber, J. W. (2013). The growth of the federal crop insurance program, 1990–2011. *American Journal of Agricultural Economics*, 95(2), 482-488.

Goodwin, B. K. (1993). An empirical analysis of the demand for multiple peril crop insurance. *American Journal of Agricultural Economics*, 75(2), 425-434.

Goodwin, B. K., Vandeveer, M. L., & Deal, J. L. (2004). An empirical analysis of acreage effects of participation in the federal crop insurance program. *American Journal of Agricultural Economics*, 86(4), 1058-1077.

Innes, R. (2003). Crop insurance in a political economy: an alternative perspective on agricultural policy. *American Journal of Agricultural Economics*, 85(2), 318-335.

Kousky, C. (2017). Disasters as learning experiences or disasters as policy opportunities? Examining flood insurance purchases after hurricanes. *Risk analysis*, 37(3), 517-530.

Kunreuther, H., and Pauly, M. (2006). Insurance decision-making and market behavior. *Foundations and Trends® in Microeconomics*, 1(2), 63-127.

Kunreuther, H. C., Pauly, M. V., and McMorrow, S. (2013). *Insurance and behavioral economics: improving decisions in the most misunderstood industry.* Cambridge University Press.

O'Donoghue, E. (2014). *The Effects of Premium Subsidies on Demand for Crop Insurance* (No. 178405). United States Department of Agriculture, Economic Research Service.

Pétraud, J.P., Boucher, S. R., & Carter, M. R. (2015). Competing Theories of Risk Preferences and the Demand for Crop Insurance: Experimental Evidence from Peru. Paper presented at 29th Internet. Conf. Agric. Econ., Milan, 8-14 August.

Sherrick, B. J., Barry, P. J., Ellinger, P. N., & Schnitkey, G. D. (2004). Factors influencing farmers' crop insurance decisions. *American Journal of Agricultural Economics*, 86(1), 103-114.

Stein, D. (2014). Dynamics of demand for rainfall index insurance: evidence from a commercial product in India. *The World Bank Economic Review*.

Sutton, R. S., and Barto, A. G. (1998). *Reinforcement learning: An introduction* (Vol. 1, No. 1). Cambridge: MIT press.

Woodard, J. D., Schnitkey, G. D., Sherrick, B. J., Lozano‐Gracia, N., and Anselin, L. (2012). A spatial econometric analysis of loss experience in the US crop insurance program. *Journal of Risk and Insurance*, 79(1), 261-286.

Xu, Z., Hennessy, D. A., Sardana, K., and Moschini, G. (2013). The realized yield effect of genetically engineered crops: US maize and soybean. *Crop Science*, 53(3), 735-745.

Yu, J., Smith, A., and Sumner, D. A. (2016). The Effects of the Premium Subsidies in the US Federal Crop Insurance Program on Crop Acreage. In *2016 Annual Meeting, July 31-August 2, 2016, Boston, Massachusetts* (No. 236022). Agricultural and Applied Economics Association.

Figures and Tables

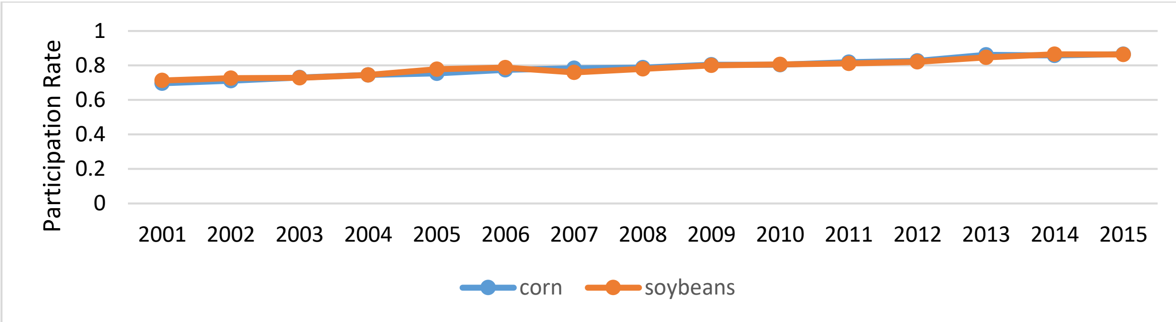


Figure 1. Average participation rates for corn and soybeans (2001-2015)

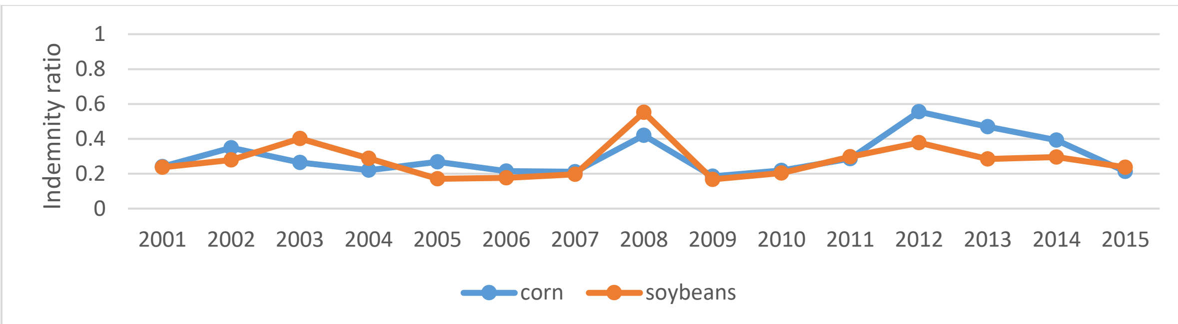


Figure 2. Average indemnity ratio for corn and soybeans (2001-2015)

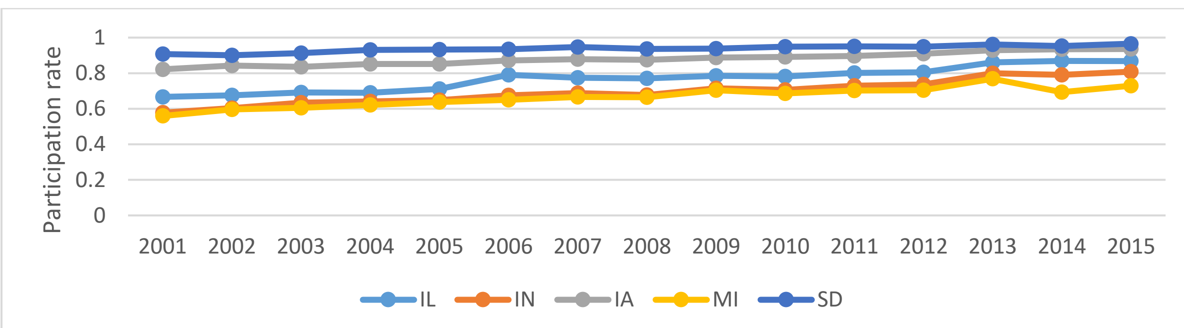


Figure 3. Average participation rates for corn in the state level (IL, LN, IA, MI, SD; 2001-2015)

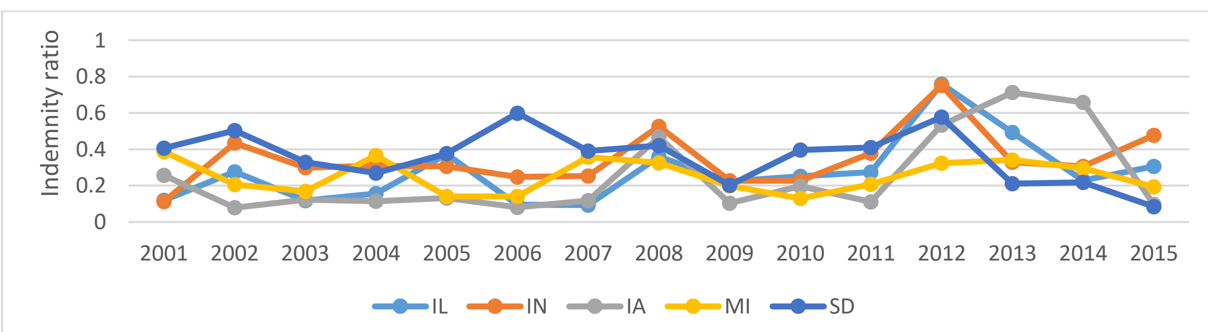
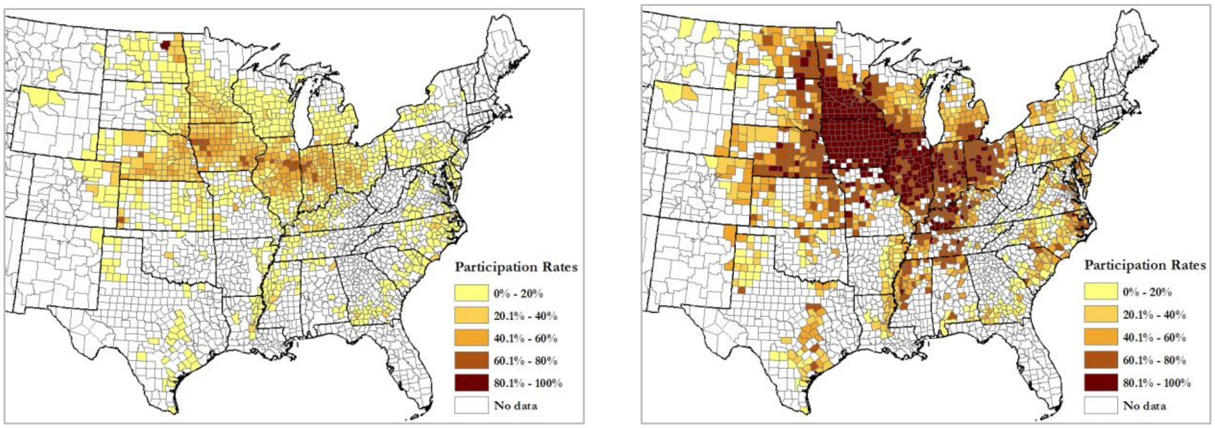


Figure 4. Average indemnity ratio for corn in the state level (IL, LN, IA, MI, SD; 2001-2015)



(a)2001 (b)2015

Figure 5. The distribution of participation rates for corn at coverage levels of at least 75% (2001, 2015)

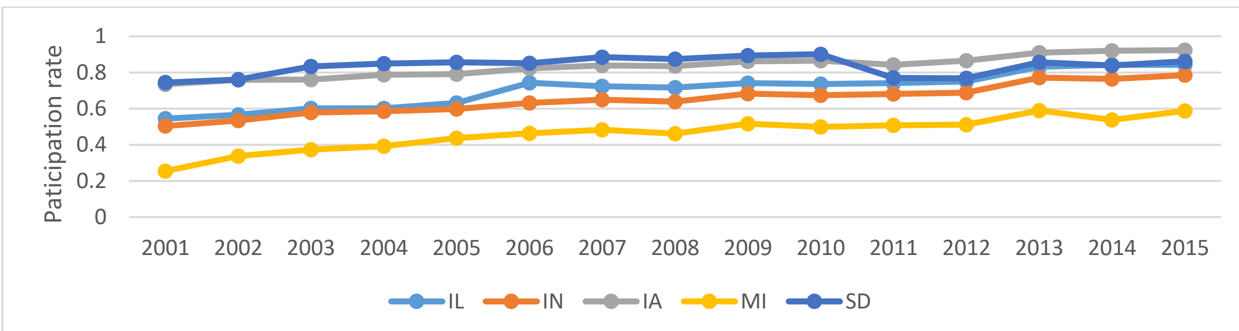


Figure 6. Average participation rates for corn at coverage levels of at least 65% in the state level (IL, LN, IA, MI, SD; 2001-2015)

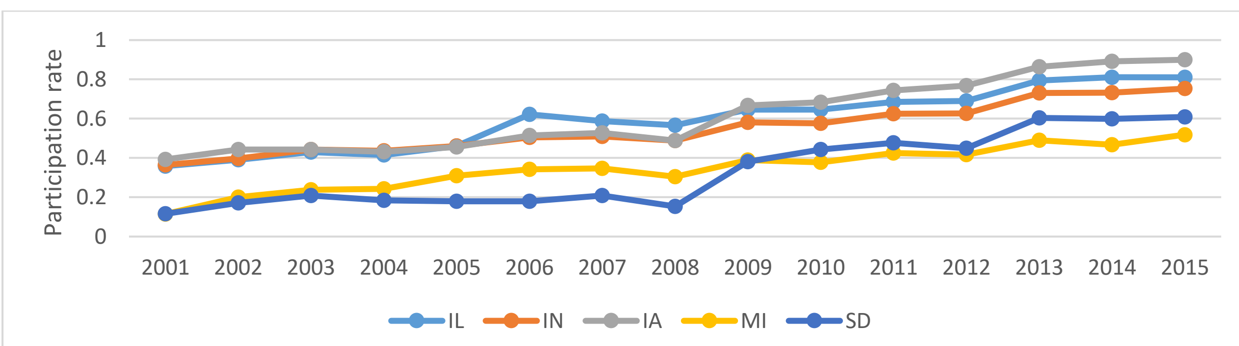


Figure 7. Average participation rates for corn at coverage levels of at least 75% in the state level (IL, LN, IA, MI, SD; 2001-2015)

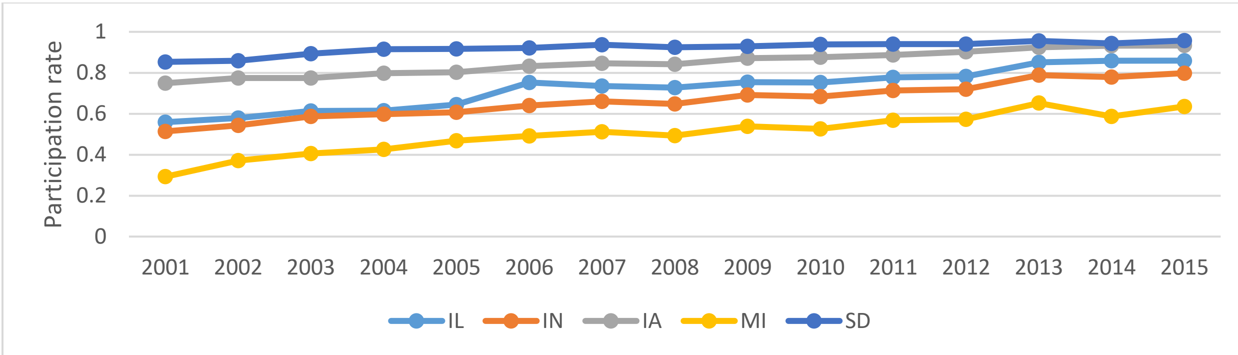


Figure 8. Average participation rates for corn of Buy-up policies in the state level (IL, LN, IA, MI, SD; 2001-2015)

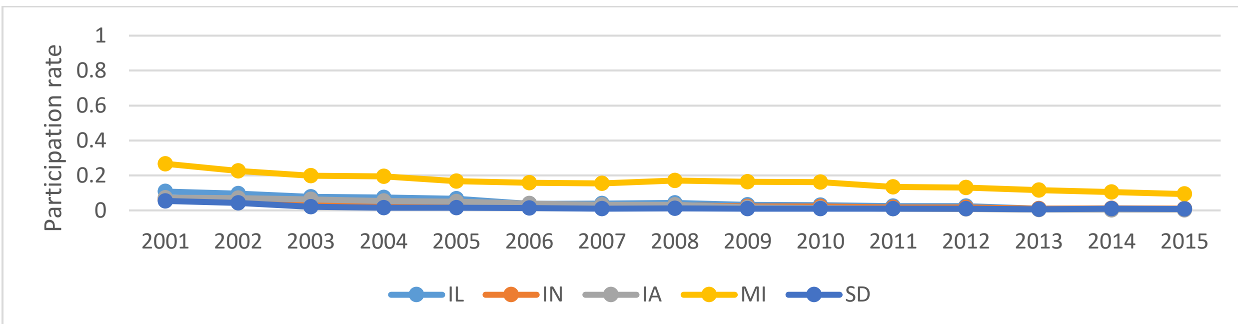
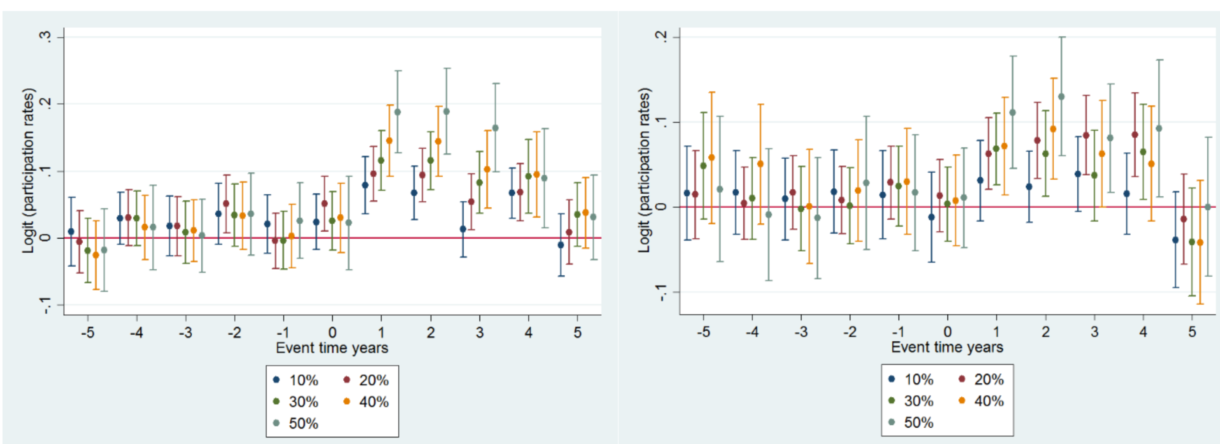
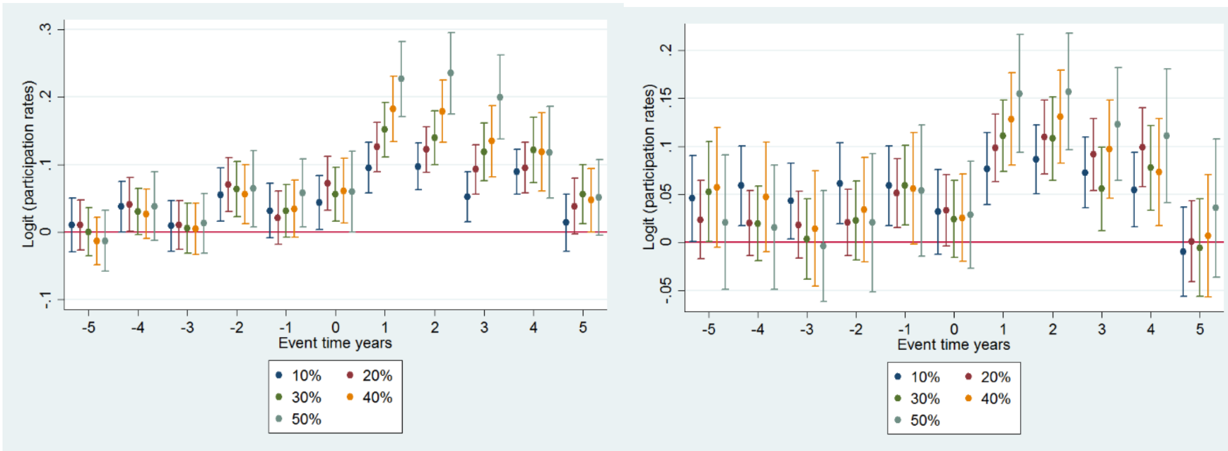


Figure 9. Average participation rates for corn of CAT policies in the state level (IL, LN, IA, MI, SD; 2001-2015)



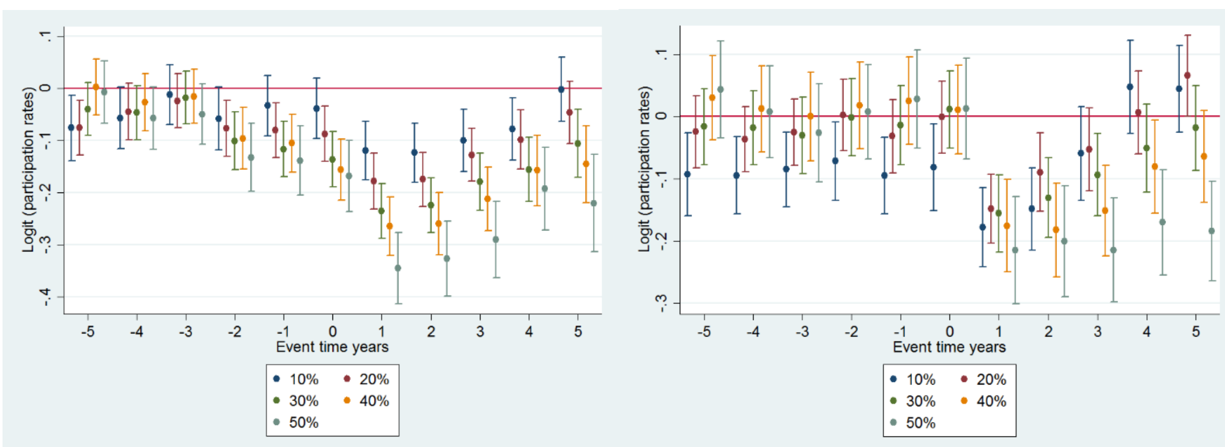
(a) Corn (b) Soybeans

Figure 10. The logit transformation of participation in crop insurance program for counties with large disaster (2001-2015; Corn, Soybeans; overall)



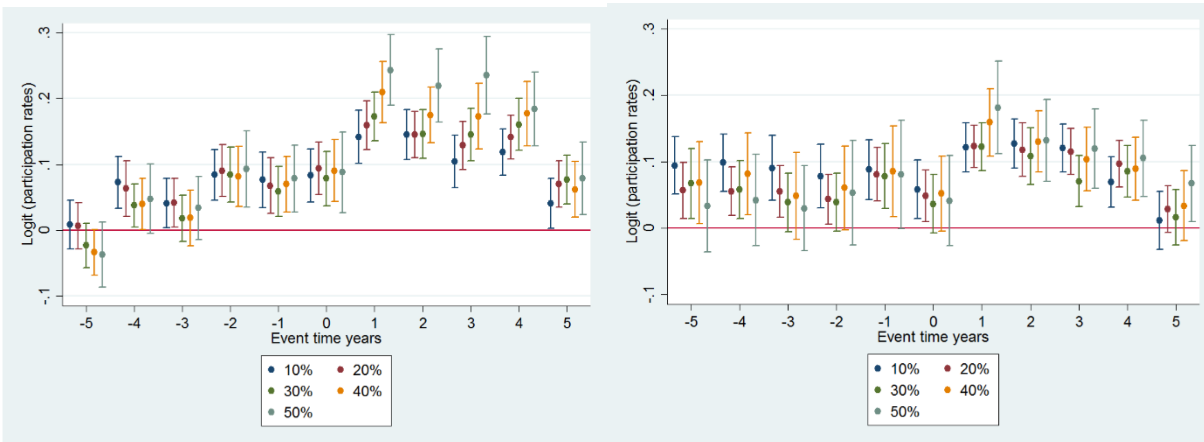
(a) Corn (b) Soybeans

Figure 11. The logit transformation of participation in crop insurance program for counties with large disaster (2001-2015; Corn, Soybeans; Buyup)



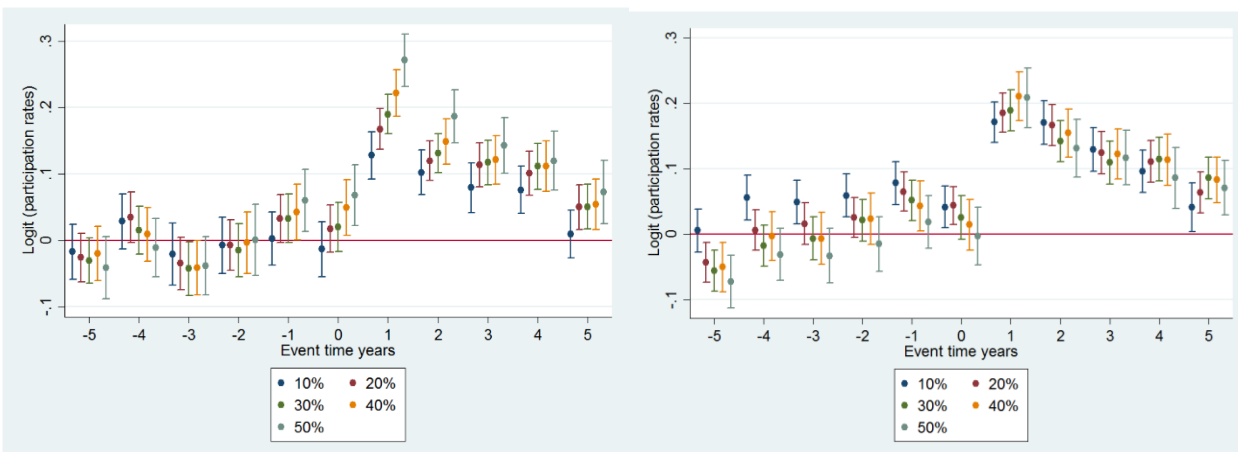
(a) Corn (b) Soybeans

Figure 12. The logit transformation of participation in crop insurance program for counties with large disaster (2001-2015; Corn, Soybeans; CAT)



(a) Corn (b) Soybeans

Figure 13. The logit transformation of participation in crop insurance program for counties with large disaster (2001-2015; Corn, Soybeans; Coverage levels of at least 65%)



(a) Corn (b) Soybeans

Figure 14. The logit transformation of participation in crop insurance program for counties with large disaster (2001-2015; Corn, Soybeans; Coverage levels of at least 75%)

Table 1. Definition of variables.

	Variable	Description
Participation rate	*r*	Net reported acres / (Planted acres + Prevented planting acres)
Indemnity payout	*indemnityratio*	Policies indemnified count/Policies earning premium count
Weather Variables	*GDDdeviation*	Deviation from the average GDD of the year 1990-1999
	SDDdeviation	Deviation from the average SDD of the year 1990-1999
	PZdry	The negative value of the minimum between 0 and the value of Palmer Z
	PZwet	The maximum between 0 and the value of Palmer Z

Table 2. Descriptive statistics of the variables for corn (Full sample).

Category	Variable		Obs	Mean	Std.Dev.	Min	Max
All levels	Participation rate	*r*	13,315	0.790	0.154	0.0350	1
	Indemnity payout	*indemnityratio*	14,377	0.332	0.253	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,885	0.0410	0.0914	0	1.416
Buyup	Participation rate	*r*	13,315	0.731	0.197	0	1
	Indemnity payout	*indemnityratio*	14,375	0.353	0.262	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,885	0.0410	0.0914	0	1.416
CAT	Participation rate	*r*	12,862	0.0618	0.0867	0	0.716
	Indemnity payout	*indemnityratio*	13,111	0.0931	0.195	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,885	0.0410	0.0914	0	1.416
Coverage >=65%	Participation rate	*r*	13,308	0.674	0.215	0	1
	Indemnity payout	*indemnityratio*	14,338	0.368	0.271	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,885	0.0410	0.0914	0	1.416
Coverage >=75%	Participation rate	*r*	13,125	0.405	0.251	0	1
	Indemnity payout	*indemnityratio*	13,850	0.414	0.299	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,885	0.0410	0.0914	0	1.416

Table 3. Descriptive statistics of the variables for corn (Balanced panels).

Category	Variable		Obs	Mean	Std.Dev.	Min	Max
All levels	Participation rate	*r*	7,185	0.798	0.153	0.135	1
	Indemnity payout	*indemnityratio*	7,185	0.316	0.247	0.00102	1
	Weather Variables	*GDDdeviation*	7,185	0.0267	0.260	-0.992	4.621
		SDDdeviation	7,185	0.0432	0.264	-0.999	4.913
		PZwet	7,185	0.0913	0.119	0	1.325
		PZdry	7,185	0.0381	0.0862	0	1.301
Buyup	Participation rate	*r*	7,395	0.746	0.189	0.0616	1
	Indemnity payout	*indemnityratio*	7,395	0.333	0.256	0	1
	Weather Variables	*GDDdeviation*	7,395	0.0262	0.257	-0.992	4.621
		SDDdeviation	7,395	0.0427	0.260	-0.999	4.913
		PZwet	7,395	0.0900	0.118	0	1.325
		PZdry	7,395	0.0377	0.0854	0	1.301
CAT	Participation rate	*r*	5,220	0.0593	0.0717	4.02e-05	0.517
	Indemnity payout	*indemnityratio*	5,220	0.0716	0.153	0	1
	Weather Variables	*GDDdeviation*	5,220	0.0213	0.174	-0.992	2.665
		SDDdeviation	5,220	0.0373	0.182	-0.989	2.745
		PZwet	5,220	0.0922	0.121	0	1.325
		PZdry	5,220	0.0390	0.0889	0	1.301
Coverage >=65%	Participation rate	*r*	7,395	0.706	0.200	0.0299	1
	Indemnity payout	*indemnityratio*	7,395	0.344	0.263	0	1
	Weather Variables	*GDDdeviation*	7,395	0.0262	0.257	-0.992	4.621
		SDDdeviation	7,395	0.0427	0.260	-0.999	4.913
		PZwet	7,395	0.0900	0.118	0	1.325
		PZdry	7,395	0.0377	0.0854	0	1.301
Coverage >=75%	Participation rate	*r*	7,170	0.463	0.243	0.000203	0.988
	Indemnity payout	*indemnityratio*	7,170	0.385	0.283	0	1
	Weather Variables	*GDDdeviation*	7,170	0.0264	0.260	-0.992	4.621
		SDDdeviation	7,170	0.0428	0.264	-0.999	4.913
		PZwet	7,170	0.0909	0.119	0	1.325
		PZdry	7,170	0.0377	0.0858	0	1.301

Table 4. Descriptive statistics of the variables for soybeans (Full sample).

Category	Variable		Obs	Mean	Std.Dev.	Min	Max
All levels	Participation rate	*r*	12,618	0.787	0.153	0	1
	Indemnity payout	*indemnityratio*	13,676	0.309	0.231	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,870	0.0410	0.0914	0	1.416
Buyup	Participation rate	*r*	13,315	0.731	0.197	0	1
	Indemnity payout	*indemnityratio*	14,375	0.353	0.262	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,870	0.0410	0.0914	0	1.416
CAT	Participation rate	*r*	11,950	0.0565	0.0763	0	0.759
	Indemnity payout	*indemnityratio*	11,901	0.0707	0.166	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,870	0.0410	0.0914	0	1.416
Coverage >=65%	Participation rate	*r*	12,618	0.688	0.201	0	1
	Indemnity payout	*indemnityratio*	13,661	0.341	0.250	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,870	0.0410	0.0914	0	1.416
Coverage >=75%	Participation rate	*r*	12,556	0.421	0.239	0	1
	Indemnity payout	*indemnityratio*	13,440	0.382	0.282	0	1
	Weather Variables	*GDDdeviation*	14,188	0.0456	0.506	-0.994	13.70
		SDDdeviation	14,188	0.0639	0.516	-0.999	15.58
		PZwet	15,825	0.0853	0.127	0	1.373
		PZdry	15,870	0.0410	0.0914	0	1.416

Table 5. Descriptive statistics of the variables for soybeans (Balanced panels).

Category	Variable		Obs	Mean	Std.Dev.	Min	Max
All levels	Participation rate	*r*	7,470	0.793	0.151	0.138	1
	Indemnity payout	*indemnityratio*	7,470	0.286	0.221	0	0.992
	Weather Variables	*GDDdeviation*	7,470	0.0277	0.267	-0.992	4.621
		SDDdeviation	7,470	0.0429	0.270	-0.999	4.913
		PZwet	7,470	0.0912	0.118	0	1.325
		PZdry	7,470	0.0348	0.0790	0	1.301
Buyup	Participation rate	*r*	7,470	0.746	0.183	0.0844	1
	Indemnity payout	*indemnityratio*	7,470	0.302	0.232	0	0.993
	Weather Variables	*GDDdeviation*	7,470	0.0277	0.267	-0.992	4.621
		SDDdeviation	7,470	0.0429	0.270	-0.999	4.913
		PZwet	7,470	0.0912	0.118	0	1.325
		PZdry	7,470	0.0348	0.0790	0	1.301
CAT	Participation rate	*r*	5,130	0.0579	0.0676	6.27e-05	0.759
	Indemnity payout	*indemnityratio*	5,130	0.0608	0.137	0	1
	Weather Variables	*GDDdeviation*	5,130	0.0252	0.200	-0.992	2.665
		SDDdeviation	5,130	0.0404	0.206	-0.989	2.745
		PZwet	5,130	0.0890	0.109	0	1.289
		PZdry	5,130	0.0348	0.0773	0	1.301
Coverage >=65%	Participation rate	*r*	7,470	0.707	0.192	0.0458	1
	Indemnity payout	*indemnityratio*	7,470	0.312	0.238	0	1
	Weather Variables	*GDDdeviation*	7,470	0.0277	0.267	-0.992	4.621
		SDDdeviation	7,470	0.0429	0.270	-0.999	4.913
		PZwet	7,470	0.0912	0.118	0	1.325
		PZdry	7,470	0.0348	0.0790	0	1.301
Coverage >=75%	Participation rate	*r*	7,410	0.463	0.234	0.000880	1
	Indemnity payout	*indemnityratio*	7,410	0.352	0.267	0	1
	Weather Variables	*GDDdeviation*	7,410	0.0273	0.268	-0.992	4.621
		SDDdeviation	7,410	0.0424	0.271	-0.999	4.913
		PZwet	7,410	0.0915	0.118	0	1.325
		PZdry	7,410	0.0349	0.0792	0	1.301

Table 6. The First Stage Regression with FE-IV for Corn (Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent Variable: L.indemnityratio				
L.GDDdeviation	-0.426***	-0.419***	-0.256***	-0.471***	-0.496***
	(0.0574)	(0.0599)	(0.0475)	(0.0617)	(0.0706)
L.SDDdeviation	0.449***	0.440***	0.265***	0.489***	0.504***
	(0.0548)	(0.0571)	(0.0454)	(0.0588)	(0.0676)
L.PZdry	0.976***	1.012***	0.674***	1.044***	1.048***
	(0.0308)	(0.0322)	(0.0257)	(0.0332)	(0.0400)
L.PZwet	0.212***	0.217***	0.175***	0.223***	0.235***
	(0.0210)	(0.0219)	(0.0175)	(0.0226)	(0.0267)
Year FE	X	X	X	X	X
Constant	0.228***	0.272***	0.0530***	0.283***	0.369***
	(0.00771)	(0.00804)	(0.00624)	(0.00828)	(0.00973)
Observations	11,110	11,109	10,339	11,097	10,749
Number of county	896	896	881	896	890
R-squared	0.247	0.233	0.132	0.239	0.208

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. The second stage regression with FE-IV for Corn (Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
L.indemnityratio	0.495***	0.613***	-1.252***	0.511***	0.629***
	(0.126)	(0.105)	(0.208)	(0.0953)	(0.0951)
Year FE	X	X	X	X	X
Constant	1.118***	0.439***	-2.348***	0.189***	-1.791***
	(0.0452)	(0.0418)	(0.0354)	(0.0393)	(0.0459)
Observations	11,110	11,109	10,339	11,097	10,749
Number of county	896	896	881	896	890

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. The First Stage Regression with FE-IV for Corn (Balanced panel; Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent Variable: L.indemnityratio				
L.GDDdeviation	-0.620***	-0.617***	-0.371***	-0.621***	-0.650***
	(0.0956)	(0.0995)	(0.0829)	(0.102)	(0.111)
L.SDDdeviation	0.631***	0.629***	0.387***	0.628***	0.645***
	(0.0866)	(0.0901)	(0.0749)	(0.0921)	(0.101)
L.PZdry	1.022***	1.073***	0.552***	1.095***	1.095***
	(0.0427)	(0.0444)	(0.0317)	(0.0454)	(0.0500)
L.PZwet	0.308***	0.317***	0.224***	0.318***	0.297***
	(0.0296)	(0.0308)	(0.0225)	(0.0315)	(0.0345)
Year FE	X	X	X	X	X
Constant	0.210***	0.250***	0.0403***	0.261***	0.343***
	(0.00970)	(0.0101)	(0.00757)	(0.0103)	(0.0114)
Observations	6,902	6,902	4,872	6,902	6,692
Number of county	493	493	348	493	478
R-squared	0.306	0.292	0.141	0.297	0.283

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9. The second stage regression with FE-IV for Corn (Balanced panel; Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
L.indemnityratio	0.466***	0.502***	-1.534***	0.507***	0.677***
	(0.142)	(0.118)	(0.267)	(0.109)	(0.0828)
Year FE	X	X	X	X	X
Constant	1.146***	0.599***	-2.339***	0.373***	-1.447***
	(0.0502)	(0.0464)	(0.0413)	(0.0438)	(0.0389)
Observations	6,902	6,902	4,872	6,902	6,692
Number of county	493	493	348	493	478

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. The First Stage Regression with FE-IV for Soybeans (Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent Variable: L.indemnityratio				
L.GDDdeviation	-0.0261	0.00737	-0.0568	0.00228	-0.0149
	(0.0513)	(0.0535)	(0.0478)	(0.0554)	(0.0631)
L.SDDdeviation	0.0324	-0.00547	0.0757*	-0.00501	0.0126
	(0.0495)	(0.0517)	(0.0438)	(0.0535)	(0.0610)
L.PZdry	0.751***	0.782***	0.405***	0.807***	0.822***
	(0.0295)	(0.0307)	(0.0272)	(0.0319)	(0.0372)
L.PZwet	0.139***	0.150***	0.176***	0.154***	0.118***
	(0.0200)	(0.0209)	(0.0178)	(0.0217)	(0.0250)
Year FE	X	X	X	X	X
Constant	0.256***	0.303***	0.0488***	0.311***	0.392***
	(0.00682)	(0.00713)	(0.00564)	(0.00738)	(0.00850)
Observations	10,495	11,386	10,053	11,377	11,173
Number of county	850	876	837	875	868
R-squared	0.292	0.300	0.052	0.299	0.305

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11. The Second Stage Regression with FE-IV for Soybeans (Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
L.indemnityratio	0.290	0.592***	-1.845***	0.625***	0.963***
	(0.207)	(0.177)	(0.439)	(0.163)	(0.123)
Year FE	X	X	X	X	X
Constant	1.442***	0.674***	-2.354***	0.384***	-1.633***
	(0.0648)	(0.0633)	(0.0444)	(0.0598)	(0.0542)
Observations	10,495	10,494	9,446	10,494	10,397
Number of county	850	850	820	850	845

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12. The First Stage Regression with FE-IV for Soybeans (Balanced panel; Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent Variable: L.indemnityratio				
L.GDDdeviation	-0.0920	-0.0387	-0.0797	-0.0438	-0.0117
	(0.0785)	(0.0819)	(0.0735)	(0.0841)	(0.0925)
L.SDDdeviation	0.0847	0.0318	0.0808	0.0310	-0.00133
	(0.0715)	(0.0747)	(0.0672)	(0.0766)	(0.0843)
L.PZdry	0.749***	0.785***	0.322***	0.809***	0.882***
	(0.0389)	(0.0405)	(0.0340)	(0.0416)	(0.0458)
L.PZwet	0.186***	0.185***	0.136***	0.185***	0.161***
	(0.0248)	(0.0258)	(0.0225)	(0.0265)	(0.0292)
Year FE	X	X	X	X	X
Constant	0.241***	0.285***	0.0509***	0.294***	0.368***
	(0.00818)	(0.00854)	(0.00700)	(0.00877)	(0.00966)
Observations	6,972	6,972	4,788	6,972	6,916
Number of county	498	498	342	498	494
R-squared	0.352	0.361	0.050	0.361	0.384

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13. The Second Stage Regression with FE-IV for Soybeans (Balanced panel; Estimation equation (7))

	All	Buyup	CAT	Coverage ≥ 65%	Coverage ≥ 75%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
L.indemnityratio	0.238	0.469***	-3.142***	0.507***	1.000***
	(0.217)	(0.176)	(0.565)	(0.156)	(0.112)
Year FE	X	X	X	X	X
Constant	1.319***	0.630***	-2.097***	0.391***	-1.427***
	(0.0659)	(0.0606)	(0.0524)	(0.0553)	(0.0479)
Observations	6,972	6,972	4,788	6,972	6,916
Number of county	498	498	342	498	494

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14. Crop insurance participation for counties hit by a large loss (Corn; Overall; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
W_{-5}	0.00957	-0.00580	-0.0184	-0.0257	-0.0184
	(0.0261)	(0.0238)	(0.0246)	(0.0261)	(0.0314)
W_{-4}	0.0296	0.0305	0.0293	0.0158	0.0160
	(0.0200)	(0.0213)	(0.0207)	(0.0245)	(0.0322)
W_{-3}	0.0184	0.0178	0.00864	0.0110	0.00349
	(0.0227)	(0.0225)	(0.0235)	(0.0235)	(0.0279)
W_{-2}	0.0362	0.0512**	0.0344	0.0333	0.0358
	(0.0233)	(0.0220)	(0.0236)	(0.0254)	(0.0313)
W_{-1}	0.0209	-0.00411	-0.00350	0.00316	0.0261
	(0.0221)	(0.0211)	(0.0220)	(0.0241)	(0.0286)
W_0	0.0243	0.0515**	0.0255	0.0301	0.0224
	(0.0210)	(0.0208)	(0.0222)	(0.0265)	(0.0356)
W_1	0.0790***	0.0959***	0.116***	0.145***	0.188***
	(0.0218)	(0.0206)	(0.0226)	(0.0269)	(0.0311)
W_2	0.0671***	0.0942***	0.115***	0.144***	0.189***
	(0.0203)	(0.0204)	(0.0221)	(0.0266)	(0.0326)
W_3	0.0132	0.0541**	0.0830***	0.103***	0.165***
	(0.0211)	(0.0211)	(0.0234)	(0.0294)	(0.0338)
W_4	0.0671***	0.0683***	0.0922***	0.0948***	0.0894**
	(0.0190)	(0.0219)	(0.0279)	(0.0324)	(0.0378)
W_5	-0.0107	0.00886	0.0356	0.0376	0.0312
	(0.0237)	(0.0243)	(0.0242)	(0.0267)	(0.0321)
Year FE	X	X	X	X	X
Constant	0.996***	1.023***	1.071***	1.083***	1.083***
	(0.0731)	(0.0519)	(0.0401)	(0.0322)	(0.0306)
Observations	9,135	9,135	9,135	9,135	9,135
R-squared	0.203	0.207	0.212	0.215	0.219
Number of county	609	609	609	609	609

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15. Crop insurance participation for counties hit by a large loss (Corn; Buy-up; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES			Dependent variable: $\ln[r/(1-r)]$		
W_{-5}	0.0106	0.0107	0.000179	-0.0132	-0.0128
	(0.0205)	(0.0190)	(0.0181)	(0.0178)	(0.0231)
W_{-4}	0.0376*	0.0407**	0.0305*	0.0271	0.0383
	(0.0192)	(0.0203)	(0.0172)	(0.0188)	(0.0258)
W_{-3}	0.00939	0.0105	0.00576	0.00504	0.0129
	(0.0191)	(0.0186)	(0.0188)	(0.0194)	(0.0225)
W_{-2}	0.0553***	0.0702***	0.0634***	0.0560**	0.0642**
	(0.0200)	(0.0204)	(0.0207)	(0.0222)	(0.0287)
W_{-1}	0.0319	0.0214	0.0314	0.0344	0.0577**
	(0.0207)	(0.0201)	(0.0199)	(0.0214)	(0.0256)
W_0	0.0440**	0.0720***	0.0561***	0.0610**	0.0601**
	(0.0202)	(0.0204)	(0.0205)	(0.0244)	(0.0303)
W_1	0.0953***	0.126***	0.152***	0.182***	0.227***
	(0.0191)	(0.0186)	(0.0207)	(0.0246)	(0.0282)
W_2	0.0971***	0.122***	0.140***	0.179***	0.235***
	(0.0177)	(0.0172)	(0.0202)	(0.0234)	(0.0308)
W_3	0.0520***	0.0928***	0.119***	0.134***	0.200***
	(0.0188)	(0.0188)	(0.0216)	(0.0267)	(0.0316)
W_4	0.0896***	0.0955***	0.122***	0.119***	0.118***
	(0.0168)	(0.0193)	(0.0245)	(0.0294)	(0.0346)
W_5	0.0139	0.0384*	0.0557**	0.0473**	0.0514*
	(0.0215)	(0.0211)	(0.0223)	(0.0240)	(0.0283)
Year FE	X	X	X	X	X
Constant	0.373***	0.393***	0.442***	0.469***	0.473***
	(0.0723)	(0.0528)	(0.0384)	(0.0303)	(0.0297)
Observations	9,135	9,135	9,135	9,135	9,135
R-squared	0.392	0.400	0.406	0.410	0.415
Number of county	609	609	609	609	609

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16. Crop insurance participation for counties hit by a large loss (Corn; CAT; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES			Dependent variable: $\ln[r/(1-r)]$		
W_{-5}	0.0106	0.0107	0.000179	-0.0132	-0.0128
	(0.0205)	(0.0190)	(0.0181)	(0.0178)	(0.0231)
W_{-4}	0.0376*	0.0407**	0.0305*	0.0271	0.0383
	(0.0192)	(0.0203)	(0.0172)	(0.0188)	(0.0258)
W_{-3}	0.00939	0.0105	0.00576	0.00504	0.0129
	(0.0191)	(0.0186)	(0.0188)	(0.0194)	(0.0225)
W_{-2}	0.0553***	0.0702***	0.0634***	0.0560**	0.0642**
	(0.0200)	(0.0204)	(0.0207)	(0.0222)	(0.0287)
W_{-1}	0.0319	0.0214	0.0314	0.0344	0.0577**
	(0.0207)	(0.0201)	(0.0199)	(0.0214)	(0.0256)
W_0	0.0440**	0.0720***	0.0561***	0.0610**	0.0601**
	(0.0202)	(0.0204)	(0.0205)	(0.0244)	(0.0303)
W_1	0.0953***	0.126***	0.152***	0.182***	0.227***
	(0.0191)	(0.0186)	(0.0207)	(0.0246)	(0.0282)
W_2	0.0971***	0.122***	0.140***	0.179***	0.235***
	(0.0177)	(0.0172)	(0.0202)	(0.0234)	(0.0308)
W_3	0.0520***	0.0928***	0.119***	0.134***	0.200***
	(0.0188)	(0.0188)	(0.0216)	(0.0267)	(0.0316)
W_4	0.0896***	0.0955***	0.122***	0.119***	0.118***
	(0.0168)	(0.0193)	(0.0245)	(0.0294)	(0.0346)
W_5	0.0139	0.0384*	0.0557**	0.0473**	0.0514*
	(0.0215)	(0.0211)	(0.0223)	(0.0240)	(0.0283)
Year FE	X	X	X	X	X
Constant	0.373***	0.393***	0.442***	0.469***	0.473***
	(0.0723)	(0.0528)	(0.0384)	(0.0303)	(0.0297)
Observations	9,135	9,135	9,135	9,135	9,135
R-squared	0.392	0.400	0.406	0.410	0.415
Number of county	609	609	609	609	609

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17. Crop insurance participation for counties hit by a large loss (Corn; Coverage levels of at least of 65%; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
W_{-5}	0.00842	0.00709	-0.0231	-0.0333*	-0.0370
	(0.0189)	(0.0179)	(0.0173)	(0.0176)	(0.0250)
W_{-4}	0.0728***	0.0634***	0.0377**	0.0402**	0.0477*
	(0.0199)	(0.0215)	(0.0168)	(0.0199)	(0.0268)
W_{-3}	0.0414**	0.0415**	0.0183	0.0188	0.0339
	(0.0192)	(0.0188)	(0.0178)	(0.0215)	(0.0245)
W_{-2}	0.0845***	0.0906***	0.0849***	0.0818***	0.0934***
	(0.0196)	(0.0201)	(0.0212)	(0.0231)	(0.0295)
W_{-1}	0.0768***	0.0679***	0.0590***	0.0699***	0.0786***
	(0.0214)	(0.0214)	(0.0195)	(0.0216)	(0.0260)
W_0	0.0832***	0.0940***	0.0787***	0.0907***	0.0881***
	(0.0204)	(0.0204)	(0.0210)	(0.0241)	(0.0312)
W_1	0.142***	0.159***	0.173***	0.210***	0.243***
	(0.0205)	(0.0188)	(0.0189)	(0.0238)	(0.0272)
W_2	0.145***	0.145***	0.146***	0.175***	0.220***
	(0.0194)	(0.0178)	(0.0189)	(0.0215)	(0.0283)
W_3	0.105***	0.129***	0.145***	0.173***	0.235***
	(0.0202)	(0.0187)	(0.0205)	(0.0253)	(0.0299)
W_4	0.119***	0.142***	0.161***	0.177***	0.184***
	(0.0179)	(0.0169)	(0.0200)	(0.0251)	(0.0284)
W_5	0.0409**	0.0704***	0.0769***	0.0622***	0.0792***
	(0.0194)	(0.0178)	(0.0187)	(0.0215)	(0.0280)
Year FE	X	X	X	X	X
Constant	0.0202	0.0990*	0.196***	0.223***	0.241***
	(0.0714)	(0.0525)	(0.0346)	(0.0293)	(0.0294)
Observations	9,135	9,135	9,135	9,135	9,135
R-squared	0.350	0.362	0.368	0.374	0.377
Number of county	609	609	609	609	609

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18. Crop insurance participation for counties hit by a large loss (Corn; Coverage levels of at least of 75%; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
W_{-5}	-0.0173	-0.0258	-0.0303*	-0.0200	-0.0412*
	(0.0211)	(0.0187)	(0.0173)	(0.0207)	(0.0240)
W_{-4}	0.0288	0.0349*	0.0148	0.00905	-0.0112
	(0.0210)	(0.0193)	(0.0183)	(0.0207)	(0.0224)
W_{-3}	-0.0208	-0.0348*	-0.0425**	-0.0410**	-0.0385*
	(0.0236)	(0.0202)	(0.0206)	(0.0207)	(0.0222)
W_{-2}	-0.00748	-0.00723	-0.0149	-0.00362	0.000674
	(0.0216)	(0.0193)	(0.0202)	(0.0235)	(0.0270)
W_{-1}	0.00283	0.0324*	0.0332*	0.0421**	0.0598**
	(0.0203)	(0.0184)	(0.0184)	(0.0213)	(0.0237)
W_{0}	-0.0132	0.0174	0.0199	0.0493**	0.0676***
	(0.0210)	(0.0181)	(0.0188)	(0.0215)	(0.0233)
W_{1}	0.128***	0.167***	0.190***	0.221***	0.271***
	(0.0181)	(0.0155)	(0.0150)	(0.0179)	(0.0200)
W_{2}	0.102***	0.120***	0.131***	0.149***	0.187***
	(0.0170)	(0.0149)	(0.0149)	(0.0173)	(0.0201)
W_{3}	0.0792***	0.114***	0.117***	0.121***	0.143***
	(0.0191)	(0.0168)	(0.0173)	(0.0184)	(0.0215)
W_{4}	0.0758***	0.101***	0.111***	0.112***	0.120***
	(0.0181)	(0.0168)	(0.0177)	(0.0191)	(0.0228)
W_{5}	0.00925	0.0499***	0.0507***	0.0540***	0.0727***
	(0.0183)	(0.0170)	(0.0172)	(0.0194)	(0.0243)
Year FE	X	X	X	X	X
Constant	-1.588***	-1.623***	-1.607***	-1.621***	-1.622***
	(0.0804)	(0.0564)	(0.0449)	(0.0412)	(0.0388)
Observations	9,097	9,097	9,097	9,097	9,097
R-squared	0.717	0.724	0.727	0.728	0.731
Number of county	609	609	609	609	609

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Crop insurance participation for counties hit by a large loss (Soybeans; Overall; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES			Dependent variable: $\ln[r/(1-r)]$		
W_{-5}	0.0163	0.0146	0.0485	0.0580	0.0211
	(0.0282)	(0.0265)	(0.0318)	(0.0393)	(0.0434)
W_{-4}	0.0172	0.00439	0.0102	0.0504	-0.00923
	(0.0250)	(0.0216)	(0.0246)	(0.0359)	(0.0396)
W_{-3}	0.00944	0.0168	-0.00213	0.000428	-0.0131
	(0.0245)	(0.0220)	(0.0252)	(0.0343)	(0.0362)
W_{-2}	0.0180	0.00821	0.00144	0.0192	0.0282
	(0.0249)	(0.0201)	(0.0230)	(0.0303)	(0.0400)
W_{-1}	0.0141	0.0288	0.0244	0.0299	0.0169
	(0.0264)	(0.0219)	(0.0239)	(0.0318)	(0.0348)
W_0	-0.0123	0.0133	0.00325	0.00765	0.0110
	(0.0271)	(0.0216)	(0.0223)	(0.0273)	(0.0299)
W_1	0.0311	0.0630***	0.0683***	0.0717**	0.112***
	(0.0241)	(0.0213)	(0.0215)	(0.0294)	(0.0338)
W_2	0.0238	0.0786***	0.0628**	0.0921***	0.130***
	(0.0212)	(0.0229)	(0.0257)	(0.0303)	(0.0356)
W_3	0.0385*	0.0845***	0.0370	0.0626**	0.0810**
	(0.0224)	(0.0238)	(0.0273)	(0.0318)	(0.0326)
W_4	0.0156	0.0848***	0.0650**	0.0509	0.0927**
	(0.0244)	(0.0251)	(0.0286)	(0.0344)	(0.0411)
W_5	-0.0388	-0.0144	-0.0412	-0.0418	0.000158
	(0.0286)	(0.0271)	(0.0324)	(0.0371)	(0.0415)
Year FE	X	X	X	X	X
Constant	1.182***	1.180***	1.206***	1.196***	1.216***
	(0.103)	(0.0622)	(0.0514)	(0.0489)	(0.0412)
Observations	9,150	9,150	9,150	9,150	9,150
R-squared	0.179	0.183	0.181	0.182	0.184
Number of county	610	610	610	610	610

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20. Crop insurance participation for counties hit by a large loss (Soybeans; Buy-up; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
W_{-5}	0.0457**	0.0235	0.0528**	0.0574*	0.0211
	(0.0229)	(0.0208)	(0.0265)	(0.0317)	(0.0356)
W_{-4}	0.0591***	0.0199	0.0195	0.0474	0.0155
	(0.0211)	(0.0173)	(0.0198)	(0.0291)	(0.0330)
W_{-3}	0.0433**	0.0184	0.00350	0.0144	-0.00402
	(0.0201)	(0.0179)	(0.0211)	(0.0305)	(0.0294)
W_{-2}	0.0615***	0.0207	0.0226	0.0340	0.0205
	(0.0215)	(0.0175)	(0.0210)	(0.0278)	(0.0367)
W_{-1}	0.0591***	0.0514***	0.0594***	0.0562*	0.0541
	(0.0211)	(0.0183)	(0.0212)	(0.0297)	(0.0348)
W_0	0.0318	0.0335*	0.0243	0.0256	0.0287
	(0.0225)	(0.0189)	(0.0204)	(0.0232)	(0.0283)
W_1	0.0767***	0.0986***	0.111***	0.129***	0.155***
	(0.0191)	(0.0179)	(0.0189)	(0.0246)	(0.0313)
W_2	0.0864***	0.109***	0.108***	0.131***	0.157***
	(0.0182)	(0.0196)	(0.0221)	(0.0248)	(0.0309)
W_3	0.0728***	0.0915***	0.0559**	0.0973***	0.123***
	(0.0188)	(0.0191)	(0.0221)	(0.0260)	(0.0299)
W_4	0.0547***	0.0988***	0.0777***	0.0731**	0.111***
	(0.0198)	(0.0209)	(0.0225)	(0.0284)	(0.0355)
W_5	-0.00976	0.000953	-0.00564	0.00656	0.0360
	(0.0235)	(0.0214)	(0.0258)	(0.0324)	(0.0367)
Year FE	X	X	X	X	X
Constant	0.349***	0.488***	0.516***	0.523***	0.557***
	(0.0810)	(0.0569)	(0.0482)	(0.0434)	(0.0365)
Observations	9,150	9,150	9,150	9,150	9,150
R-squared	0.405	0.409	0.408	0.408	0.410
Number of county	610	610	610	610	610

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21. Crop insurance participation for counties hit by a large loss (Soybeans; CAT; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
W_{-5}	-0.0932***	-0.0243	-0.0163	0.0304	0.0432
	(0.0340)	(0.0295)	(0.0312)	(0.0345)	(0.0397)
W_{-4}	-0.0943***	-0.0366	-0.0181	0.0123	0.00760
	(0.0314)	(0.0268)	(0.0304)	(0.0351)	(0.0376)
W_{-3}	-0.0847***	-0.0250	-0.0304	0.000194	-0.0261
	(0.0305)	(0.0272)	(0.0314)	(0.0362)	(0.0403)
W_{-2}	-0.0714**	0.00259	-0.00123	0.0179	0.00737
	(0.0320)	(0.0292)	(0.0315)	(0.0354)	(0.0386)
W_{-1}	-0.0948***	-0.0316	-0.0134	0.0254	0.0279
	(0.0313)	(0.0300)	(0.0324)	(0.0359)	(0.0403)
W_0	-0.0813**	-0.000990	0.0113	0.0108	0.0127
	(0.0354)	(0.0295)	(0.0317)	(0.0363)	(0.0411)
W_1	-0.178***	-0.148***	-0.155***	-0.175***	-0.215***
	(0.0324)	(0.0281)	(0.0316)	(0.0380)	(0.0440)
W_2	-0.148***	-0.0892***	-0.130***	-0.182***	-0.200***
	(0.0338)	(0.0322)	(0.0326)	(0.0385)	(0.0454)
W_3	-0.0594	-0.0533	-0.0933***	-0.151***	-0.214***
	(0.0382)	(0.0339)	(0.0337)	(0.0369)	(0.0424)
W_4	0.0471	0.00653	-0.0508	-0.0805**	-0.170***
	(0.0381)	(0.0339)	(0.0359)	(0.0382)	(0.0432)
W_5	0.0447	0.0657**	-0.0183	-0.0642*	-0.184***
	(0.0354)	(0.0330)	(0.0346)	(0.0375)	(0.0408)
Year FE	X	X	X	X	X
Constant	-2.030***	-2.370***	-2.400***	-2.448***	-2.431***
	(0.120)	(0.0815)	(0.0682)	(0.0562)	(0.0423)
Observations	8,792	8,792	8,792	8,792	8,792
R-squared	0.557	0.554	0.555	0.557	0.559
Number of county	610	610	610	610	610

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22. Crop insurance participation for counties hit by a large loss (Soybeans; Coverage levels of at least of 65%; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES	Dependent variable: $\ln[r/(1-r)]$				
W_{-5}	0.0945***	0.0567***	0.0674**	0.0681**	0.0332
	(0.0219)	(0.0214)	(0.0268)	(0.0314)	(0.0352)
W_{-4}	0.0985***	0.0553***	0.0580***	0.0820***	0.0422
	(0.0222)	(0.0185)	(0.0220)	(0.0315)	(0.0349)
W_{-3}	0.0905***	0.0549***	0.0388*	0.0489	0.0299
	(0.0248)	(0.0197)	(0.0225)	(0.0334)	(0.0326)
W_{-2}	0.0781***	0.0435**	0.0390*	0.0606*	0.0531
	(0.0244)	(0.0191)	(0.0223)	(0.0322)	(0.0402)
W_{-1}	0.0880***	0.0810***	0.0780***	0.0856**	0.0807*
	(0.0230)	(0.0207)	(0.0249)	(0.0349)	(0.0414)
W_0	0.0583***	0.0481**	0.0365	0.0519*	0.0411
	(0.0225)	(0.0199)	(0.0226)	(0.0286)	(0.0346)
W_1	0.122***	0.123***	0.123***	0.159***	0.182***
	(0.0188)	(0.0162)	(0.0185)	(0.0258)	(0.0355)
W_2	0.127***	0.118***	0.109***	0.131***	0.132***
	(0.0187)	(0.0205)	(0.0218)	(0.0236)	(0.0314)
W_3	0.120***	0.115***	0.0708***	0.104***	0.120***
	(0.0183)	(0.0175)	(0.0197)	(0.0244)	(0.0304)
W_4	0.0694***	0.0970***	0.0853***	0.0895***	0.105***
	(0.0195)	(0.0181)	(0.0199)	(0.0242)	(0.0293)
W_5	0.0112	0.0287	0.0163	0.0336	0.0673**
	(0.0223)	(0.0180)	(0.0212)	(0.0269)	(0.0292)
Year FE	X	X	X	X	X
Constant	0.00980	0.210***	0.280***	0.293***	0.343***
	(0.0907)	(0.0601)	(0.0503)	(0.0486)	(0.0390)
Observations	9,150	9,150	9,150	9,150	9,150
R-squared	0.345	0.346	0.342	0.344	0.342
Number of county	610	610	610	610	610

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23. Crop insurance participation for counties hit by a large loss (Soybeans; Coverage levels of at least of 75%; 2001-2015; Estimation equation (8))

	(1)	(2)	(3)	(4)	(5)
	10%	20%	30%	40%	50%
VARIABLES			Dependent variable: $\ln[r/(1-r)]$		
W_{-5}	0.00553	-0.0436***	-0.0561***	-0.0505***	-0.0730***
	(0.0167)	(0.0154)	(0.0161)	(0.0193)	(0.0206)
W_{-4}	0.0554***	0.00595	-0.0179	-0.00309	-0.0312
	(0.0174)	(0.0158)	(0.0160)	(0.0191)	(0.0201)
W_{-3}	0.0485***	0.0159	-0.00668	-0.00669	-0.0334
	(0.0171)	(0.0160)	(0.0167)	(0.0203)	(0.0213)
W_{-2}	0.0589***	0.0252	0.0211	0.0233	-0.0153
	(0.0169)	(0.0155)	(0.0163)	(0.0200)	(0.0211)
W_{-1}	0.0780***	0.0650***	0.0513***	0.0428**	0.0181
	(0.0168)	(0.0150)	(0.0157)	(0.0194)	(0.0205)
W_0	0.0411**	0.0435***	0.0253	0.0140	-0.00289
	(0.0162)	(0.0150)	(0.0169)	(0.0198)	(0.0225)
W_1	0.171***	0.186***	0.189***	0.211***	0.208***
	(0.0158)	(0.0151)	(0.0160)	(0.0191)	(0.0233)
W_2	0.171***	0.167***	0.142***	0.154***	0.131***
	(0.0170)	(0.0158)	(0.0161)	(0.0188)	(0.0223)
W_3	0.129***	0.124***	0.110***	0.122***	0.117***
	(0.0169)	(0.0166)	(0.0167)	(0.0194)	(0.0212)
W_4	0.0963***	0.111***	0.115***	0.114***	0.0858***
	(0.0165)	(0.0162)	(0.0168)	(0.0198)	(0.0236)
W_5	0.0410**	0.0633***	0.0857***	0.0828***	0.0708***
	(0.0188)	(0.0161)	(0.0164)	(0.0179)	(0.0213)
Year FE	X	X	X	X	X
Constant	-1.580***	-1.431***	-1.378***	-1.372***	-1.336***
	(0.0690)	(0.0507)	(0.0410)	(0.0386)	(0.0326)
Observations	9,137	9,137	9,137	9,137	9,137
R-squared	0.739	0.746	0.745	0.743	0.739
Number of county	610	610	610	610	610

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1