Manuscript title: Recency Effects and Participation at the Extensive and Intensive Margins in U.S. Federal Crop Insurance Programs

Running title: Recency and Crop Insurance Participation

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Abstract

Participation in U.S. Federal Crop Insurance Programs (FCIP) has increased over time at both extensive (insured acres) and intensive (coverage levels) margins, but clear spatio-temporal variations exist in these trends. Farmers' decisions are likely influenced by recent indemnity or weather experiences (i.e., recency effects). We develop a model to identify two channels through which recent adverse weather experiences may affect participation, one where weather shocks directly affect participation and the other where they affect participation through indemnity payouts. With historic FCIP data over 2001-2017, we use parametric and non-parametric methods to estimate these effects. At both extensive and intensive margins, higher past indemnities are found to encourage participation. This provides evidence that prior adverse weather shocks work indirectly. Less evidence is found in favour of direct weather effects. We also find that the increase in participation due to indemnities peaks in the year following a loss.

Keywords: Coverage level, Direct and indirect responses, Event study, Recency bias, Weather shocks

JEL codes: D83, D91, G22, Q10, Q54

Introduction

Understanding how recent experience can affect the decision-making of individuals under uncertainty is a crucial question in behavioral economics. Decision makers typically encounter at least some difficulties with making decisions about managing uncertain future outcomes. Many important economic decisions are influenced by the utility derived from recent experiences or the occurrence of a certain event (i.e., recency effects) when facing risks. Recency effects refer to how the strength of recent information affects a decision-maker's working memory and probability judgement (Camerer and Loewenstein 2011). However, to the extent that risks materialize independently over time, these events should have limited effect on a decision-maker's choice whenever her goal is to maximize expected payouts or utility. The extant experimental economics literature in experienced utility and recency effects finds that experiences at the last moments of an experiment have privileged roles in evaluations of subsequent choices (Fredrickson and Kahneman 1993; Schreiber and Kahneman 2000).

Many studies have investigated recency effects in different types of insurance markets, and also in situations beyond insurance. Stein (2016) analyzes the dynamic nature of rainfall insurance purchasing decisions. Based on customer data from the Indian microfinance institution BASIX between 2005 and 2007, that paper shows the prior year's insurance payout to be associated with a 9 to 22 percentage point increase in participation. For the direct weather effects the paper tests how prior year rainfall affects insurance purchases, finding evidence that previous rainfall shocks decrease purchases. Based on a nationwide panel dataset of large regional floods and flood insurance policies, Gallagher (2014) applies a flexible event study framework to show that insurance take-up spikes the year after a flood and then steadily declines back to its baseline. Kousky (2017) applies a fixed-effect model to a flood insurance policy dataset when testing for whether hurricane and tropical storm events affect flood insurance choices across all Atlantic and Gulf coast states between 2001 and 2010. The results show that a prior year hurricane increases net flood insurance purchases and also that this effect dies out after three years.

Cai and Song (2017) use a novel experimental design to ascertain any roles for experience or information in insurance take-up in rural China. In light of the finding that experience gained in a recently played insurance game has a stronger effect on actual insurance take-up, they conclude that learning from experience displays strong recency bias. In Cai et al. (2016), data from a two-year field experiment in rural China support the belief that experiencing a year one payout increases year two weather insurance demand. The study provides only an indirect channel for how exogenous shocks affect insurance demand, which is through the prior indemnity payouts. Perhaps closest to our work is that of Bjerge and Trifkovic (2018), who relate extreme weather events to a household panel data set that recorded weather insurance index choices in Gujarat, India. They find a positive response to excessive rainfall but no response to dry conditions, the latter effect likely being due to the presence of irrigation. The above work, and also many other lines of recent economic research, have brought attention to what is salient in the minds of decision-makers and how objective data are processed (Bakkensen et al. 2019; Royal and Walls 2019). Questions that naturally arise are whether responses to different risk sources differ and whether past indemnification matters in determining these responses.

In this paper, we examine whether and how recent experience affects insurance choices at extensive (how many acres to insure) and intensive margins (which coverage level to choose). We are not concerned with how learning about a product through social and other interactions can affect diffusion. An extensive literature exists on the economics of product and practice diffusion, including the Cai et al. (2015) social network experiment analysis of weather insurance adoption in rural China and the Santeramo (2019) study of crop insurance uptake in Italy. Rather, we are concerned with the impact of recent events on demand. Our interest is in the U.S. Federal Crop Insurance Program (FCIP), which provides an important setting in which to examine real-world recency effects. FCIP is a large insurance market with more than $106 billion of insurance protection (i.e., liability) for over 130 different kinds of crops on about 335 million acres in 2018. The total premium from about 1.1 billion policies that year was about $9.9 billion, of which the government subsidized about 63% and farmers paid about 37% out of their own pockets for insurance protection.[1] Extensive margin participation in FCIP is high for major crops. For example, about 86% of corn and soybeans were insured in 2017, so there is limited potential for information asymmetry to affect extensive margin participation.

FCIP is also a near-ideal setting in which to examine real-world recency effects. The primary cause for payouts, being weather events, is exogenous, difficult to predict in advance, and varies spatially within a given year. Furthermore, and by contrast with private insurance markets, FCIP is not concerned about short-run solvency and adjusts premium rates according to pre-set rules such that premiums are largely unaffected by prior year indemnification. In addition, as with other insurance markets, there is evidence that crop insurance purchase decisions do not conform to predictions based on standard expected utility theory (Du et al. 2017; Pétraud et al. 2015). Our hypothesis is that recency effects can explain part of this non-conformity. For example, farmers who experienced a natural event or received a higher indemnity in a given year may overestimate the year later recurrence probability. Similarly, farmers who did not have such an experience may underestimate the probability of an indemnity.

[1] Detailed are available at https://legacy.rma.usda.gov/data/sob.html.

While recency effects have been examined extensively by psychologists and economists in general, there is limited research on how variations in participation relate to recent experience in FCIP. Chong and Ifft (2016) have regressed the share of planted acres insured on spatial and space-time interaction fixed effects as well as county mean yield deviations from trend. They show that corn acres insured increases in the year after an adverse yield shock and, to a lesser extent, decreases in the year after a good harvest. But our approach is distinct in that we work directly with weather and indemnity variable metrics. This allows us to identify how recent experiences in risks posed, rather than the yield deviations that they impact, affect participation decisions. This approach also allows us to compare two alternative channels through which recency effects can arise, where either the indemnities themselves or the underlying weather shocks may motivate the participation response to recent events.

Our paper contributes to the literature in the following ways. First, we construct a theoretical model that includes recency effects in which individuals use recent experiences to update their information on the benefits of insurance choices. This model adds to the literature by extending the updating model applied in Cai et al. (2016) to include recency effects in the experienced utility function. Second, we estimate the impacts of recently experienced indemnity payouts and a variety of weather shocks on crop insurance participation through two approaches: a two-step parametric approach and a flexible non-parametric approach. The two-step parametric model allows us to examine the direct effect of prior year indemnities' experience, and also the indirect and direct effects of prior adverse weather on crop insurance participation. The nonparametric flexible event study model (Gallagher 2014) enables us to estimate longer-run impacts of large indemnity on participation in subsequent years. Third, our paper provides an integrated perspective on crop insurance participation at the extensive and intensive margins. To our knowledge, no study has examined crop insurance demand in terms of these two margins.

Our findings are as follows. First, in support of the Cai et al. (2016) experimental setting conclusion on extensive margin demand under higher prior period indemnity payouts, we find that actual prior year indemnities encourage higher extensive and intensive margin participation. Second, prior adverse weather events work indirectly by inducing higher participation through providing indemnities. Third, the direct effects of prior adverse weather on participation are not consistent across different weather events and are insignificant for some events. Fourth, there is an immediate but largely transient rise in participation after either a weather shock event or a large indemnities' experience. For example, consider when the indemnity ratio is 70 percent for corn (i.e., 70% of policies earning premium in a county are indemnified).[2] Then we find that the effect of a weather shock event on the logit of participation, as measured by the percent of insured acres, peaks at about 13.6 percent in the first year just after that event and declines steadily thereafter.

In what follows we briefly explain FCIP and how it relates to variations in participation. We then adapt the standard expected utility modeling framework to identify and decompose recency effects, including direct and indirect roles. Next, we explain the crop insurance and weather data that we analyze and also the variables that we construct. Then we apply a two-step parametric model to examine the direct and indirect effects of recent experience on participation, and we also use a nonparametric event model to test for the lasting effects of large indemnities. After reporting and analyzing the estimation results, we conclude with some brief comments.

U.S. Federal Crop Insurance Program Details and Participation Trends

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[2] Indemnity ratio, as defined above, depends on intensive margin choices. All else equal, the indemnification rate will be higher when average coverage level is higher.

FCIP was first authorized under the U.S. Agricultural Adjustment Act of 1938 and was run on an experimental basis for many decades. Crop and region coverage was limited and contract availability might be removed when experience called actuarially soundness into question (Kramer 1983). Even where available, participation remained low during the initial decades. Reasons for small uptake include comparatively low institutional commitment to the program, product novelty, token premium subsidy rates, grower liquidity constraints, uninformed rate-setting procedures and the prospect of federal enactments to provide region-wide ad hoc free disaster relief transfer payments or loans in the event of a general crop failure.

Participation grew in the decade after the Federal Crop Insurance Act (FCIA) of 1980, which finally provided strong federal commitment to the policy. FCIP obtained continuous authorization under FCIA while periodic revisions were written into Farm Bill and other enactments. FCIA funded premium subsidies at up to 30% and expanded program breadth to cover more crops and regions, but sign-up levels did not attain policymaker expectations (Glauber 2004). The Federal Crop Insurance Reform Act of 1994 further increased premium subsidies and added a new insurance policy, Catastrophic Risk Protection Endorsement (CAT). CAT compensates farmers for losses in excess of 50% of normal yield paid at 55% of the estimated market price of the crop. CAT is free apart from an administrative fee. It is viewed as distinctive, where contracts that provide higher coverage at a positive charge are referred to as buy-up contracts (Shields 2015).

Acreage participation expanded further after the 1994 Reform Act, and again in the late 1990s when revenue insurance contracts were introduced. Additional impetus for expansion, and especially for higher coverage levels, was provided by further premium mark-downs funded under the Agricultural Risk Protection Act of 2000 as well as Farm Bill legislation in 2008 and 2014 (O'Donoghue 2014). As is shown in Figure 1a, which provides average participation trend lines in a 12 state U.S. Midwestern and Great Plains Region[3] for corn and soybean, the percent of planted acres that were insured increased markedly between 2001 and 2017. For both corn and soybeans acres, average area participation increased from about 70% in 2001 to about 86% in 2017.

Throughout FCIP's history the changes in outcomes, especially regarding the percent of insured acres and coverage levels, have been closely related to subsidy rates and the development of new contract policy designs. Many previous studies have examined the effect of premium subsidies on either acreage participation or coverage levels choices.[4] Using data from 1985 to 1993, Goodwin et al. (2004) focus on corn and soybeans in the Corn Belt and also wheat and barley in the Northern Great Plains. Their results, for the 1986-1993 time frame, confirm the hypothesis that premium subsidies will modestly increase crop insurance participation. Working with 2011 county-level contract choice data, Du et al. (2014) find that higher coverage levels are chosen where production conditions are better and yields are less risky. O'Donoghue (2014) tests the effect of premium subsidies on demand for crop insurance across major crops, including corn, soybeans and wheat. Based on county-level data from 1989 to 2012, he shows that an increase in subsidies can induce higher enrollment at higher coverage levels, but the effect is not strong.

With reference to 2009 data, Du et al. (2017) point out that intensive margin participation has been far from complete where FCIP is intended to assess pre-subsidy premiums as actuarially fair in the aggregate. These observations are noteworthy given the high subsidy rates and Mossin's (1968) argument that risk averse individuals should purchase full coverage when faced with an actuarially fair insurance policy. Employing a large insurance unit-level dataset for corn and

[3] The twelve states are Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota and Wisconsin.

[4] More generally insurance studies have typically covered either the intensive margin or the extensive margin, but not both. See analysis by Geruso et al. (2019), on equilibrium under adverse selection, for reasoning on why considering these margins separately may be problematic.

soybeans and a mixed logit framework, Du et al. also show that the probability of choosing an insurance product would decline with an increase in out-of-pocket premium expenditures. This suggests that participation may be dampened by behavioral concerns, including placing a heavier weighting on more definite expenditures than on less certain indemnity receipts. Ramirez and Shonkwiler (2017) and Price et al. (2019) suggest an alternative motivation for reluctance to participate, namely that premiums may be fair on the whole but still very bad deals for a significant fraction of potential users.

While extensive margin participation has increased over time, temporal variations in participation exist. As can be seen from variations along trend lines in figures 1a and 2b, which refer to the previously defined 12 State Region. As seen in Figure 1a, the increase in the percent of planted acres that are insured is uneven over time and is especially large after a higher indemnity ratio year. Figure 1b provides temporal data on indemnity ratios for the 12 State Region. The indemnity ratio depends largely on weather events, and in particular on extreme rainfall and/or temperature outcomes during the course of the growing season. It can be seen from boxed segments in the figure that the large indemnity ratio increases between 2007 and 2008 (when a price decline caused revenue insurance payouts) and also between 2011 and 2012 (a drought year) were followed immediately by insured acres increases. The temporal pattern for the Midwestern and Great Plains region is also reflected at the state level even though different states have different insured acres percentages. For the 2001-2017 interval, Figure 2a shows that corn acreage participation increased from 88% to 96% in South Dakota, from 62% to 85% in Illinois, and from 57% to 77% in Michigan. Furthermore, many locations saw strong acreage participation increases in years when others did not. State indemnity ratio data in Figure 3 can be seen to correspond with Figure 2 state area participation data, but at a lag.

At the intensive margin, average coverage levels demonstrate somewhat similar patterns. Figure 4 provides two maps, one for 2001 and the other for 2017, declaring the fraction of corn acres in a county that took out 75% coverage or higher in yield and/or revenue insurance. In a given year it is clear that Western Corn Belt coverage levels are higher than those in Great Plains, Wisconsin, Michigan, Eastern Ohio and other fringe Corn Belt areas. Comparing the two years, in most areas the 2017 participation rate at this coverage level far exceeded the 2001 rate.

Data suggest that intensive margin participation has grown after an indemnity ratio increase. Figure 5 considers counties with indemnity ratio greater than 70% in the 2012 drought year to be event counties. These maps indicate changes in area participation among those event counties in 2013 when compared with 2012 for three categories: CAT, buy-up policies, and coverage level of at least 75%. It is evident that participation in most event counties increased in 2013 for buy-up and at higher coverage levels, but decreased for CAT policies. One way to measure this shift toward higher coverage levels is with cumulative area participation curves (CAPC), which sum total acres in a crop that have no more than total acreage fraction *x*, as given on the curve's *x* axis. Figure 6 provides CAPC in 2012 and 2013 for both corn and soybeans. The figure shows that for each crop the 2013 CAPC is below that in 2012. Growers increased insurance program participation at the intensive margin after the drought year while area participation decreased for CAT policies. The change in participation may be caused by the prior large indemnities or by severe weather shocks, where recency effects arise.

To further investigate variation in participation as measured by both the insured acres and coverage levels, we will incorporate recency effects into the standard expected utility theoretical model of demand for crop insurance. The model is to be viewed as illustrative rather than assertive. Its purpose is to provide guidance on the incentives that shape intensive and extensive margin responses.

Theoretical framework

For a given farm, write crop revenue in year *t* as R_t. It is held to be random with year-invariant cumulative distribution function $F(R_t)$, support $[0, \infty)$ and mean value $\bar{R}$. Farmer can choose revenue insurance at coverage level ψ_t. When $R_t < \psi_t\bar{R}$ then the insurance contract will pay the farmer $\psi_t\bar{R} - R_t$, and when $R_t \geq \psi_t\bar{R}$ then the contract will pay 0. The actuarially fair premium of coverage level ψ_t is

$$a(\psi_t) = \int_0^{\psi_t\bar{R}} (\psi_t\bar{R} - R_t)dF(R_t). \tag{1}$$

The premium subsidy rate is $s(\psi_t) > 0$, which is a declining function of coverage level according to the current government policy. The farmer will pay $(1 - s(\psi_t))a(\psi_t)$ when purchasing coverage level ψ_t. Farm production costs are given as *C*. At coverage level ψ_t, the farmer's profit is

$$\pi(\psi_t) = \max\{R_t, \psi_t\bar{R}\} - C - n(\psi_t), \tag{2}$$

where $n(\psi_t) = (1 - s(\psi_t))a(\psi_t)$ is the net (after subsidy) premium. Whenever the farmer does not participate in crop insurance, i.e., whenever $\psi_t = 0$, then profit is $\pi(0) = R_t - C$.

For a farmer with an increasing and concave utility of profit function $U(.)$, the utility of choosing coverage level ψ_t is $U[\pi(\psi_t)]$ and the farmer's expected utility will be

$$E[U(\pi(\psi_t))] = \int_0^{\infty} U(\max\{R_t, \psi_t\bar{R}\} - C - n(\psi_t))dF(R_t). \tag{3}$$

It is held to be concave in coverage level, i.e., to display decreasing marginal value of coverage. The farmer faces the two-step maximization problem

$$\max\left\{\max_{\psi_t} E[U(\pi(\psi_t))], E[U(R_t - C)]\right\}, \tag{4}$$

where the second argument in the outer max{.,.} statement represents the extensive margin non-participation choice. A risk-averse individual should purchase full coverage when faced with an actuarially fair insurance policy (Mossin 1968). Thus the expected utility maximizing grower faced with actuarially fair and subsidized insurance contracts will both participate and take out the highest coverage level available. In this standard model of insurance decisions, past events do not enter equation (4) directly as the utility in period t depends solely on the net return in period t.

As mentioned in the introduction, be it for crop insurance or other asset insurance, this theoretical result is not fully supported by empirical data. Anomalies have been observed between data and standard model. Over-insurance and under-insurance are both found in some insurance markets such as automobile insurance, home insurance and health insurance (Kunreuther et al. 2013). For FCIP there exist high variations in the growth of participation (Makki and Somwaru 2001), and under-insurance has been observed (Du et al. 2017), where potential reasons include nonlinear probability weighting or loss aversion. Other events may also affect demand, including events that affect the availability of alternative risk management tools, moral hazard, and adverse election (Just et al. 1999; Sherrick et al. 2004). Here we focus on recency effects as a possible explanation for non-optimal choices. We examine how crop insurance participation decisions are affected by past experience with a simple updating model that seeks to account for recency effects. Our model is somewhat similar to the temporal difference reinforcement learning model introduced by Sutton and Barto (2018) and applied by Cai et al. (2016). However, in our model decision makers update their belief regarding the insurance product's value, which is impacted by both the indemnity experience and prior weather events.

As shown in Figure 7, extensive and intensive margin participation decisions are made in early Spring, labeled as time t. Any prior year indemnity occurred in the prior fall at time $t - 0.5$, and weather events causing these indemnities occurred during the prior Summer, labeled $t -$

0.75. One channel through which adverse weather events can have an effect is directly on participation, which is route A. The other is indirectly as mediated through indemnities, i.e., first B and then C.

To account for potential recency effects, we expand the traditional expected utility of profit function as follows:

$$E[V(\psi_t, W_{t-1})] = E[U(\pi(\psi_t), B[J(W_{t-1}), W_{t-1}])|W_{t-1}], \tag{5}$$

where larger values of W_{t-1} represent worse weather. Function $V(.)$ is the farmer's expanded utility and it incorporates recency effects into the standard utility function, $U(.)$. Note several major differences between equations (3) and (5) but they all stem from allowing lagged weather event variables, W_{t-1}, to appear in equation (5). By conditioning expected utility on recent events we allow for adjustments in a farmer's assessments of yield or revenue outcome probabilities, requiring a Bayesian update of expected utility as suggested by Chong and Ifft (2016).

In addition, recency effects are allowed for by letting preferences depend on past weather events by way of the function $B[J(W_{t-1}), W_{t-1}]$, to be explained shortly. The utility function can change with the value of this recency effects function. For example, bad recent weather can make the grower more risk averse in the manner of Pratt (1964), so that demand for higher coverage levels increases. Or losses arising from incomplete insurance may tighten credit constraints on a grower such that she or her bank manager see the need for higher coverage levels. Thus we allow preferences to shift with context. The stability of risk preferences has long been a matter of some controversy, if only because measurement of preferences is imprecise (Schildberg-Hörisch 2018). For example, the 2011 Japanese earthquake was found to reduce risk aversion among men but not women (Hanaoka et al. 2018). In our case the matter of stability is somewhat moot because model (3) is static and accounting for recent events requires a somewhat more dynamic model. Adverse recent events may reflect a decline in wealth so that when the utility function adhered to the decreasing absolute risk aversion (DARA) property then a larger value of W_{t-1} should lead to greater risk aversion, which would likely induce higher demand for insurance. Thus risk preference may be stable over time and yet might not appear to be so absent an accounting for changing circumstances.

The recency effects component is itself a function of two arguments: the previous year's indemnity experience as represented by indemnity payout $J(W_{t-1})$, and also direct weather shocks in the previous time period with $B_2 > 0$, B_2 being the partial derivative of $B[.,.]$ with respect to the second term W_{t-1}. The past indemnity payout is of course a function of weather variables where $J(W_{t-1})$ is a continuously differentiable and increasing function, $J_{W_{t-1}} > 0$. Whether recent weather when acting through indemnities should have qualitatively the same recency effect as when acting directly is debatable, i.e., the recency function derivative with respect to indemnities, B_1, might be positive or negative. Indemnities are, in themselves, likely to increase wealth and so at least partially offset the direct effect of adverse weather. On the other hand, indemnities may in their own right signal the merits of insurance and so render growers averse to the risk associated with not having insurance. The total impact of an adverse weather shock on the recency effect is given as $B_{W_{t-1}} = B_1 J_{W_{t-1}} + B_2$. We will hold that this is positive in sign because even if one takes the perspective that indemnities act only on replenishing wealth, having no other effect on preferences, then incomplete coverage will leave the grower less wealthy, and so more risk averse under DARA.

Extending the above notation to the entire participation problem, eqn. (4) becomes:

$$\max\left\{ \max_{\psi_t} E[V(\psi_t, W_{t-1})], E[U(R_t - C, B[J(W_{t-1}), W_{t-1}])|W_{t-1}] \right\}, \tag{6}$$

where $J(W_{t-1})$ remains in the non-participation alternative because it is the consequence of a previously made decision. We will consider the inner, intensive margin coverage level optimization problem first and then turn to the extensive margin discrete choice problem. The optimal coverage level is given by setting the derivative of equation (5) with respect to ψ_t equal to zero, i.e.,

$$\frac{\partial \mathrm{E}[V(\psi_t, W_{t-1})]}{\partial \psi_t} = \frac{\partial \mathrm{E}[U(\pi(\psi_t), B[J(W_{t-1}), W_{t-1}])|W_{t-1}]}{\partial \psi_t} = 0. \tag{7}$$

Expression (7) may be rewritten as:

$$\bar{R} \int_0^{\psi_t \bar{R}} U'[\pi(\psi_t), B[.,.]|W_{t-1}] dF(R_t) = \frac{\partial n(\psi_t)}{\partial \psi_t} \int_0^{\infty} U'[\pi(\psi_t), B[.,.]|W_{t-1}] dF(R_t). \tag{8}$$

It can be readily shown that an increase in risk aversion is likely to increase the optimal coverage level because it will make marginal utility over interval $[0, \psi_t \bar{R}]$ larger in comparison with marginal utility when averaged over the entire support $[0, \infty)$. Thus, to the extent that an increase in the recency effects aggregator $B[.,.]$ increases risk aversion it should lead to an increase in coverage level.

The effect of a past weather event on the marginal value of coverage is given as a further derivation of (7):

$$\frac{\partial^2 \mathrm{E}[V(\psi_t, W_{t-1})]}{\partial \psi_t \partial W_{t-1}} = \frac{\partial^2 \mathrm{E}[U(\pi(\psi_t), B[.,.])|W_{t-1}]}{\partial \psi_t \partial W_{t-1}} + \frac{\partial \mathrm{E}[U(\pi(\psi_t), B[.,.])|W_{t-1}]}{\partial \psi_t \partial B} \times \left(B_1 J_{W_{t-1}} + B_2\right). \tag{9}$$

If adverse past weather events increase the expected marginal value of coverage, i.e., if expression (9) has positive value, then the grower will increase coverage. One way in which this could occur is through revised expectations, i.e., shifting the conditioner W_{t-1}, as reflected by the first right-hand expression in (9). This is a direct effect. If production is held to be more risky than had previously been believed then demand for insurance might increase. Another way in which the expected marginal value of coverage could increase is through changing the history-conditioned utility function, as reflected by right-hand product expression in (9). One part of the product term, that involving B_2, is a direct effect. The other part, involving $B_1 J_{W_{t-1}}$, is indirect in that it is mediated through indemnity payouts. We have already argued that each of these product terms in (9) is likely to be positive, and so the entire expression is likely to be positive. Thus we argue that recency is likely to increase intensive margin participation.

We turn now to the extensive margin choice in (6). When including recency effects then the grower's value of expected utility of profit absent insurance is likely to decline more severely after an adverse weather shock than does the grower's value of expected utility given at least some coverage. After all, the purpose of participation is to provide buffering. This should be true regardless of the way in which recency affects the utility function, be it through leading to a revision of probability assessments or through changing preferences. Thus extensive margin participation is also likely to increase as a result of adverse recent weather shocks.

Growers will come to different participation choices depending on their own preferences and technologies. Specify $\square(W_{t-1}) > 0$ as the history-dependent share of growers who participate in a region, in our case a county, and $\square(W_{t-1}) > 0$ as the region's mean coverage level conditional on participation. Then unconditional mean coverage level is equal to $\square(W_{t-1}) = \square(W_{t-1})\square(W_{t-1})$ where residual share $1 - \square(W_{t-1})$ all have coverage level 0. Upon logging this expression and then considering the response to recent weather, the total recency effect can be characterized as

$$\frac{d\ln[\square(W_{t-1})]}{dW_{t-1}} = \frac{d\ln[\square(W_{t-1})]}{dW_{t-1}} + \frac{d\ln[\square(W_{t-1})]}{dW_{t-1}}, \tag{10}$$

where the first right-hand derivative is the extensive margin response when aggregated over all of a region's growers and the second right-hand is the intensive margin response. We have argued that both terms should be positive, and so the total recency effect should be positive. The remains of this paper will bring data to both right-hand terms in equation (10).

Data Description and Variable Construction

In our empirical analysis, we will examine how past years' weather conditions W_{t-1}, and past indemnity experience $J(W_{t-1})$ affect decisions on coverage levels ψ_t. In the current FCIP, ψ_t could be zero, i.e., no participation, or any of {0.5, 0.55, 0.6, 0.65, 0.75, 0.8, 0.85, 0.9} where 0.5 can be CAT or buy-up. We examine the extensive margin by studying insured acreage share, where $\psi_t > 0$, and the intensive margin share by studying the weighted average coverage level conditional on $\psi_t > 0$.

We employ crop insurance participation data from U.S. Department of Agriculture's (USDA) Risk Management Agency (RMA) data. Data are obtained from Summary of Business (SOB) reports and also RMA Data and Cause of Loss (COL) historical data files. The SOB dataset contains county-level crop insurance participation information, including net reported acreage, the number of policies earning premium, as well as the number of indemnified policies under different coverage categories and coverage levels for major crops across the United States.[5] The COL dataset includes determined acreage data at different stages.[6] County-level planted acreage data for corn and soybeans are obtained from a USDA National Agricultural Statistics Service (NASS) survey.[7] We focus on insured acres and coverage levels participation choices each year during 2001-2017 for two primary crops (corn and soybeans) in the counties of the 12 State Region, as previously defined. These states account for the vast majority of the country's corn and soybean crops.

Let $P_{i,t}^{l}$ represent participation, where we use the notation to refer to both intensive margin and intensive margin participation. In what follows we explain in some detail our calculation of the

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[5] Detailed dataset variable lists are available at https://www.rma.usda.gov/data/sob/sccc/sobsccc_1989forward.pdf.
[6] Detailed dataset variable lists are available at https://www.rma.usda.gov/SummaryOfBusiness/CauseOfLoss.
[7] Detailed data are available at https://quickstats.nass.usda.gov/.

extensive margin participation variable. The percent of insured acres is calculated by dividing net reported acres by the sum of planted acres and prevented planting acres for each county-crop-year observation. Prevented planting acres indicate the number of acres that cannot be planted because of flood, drought, or some other natural disaster. These acres are included in net reported acres but not in planted acres. We compute prevented planting acres by summing determined acres (i.e., the number of acres lost due to damage) across loss stage codes labels P2, PF and PT, which are the prevented planting codes in COL Data Files. Let $NR_{i,t}^{l}$ denote the net acres reported as insured, $PA_{i,t}^{l}$ indicate the planted acres, and $PP_{i,t}^{l}$ be the prevented planting acres for crop $l \in$ {corn, soybeans} in county *i* in year *t*. Then the participation at the extensive margin can be specified as

$$P_{i,t}^{l} = NR_{i,t}^{l}/(PA_{i,t}^{l} + PP_{i,t}^{l}). \tag{11}$$

In addition, participation at the intensive margin is measured by weighted average coverage level, which is computed by using net reported acres at different coverage levels.

To consider the effect of prior year indemnities on participation choices, we define the indemnity ratio to be the ratio of the number of policies indemnified to policies earning premium. Let $H_{i,t}^{l}$ represent indemnity ratio, $I_{i,t}^{l}$ denote the number of yield and revenue insurance policies indemnified, and $E_{i,t}^{l}$ be the number of policies earning a premium. Then the indemnity ratio is

$$H_{i,t}^{l} = I_{i,t}^{l}/E_{i,t}^{l}. \tag{12}$$

Weather outcomes are fundamental inputs into crop growth, so we use growing degree days (*G*) to measure beneficial heat, stress degree days (*S*) to measure heat stress, and the Palmer Z index to measure moisture stress. We study these variables separately because no commonly accepted summary corn favorability weather variable is available and also because a separated analysis will allow us to assess whether any recency effects vary by source of shock. Variable *G* is defined as the sum over growing season days of degrees in Celsius between lower (T^l) and upper (T^h) thresholds, a temperature interval for which the plant is well-adapted to convert this heat into growth. Variable *S* provides a way of measuring temperature stress for a specific crop within its growing season. This variable is defined as the sum over growing season days of degrees in Celsius in excess of threshold T^k, a number exceeding T^h and above which the plant is poorly-adapted to even survive in the long run. May-August is the assumed growing season for corn and soybeans. The formulas for variable *G* and *S* are

$$G_{i,t} = \sum_{d\in\Omega_t}[0.5(\min(\max(T_{i,d}^{max}, T^l), T^h) + \min(\max(T_{i,d}^{min}, T^l), T^h)) - T^l], \qquad (13)$$

$$S_{i,t} = \sum_{d\in\Omega_t}[0.5(\max(T_{i,d}^{max}, T^k) + \max(T_{i,d}^{min}, T^k)) - T^k], \qquad (14)$$

where *i* is county, *t* is year, *d* is day, and Ω_t is the year *t* set of growing season days for both corn and soybeans. The thresholds are $T^l = 10°\text{C}$, $T^h = 30°\text{C}$, $T^k = 32.2°\text{C}$ (Xu et al. 2013).[8]

We use daily temperature to calculate annual variables *G* and *S* at the 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).[9] In order to calculate $G_{i,t}$ and $S_{i,t}$ we transfer station-level daily maximum and minimum temperatures into county-level daily data. We do so by taking the average daily maximum and average daily minimum temperatures for all stations in each county. We insert these county-level daily maximum and minimum temperatures during the growing season into equations (13) and (14). Then we construct deviations of variables *G* and *S* from their ten-years' average over 1991-2000, the decade just before our 2001-2017 research period, letting $\overline{G} = 0.1\sum_{j=1991}^{2000} G_{i,j}$, and $\overline{S} = 0.1\sum_{j=1991}^{2000} S_{i,j}$. The fractional deviations are

[8] The conversions are $10°\text{C} = 50°\text{F}, 30°\text{C} = 86°\text{F}, 32.2°\text{C} = 90°\text{F}$.
[9] Detailed data are available at ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/.

$$GD_{i,t} = (G_{i,t} - \overline{G})/\overline{G}, \tag{15}$$

$$SD_{i,t} = (S_{i,t} - \overline{S})/\overline{S}. \tag{16}$$

These two constructions represent normalized county-conditioned temperature deviations from historical weather conditions.

Moisture stress is measured by the Palmer Z index (Xu et al. 2013). It reflects the departure of a particular month's weather from that month's average moisture condition, regardless of what has occurred in prior or subsequent months (Heim, 2002). Monthly Palmer Z (*PZ*) statistics for climate divisions in the conterminous U.S. are obtained directly from the NOAA website.[10] To transfer these climate division data into county-level data, we calculate the area intersections between climate divisions and each county, and the weight PZ by county intersection areas. Then we take the average monthly county-level *PZ* for May-August to represent water stress for the corn and soybean growing seasons. The value $PZ = 0$ is to be expected, while $PZ \leq -2$ represents drought and $PZ \geq 5$ represents flooding (Xu et al. 2013). In order to consider dry and wet weather conditions separately, we calculate

$$dry_{i,t} = -\min(0, PZ_{i,t}), \tag{17}$$

$$wet_{i,t} = \max(0, PZ_{i,t}), \tag{18}$$

where $PZ_{i,t}$ is the average *PZ* value for county *i* in year *t*. Therefore, the larger the value of 'dry' (respectively, 'wet') the drier (respectively, wetter) the weather. The preferred weather condition for crop growth is neither too dry nor too wet.

We construct the county-year-crop panel from NASS, RMA and NOAA data. The panel is unbalanced since county×year observations can be lost in many ways. For example, NASS

[10] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/, accessed on 06 September 2018.

combines counties with small planted acreage into one combined county observation for each state in each year, which is labeled as “other (combined) counties.” In addition, county-level GD and SD are calculated from station-level data. Some counties do not contain a station observation for some years so that we cannot generate GD and SD variables for these counties in some years. When constructing a balanced panel, we do not include either the combined counties from NASS or the missing counties from NOAA. However, our estimation focuses on the time variability in participation related to recent events, so the imbalance is not expected to be an issue. We have regressed our model, applying both the unbalanced and balanced panels. The estimation results are similar, so we only present the results for unbalanced panel here. Variable definitions can be found in Table 1. Table 2 shows the variable descriptive statistics.

Model specification

Two-step parametric estimation

We estimate a two-step parametric model to examine the direct effect of prior year indemnities, and also the indirect and direct effects of prior adverse weather on crop insurance participation choices at both extensive and intensive margins. This allows us to decompose the effect of adverse weather on participation choices into the effects on indemnities in the first step, and also the effects of prior indemnities and prior adverse weather on insurance participation in the second step. Then we also develop estimations for corn and soybeans based on different policies (buy-up vs CAT).

In the first step, we estimate the effect of adverse weather on indemnity in order to further test for the indirect effect on participation through the response to indemnity experience. The indemnity ratio $H_{i,t}^{l}$ for crop *l* in county *i* and year *t* is specified as the dependent variable. The weather variables are denoted as the vector $W_{i,t} = (GD_{i,t}, SD_{i,t}, dry_{i,t}, wet_{i,t})'$ for county *i* in year

t. The time-fixed regression equation is

$$H_{i,t}^{l} = \alpha_0^l + \alpha_1^l W_{i,t} + \delta_t^l + \varepsilon_{i,t}^l, \tag{19}$$

where δ_t^l denotes the year fixed effect, and $\varepsilon_{i,t}^l$ denotes the error item.

In the second step, to test for the direct effects of prior indemnities and adverse weather shocks on participation choices, let $P_{i,t}^l$ denote participation choices with our two measures: extensive margin and intensive margin. We specify the dependent variable as the logit transformation of participation $P_{i,t}^l$, which is $\ln[P_{i,t}^l/(1 - P_{i,t}^l)]$. The main explanatory variables are indemnity ratio $H_{i,t}^l$ and weather variables $W_{i,t}$. The time-fixed regression equation is

$$\ln[P_{i,t}^l/(1 - P_{i,t}^l)] = \beta_0^l + \beta_1^l H_{i,t-1}^l + \beta_2^l W_{i,t-1} + \theta_t^l + u_{i,t}^l, \tag{20}$$

where θ_t^l denotes the year fixed effect, and $u_{i,t}^l$ denotes the error item. When we apply the logit transformation on participation $P_{i,t}^l$ within its domain [0, 1] for the percent of insured acres and [0,1) for weighted average coverage level, zero-valued participation is replaced with 0.0001 before transformation, while one-valued participation is replaced with 0.9999 before transformation, since the domain of the logit transformation function is (0,1). The logit transformation is applied because $P_{i,t}^l$ is bounded between 0 and 1, so the effect of any particular independent variable cannot be constant throughout the range. After applying the logit transformation, the logit of $P_{i,t}^l$ can take on any real value, so it is natural to model the regression as a linear function (Papke and Wooldridge 1996).

Nonparametric estimation

We employ a nonparametric flexible event study model (Gallagher, 2014) to estimate the longer-run impact of large indemnities on subsequent participation choices, in which we include state-by-year effects and crop reporting district (CRD) fixed effects. The fixed effects nonparametrically control for state-specific yearly factors and unobserved or unchanging CRD characteristics. State-by-year fixed effects account for state-specific yearly trends that may affect participation, such as commodity prices, state-level responses to weather shocks, state economic conditions, and policy changes in FCIP. CRD fixed effects preclude inclusion of the underlying location-specific factors, such as soil conditions. The causal interpretation of estimation comes from the assumption that whether a county experiences a large loss in a particular year is random conditional on state-by-year and CRD fixed effect. Our main estimation equation is:

$$\ln[P_{i,t}^{l}/(1-P_{i,t}^{l})] = \sum_{\tau=-T}^{T} \phi_{\tau}^{l} D_{i,t,\tau}^{l} + \eta_{s,t}^{l} + \sigma_{c}^{l} + \xi_{i,t}^{l}. \quad (21)$$

The independent variables are the event time indicator variables, $D_{i,t,\tau}^{l}$, which track the year of a large indemnity ratio as well as the years before and after a large loss. Here we assert that a large loss event occurs in one county when the county's indemnity ratio is greater than a specific cutoff point where we consider 0.1, 0.3, 0.5, 0.7 and 0.9. The value of a cutoff point can denote the magnitude of a large loss. For calendar year t and crop l, the indicator variable $D_{i,t,0}^{l}$ equals to 1 whenever a large loss appears in county i for year t; the indicator variable $D_{i,t,\tau}^{l}$ equals 1 whenever a large loss appears in county i in year $t-\tau$. As counties may have more than one large loss during the event study, each loss is coded with its own indicator variable. For example, were county i to have a large loss in years 2006 and 2012, then for the calendar year 2010 the indicator $D_{i,2010,4}^{l}$ would equal 1 since it is 4 years after the loss year 2006 while the indicator $D_{i,2010,-2}^{l}$ would also equal 1 since it is 2 years before the loss year 2012. We take $\tau \in \{-5, \dots, 0 \dots, 5\}$ in equation (21), since we are interested in the participation response in the years around a large loss. Regarding the other terms in (21), parameter $\eta_{s,t}^{l}$ represents the state-by-year fixed effects term, parameter σ_{c}^{l} denotes the CRD fixed effects term, and $\xi_{i,t}^{l}$ is an error term.

Estimation Results

We estimate equations (20) and (21) for both types of participation measures, extensive margin and intensive margin.

The effects of indemnities and weather shocks on participation

Table 3 shows the estimated results for equation (19) in the first step when applied to corn. As expected, for all of full samples, buy-up and CAT policies adverse weather conditions are shown to be important determinants of the proportion of policies that are indemnified. The strong significance of these results and the availability of the data used also underpin our earlier claim that crop insurance is a near-ideal real-world setting in which to study recency effects.

The second step regression results for equation (20) are presented in Table 4, in which we apply our two measures of participation. At the extensive margin we can observe that past year indemnity ratio plays a positive and significant role in participation for full samples and buy-up. For buy-up policies, the coefficient for *L.IndemnityRatio* is 0.393, where L. represent the one-year lag operator on the relevant variable, in this case *IndemnityRatio*. On the contrary, the *L.IndemnityRatio* coefficient for CAT is -0.548, indicating that prior indemnity ratio can discourage CAT policy participation. Although we do not know for sure, because we do not have grower-level contract choice data, this is likely an intensive margin effect whereby growers switch from CAT to buy-up policies in response to a large loss event.

When it comes to the direct effect of prior weather shocks, at the extensive margin only the $L.wet$ coefficients are significantly negative and only for full samples and buy-up policies. Furthermore, the data suggest that excess moisture can decrease subsequent area participation in crop insurance. For CAT policies, the $L.dry$ coefficient is significant at the 1% level. Drought can decrease acreage participation in CAT policies. At the intensive margin, the results show that severe heat stress and excess moisture may decrease coverage levels chosen. Therefore, the direct effects of prior indemnity ratio on participation at both extensive and intensive margins are positive, while the direct effects on participation are not consistent across different weather events and they are partially insignificant.

Combining the Table 3 and Table 4 results, adverse weather shocks are shown to have indirect effects on participation at both margins. First, the weather variables' vector allows for the identification of recency effects in regard to risks posed. Then, past indemnities provide a positive channel through which recent adverse weather shocks have indirect effects on both the insured acres and coverage level chosen. But the direct effects of weather shocks are not consistent across different weather events. Tables 5 and 6 report the soybeans regression results in the first and second step, respectively. The results are similar to those for corn.

The lasting effects of large indemnities on participation

The short- and long-run effects of large indemnities on participation for buy-up and CAT policies can be found in figures 8-10. These figures plot the coefficients of event time indicator, ϕ_{τ}^{l}, which are estimated when implementing equation (21) on the 2001-2017 county-year panel. Event times are plotted on the x-axis. Year 0 is a large loss year while years -1 through -5 are the years before that large loss, and years 1 through 5 are the years after the loss, respectively. The bands represent the 95 percent confidence intervals.

Panels 8a and 8b in Figure 8 plot point estimates with the buy-up data for corn and soybeans, respectively, and the corresponding estimation results on participation are given in Table 7. Taking corn as example in Figure 8a, as is to be expected there is no noticeable trend in area participation in the years up to and including a large loss. For the first year after a large loss year, there is a greater significant increase in the insurance's participation relative to the loss year. The increased effect on participation then remains positive and statistically significant for the next four or five years, but it tapers off year by year. This trend is consistent when our definition of a large loss is given as indemnity ratio greater than 0.3, 0.5, 0.7 or 0.9, but it is not significant when the criterion is that the indemnity ratio be greater than 0.1. As the cutoff point values increase, the severity of loss increases. The figure also shows that participation has a greater increase after the event year when facing a severe loss, which is defined with a larger cutoff point. The lasting effects on participation are longer when higher indemnity ratio cutoffs are invoked.

Figures 9 plots the event time indicators' coefficients for CAT policies. CAT policy enrollment responses are the reverse of the buy-up responses given in Figure 8. This would appear to be an intensive margin response. Rather than exit the program, growers respond to the adverse weather shock by replacing CAT policies with buy-up policies. Figure 10 presents the event time indicator coefficients for participation as measured by the weighted average coverage level at the intensive margin. The average coverage level chosen increases after a large loss and the gain taper off over time. Moreover, the regression results (available in supplemental materials) for full samples and higher coverage levels at the extensive margin and for buy-up samples at the intensive margins are similar to the buy-up policies at the extensive margin, as presented in Table 7.

Conclusion

It is important to understand how recent experience affects individuals' decision-making when they face uncertain risks. FCIP has become a cornerstone of agriculture programs in the United States while similar programs in other countries are either well-established or in development. This paper seeks to better understand how recency effects influence farmers' crop insurance participation decisions at extensive and intensive margins. We not only document the existence of recency effects in farmers' decision-making processes but also examine the impacts of recent events through different channels. A better understanding of recency effects may provide more useful information for the improvement of crop insurance programs.

Our paper extends the standard theoretical model of insurance demand by incorporating recency effects caused by weather shocks or large indemnities. We construct two channels through which recent experience can affect insurance product's valuation. One is the direct effect; the other is the indirect effect as mediated through indemnities. We apply two estimation approaches to examine these recency effects. In one a two-step parametric model is applied, and we decompose the effects of adverse weather events on participation into the effect on indemnities in the first step and also the effects of prior indemnities and prior adverse weather shocks on insurance participation in the second step. In the other approach we use a nonparametric flexible event study model to test for the long-run impacts of large indemnities on subsequent participation. Moreover, we apply the above estimations at both extensive and intensive margins.

Our estimation results contribute to the literature by highlighting the importance of considering recency effects in the insurance participation. First, for both extensive and intensive margins we provide additional evidence that prior large indemnities promote higher crop insurance participation in the following year. Our work adds to those of Cai et al. (2016) for rice production insurance in China, and to Stein (2016) and Bjerge and Trifkovic (2018) for weather index insurance in India, where our data are much more extensive, regard multiple shock sources and apply to actual market choices. Second, we explore how weather shocks affect insurance participation. Our results show that the direct effects of weather are not consistent across different weather events and are insignificant for some events. This finding, when combined with the clear-cut effects of indemnity, suggests that adverse weather events affect insurance participation largely indirectly through the indemnity channel. We also show that the total effect of a large loss on participation peaks just after the event, and then begins to steadily decline. In doing so we provide support for the generality of findings in Gallagher (2014) regarding flood insurance.

From a policy perspective, promoting crop insurance participation at low cost outlay has been an ongoing challenge for the U.S. Federal Government. A better understanding of recency effects may help in this regard although our current understanding of these effects is insufficient to make policy proposals. One matter is whether there exist opportunities to take advantage of human psychological inertia, i.e., the tendency to make a decision such as enrolling in crop insurance or choosing a higher coverage level and then being unmotivated to change it unless shocked into doing so. A development on our inquiries is to decompose the temporal response to a weather shock into permanent and transient components. If the response is largely temporary then there may be little to gain from a policy strategy to take account of these demand effects.

A further matter is whether responses are stronger for some shocks than for others. We found strong responses to four sorts of weather shocks. However, revenue insurance also covers adverse price shocks. Currently our analysis cannot address price shocks because they are likely to be captured by our time fixed effects, but an alternative specification might be able to allow for the measurement of responses to price shocks. Doing so could provide interesting additional insights. For many crops, substitute risk management instruments are available and are widely used, including forward and futures contracts and also put options. Given these alternatives, the insurance contract response to a price shock may be different. The response may be muted while shifting between revenue and yield contracts may also occur. Responses may differ between crops for which price derivative markets are deep, as in corn or wheat, and those for which they are not, as in sorghum.

Our empirical analysis has not sought to clarify whether recency effects are rational. This would be a challenging endeavour, but certain strategies for doing so may be feasible. Perhaps the easiest way to do so is to consider how yield probabilities are revised in light of a weather event. One approach might follow Royal and Walls (2019) in eliciting yield probabilities through a grower survey and correlating these with weather histories. To be most informative, such a data set would have to be in panel form so that an assessment could be made of updating after a weather shock. Historical farm-level yield data and Bayesian methods might be used to develop plausible bounds on objective revisions, to be compared with grower revisions.

A fourth matter that merits further scrutiny is whether the group response to a shock differs from private responses. Weather risk is generally, but not always, systemic in nature. Thus it is difficult to ascertain whether the aggregate response equals the sum of private responses or is also in part determined by how others in the area respond to the same shock. This is a version of Manski's (1993) reflection problem. But some weather shocks can be quite localized, as with hail and with minor flooding events. This distinction may allow for insights into the social dimension of responses when compared with the private dimension. However, grower-level data might be necessary to pursue that line of thought.

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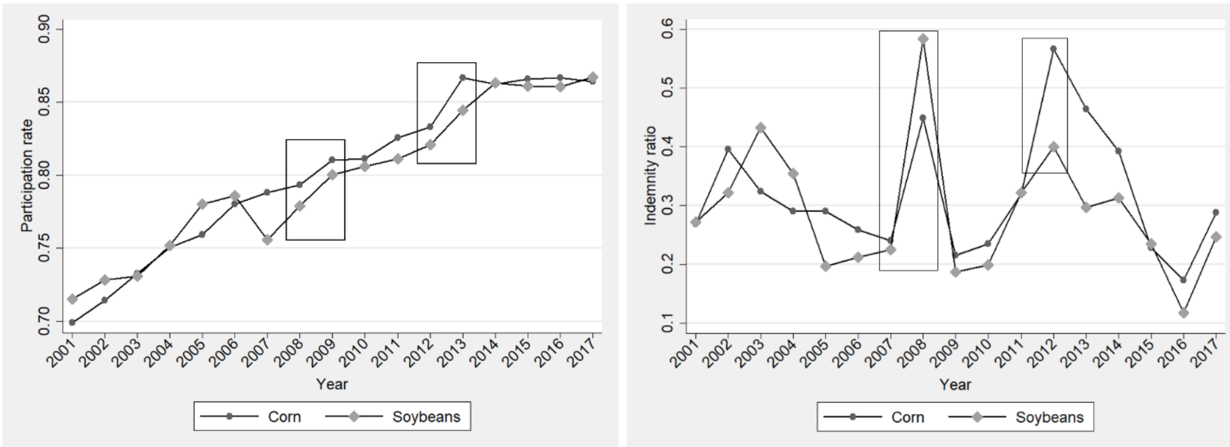
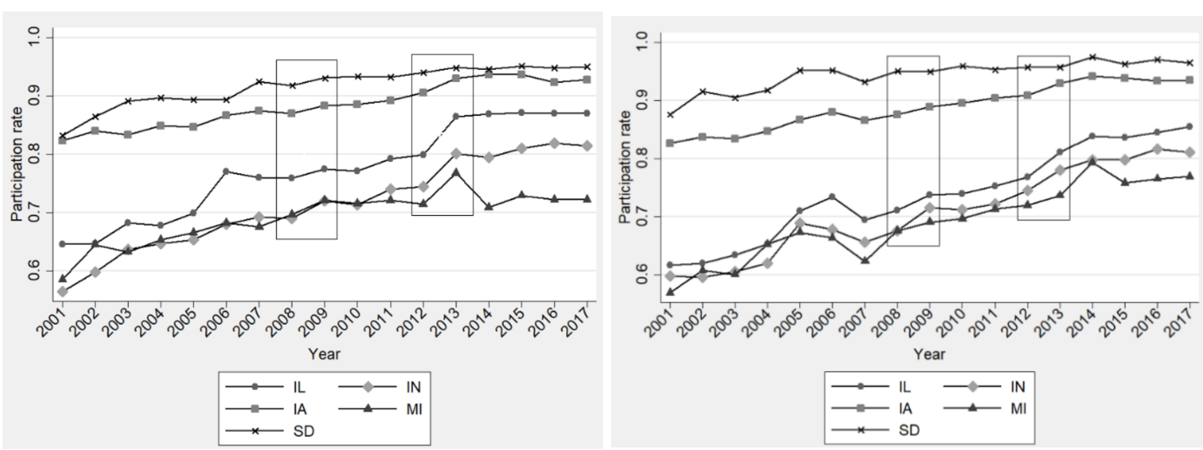
Figures and Tables



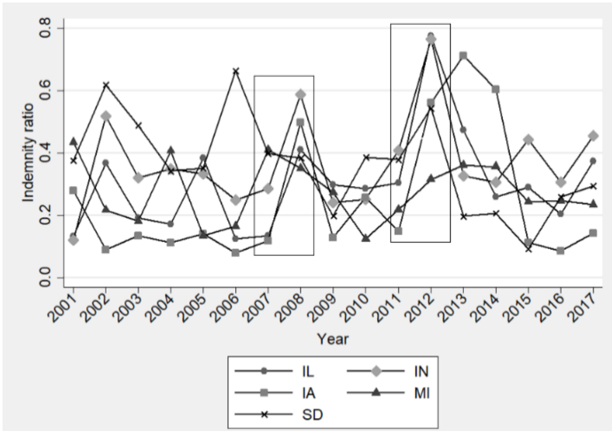
(1a) Acreage participation (1b) Indemnity ratio

Figure 1 Extensive margin participation, as measured by percent of planted acres that are insured, and also indemnity ratio for corn and soybeans in the 12 State Region for the period 2001-2017. The states are Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota and Wisconsin. See Table 1 for formal definitions of participation rate and indemnity ratio

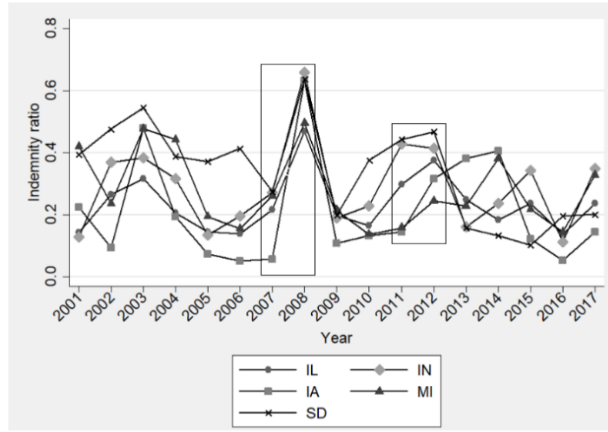


(2a) Corn (2b) Soybeans

Figure 2 Extensive margin participation, as measured by percent of planted acres that are insured acres for corn and soybeans by selected states over the period 2001-2017

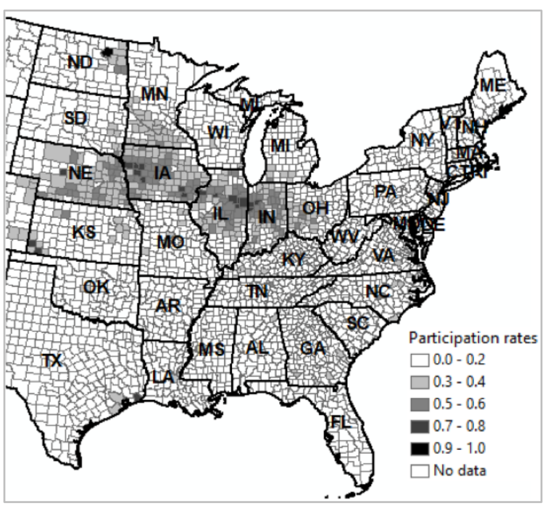


(3a) Corn

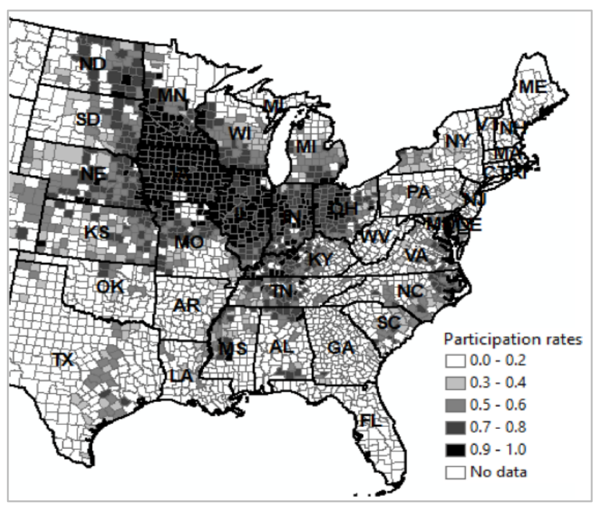


(3b) Soybeans

Figure 3 Average indemnity ratio for corn and soybeans in selected states over the period 2001-2017

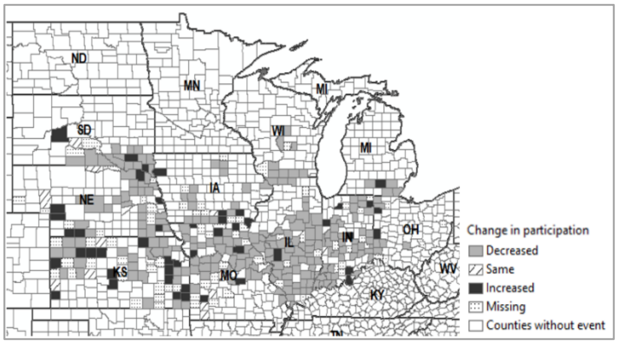


(4a) 2001

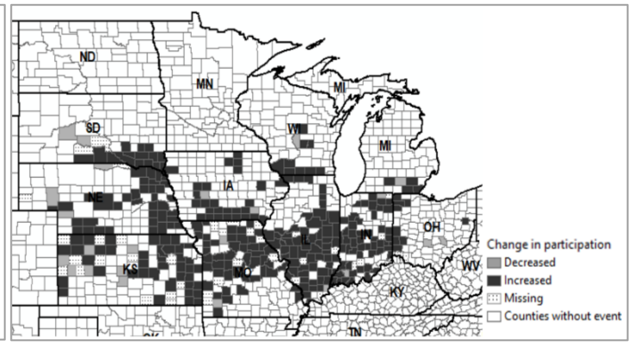


(4b) 2017

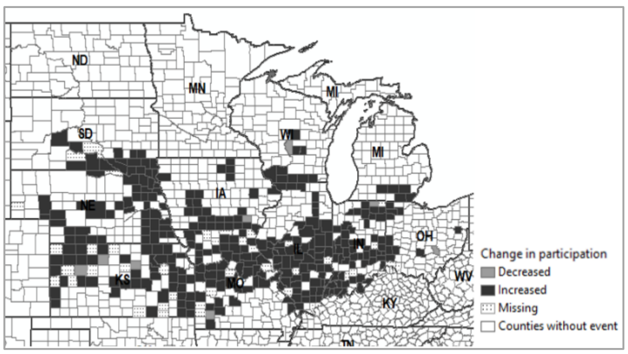
Figure 4 Change in intensive margin participation east of the Rockies between 2001 and 2017, as measured by percent of insured acres for corn acres that are insured at coverage levels of at least 75%



(5a) CAT

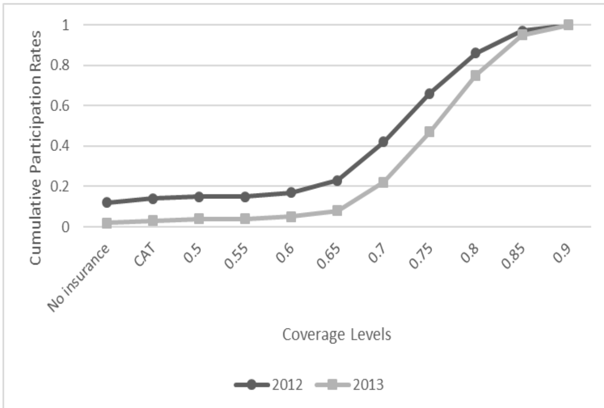


(5b) Buy-up

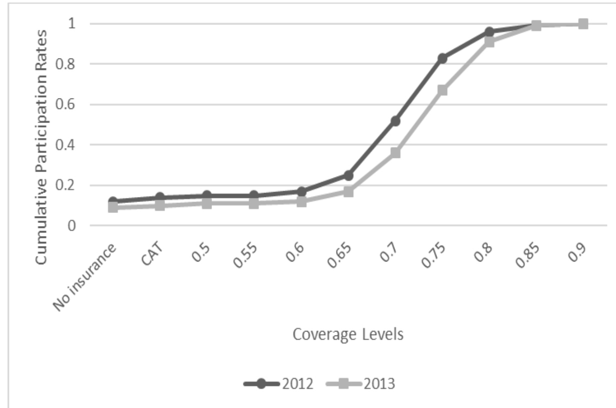


(5c) At coverage levels of at least 75%

Figure 5 Changes in intensive margin participation in the Upper Midwest, as measured by percent of insured acres in event counties in 2013 when compared with the drought year 2012 for CAT, buy-up policies and at coverage levels of at least 75%. Here the event counties are defined as those whose indemnity ratio was greater than 0.7 in 2012



(6a) Corn



(6b) Soybeans

Figure 6 Cumulative participation in the 12 State Region, as measured by percent of insured acres for corn and soybeans in drought year 2012 and the following year 2013

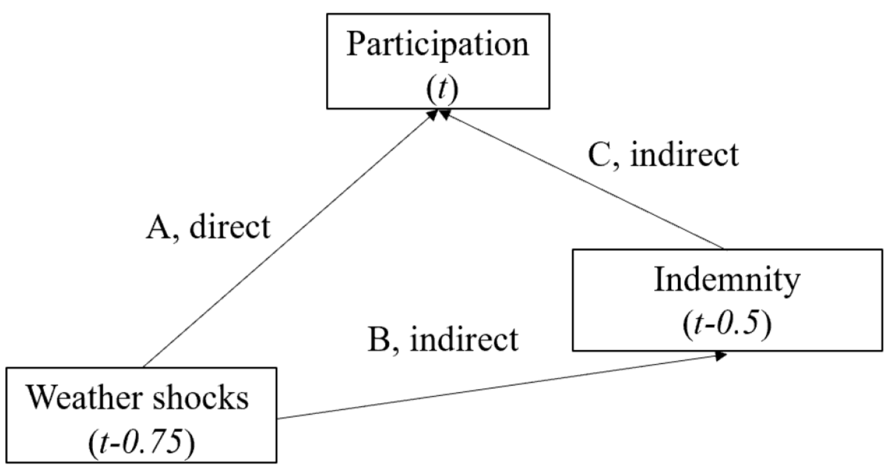
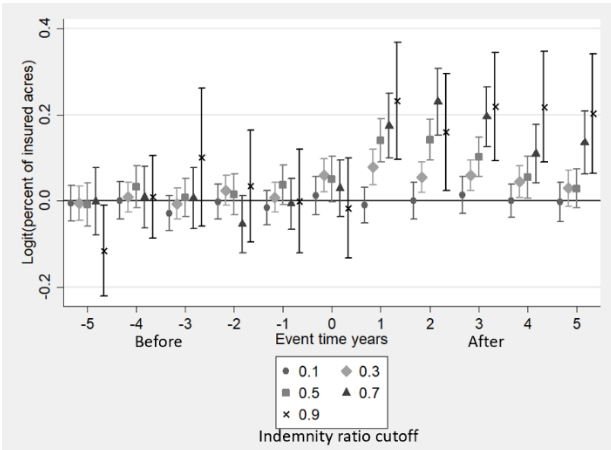
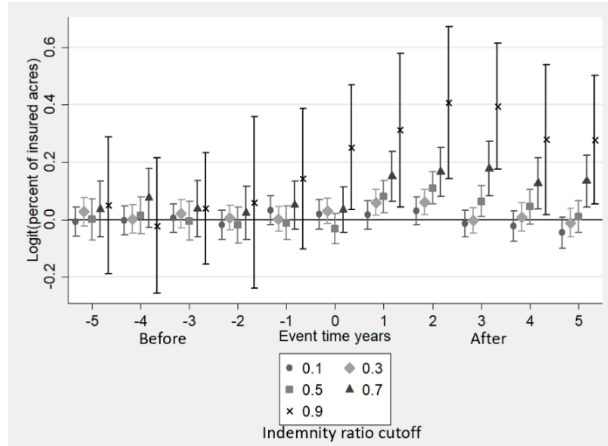


Figure 7 The effects of recent experience on participation

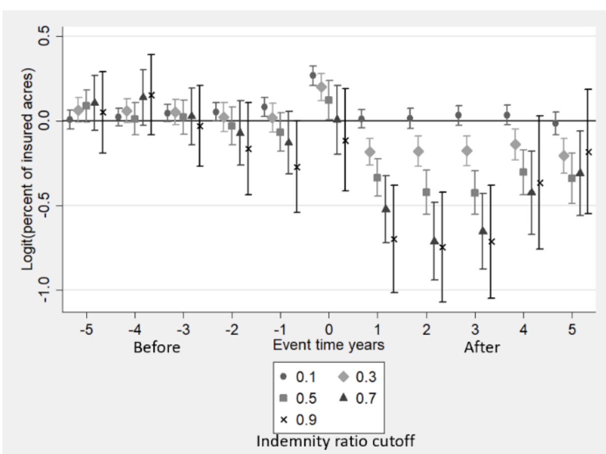


(8a) Corn

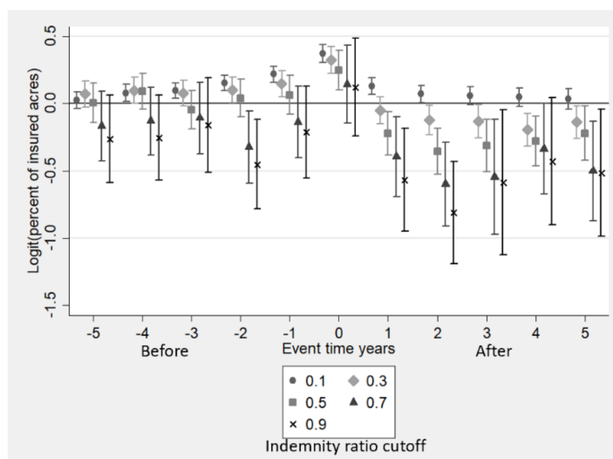


(8b) Soybeans

Figure 8 How the logit transformation of buy-up contract participation, as measured by percent of insured acres in buy-up contracts, responds to a large disaster event. Data are for 12 State Region and 2001-2017 period. The corresponding event coefficient estimates for corn can be found in Table 7

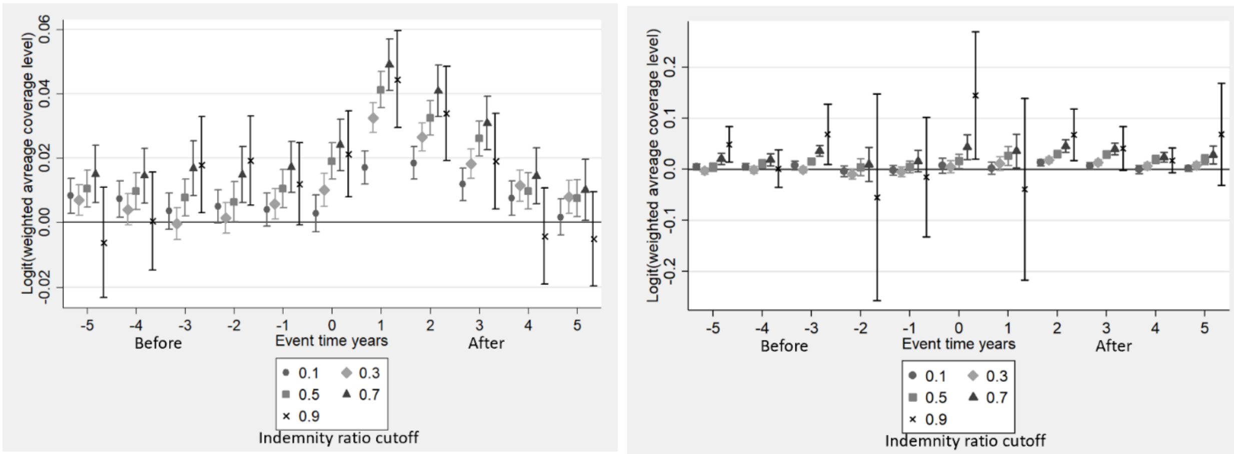


(9a) Corn



(9b) Soybeans

Figure 9 How the logit transformation of CAT participation, as measured by percent of insured acres in CAT, responds to a large disaster event. Data are for 12 State Region and 2001-2017 period



(10a) Corn (10b) Soybeans

Figure 10 How the logit transformation of intensive margin participation, as measured by acreage weighted average coverage level for participating acres, responds to a large disaster event. Data are for 12 State Region and 2001-2017 period. Coverage level for the CAT contract is set equal to 0.5

Table 1 Definition of variables

	Variable	Description
Participation	*P*	(*Extensive margin*) Percent of insured acres = Net reported acres / (Planted acres + Prevented planting acres) (*Intensive margin*) Weighted average coverage level
Indemnity ratio	*H*	Number of policies indemnified/Number of policies earning premium
Weather variables	*GD*	Deviation from the average GDD over 1991-2000
	SD	Deviation from the average SDD over 1991-2000
	dry	Negative value of the minimum among 0 and the Palmer Z value
	wet	The maximum among 0 and the Palmer Z value

Note: For participation we have two measures, extensive margin (percent of insured acres) and intensive measure (weighted average coverage level), where "net reported acres" and "coverage level" are from summary of business (SOB) of RMA and "prevented planting acres" is from the RMA cause of loss (COL) dataset. "Planted acres" is from NASS. For indemnity ratio, both the number of policies indemnified and the number of policies earning premium are from RMA.

Table 2 Variable descriptive statistics

	Variables		Obs	Mean	Std.Dev.	Min	Max
Corn	Percent of insured acres (*P*)	Full samples	14,961	0.799	0.152	0.035	1.000
		Buy-up	14,961	0.744	0.194	0.000	1.000
		CAT	14,195	0.058	0.085	0.000	0.716
	WACL (*P*)	Full samples	14,961	0.684	0.080	0.000	0.897
	Indemnity Ratio (*H*)	Full samples	14,961	0.318	0.245	0.000	1.000
		Buy-up	14,960	0.338	0.254	0.000	1.000
		CAT	13,515	0.084	0.182	0.000	1.000
Soybeans	Percent of insured acres (*P*)	Full samples	14,191	0.796	0.151	0.000	1.000
		Buy-up	14,191	0.747	0.188	0.000	1.000
		CAT	13,220	0.053	0.074	0.000	0.759
	WACL (*P*)	Full samples	14,191	0.692	0.076	0.000	0.893
	Indemnity Ratio (*H*)	Full samples	14,189	0.290	0.220	0.000	1.000
		Buy-up	14,188	0.308	0.232	0.000	1.000
		CAT	12,452	0.064	0.155	0.000	1.000
Weather variables	*GD*		13,296	0.011	0.120	-1.000	0.807
	SD		13,296	0.404	1.767	-1.000	27.455
	dry		14,961	0.038	0.088	0.000	1.330
	wet		14,961	0.086	0.121	0.000	1.372

Note: WACL represents weighted average coverage level. Coverage level for the CAT contract is set equal to 0.5.

Table 3 The first-step indemnity regression with FE for corn, equation (19)

Dependent variable	Indemnity ratio		
Categories	Full samples	Buy-up	CAT
GD	-0.054**	-0.064***	-0.031*
	(0.021)	(0.022)	(0.018)
SD	0.023***	0.025***	0.011***
	(0.002)	(0.002)	(0.001)
dry	0.927***	0.958***	0.612***
	(0.031)	(0.032)	(0.025)
wet	0.249***	0.258***	0.200***
	(0.021)	(0.022)	(0.017)
Year FE	Yes	Yes	Yes
Constant	0.221***	0.262***	0.047***
	(0.007)	(0.008)	(0.006)
Observations	11,976	11,975	10,935
R-squared	0.290	0.283	0.134
Number of counties	892	892	877

Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4 The second-step participation regression with FE for corn, equation (20)

Dependent Variables	Extensive margin Logit of insured acres percentage			Intensive margin Logit of WACL
Categories	Full samples	Buy-up	CAT	Full samples
L.IndemnityRatio	0.357***	0.393***	-0.548***	0.135***
	(0.041)	(0.034)	(0.059)	(0.005)
L.GD	0.090	0.057	0.033	0.003
	(0.093)	(0.080)	(0.105)	(0.011)
L.SD	0.010	0.006	-0.012	-0.002**
	(0.007)	(0.006)	(0.008)	(0.001)
L.dry	-0.059	0.154	-0.588***	0.023
	(0.139)	(0.120)	(0.150)	(0.016)
L.wet	-0.326***	-0.243***	0.011	-0.027***
	(0.091)	(0.078)	(0.100)	(0.010)
Year FE	Yes	Yes	Yes	Yes
Constant	1.170***	0.524***	-2.378***	0.716***
	(0.033)	(0.028)	(0.033)	(0.004)
Observations	11,976	11,975	10,935	11,976
R-squared	0.153	0.302	0.503	0.695
Number of counties	892	892	877	892

Note: WACL represents weighted average level. Coverage level for the CAT contract is set equal to 0.5. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5 The first-step indemnity regression with FE for soybeans, equation (19)

Dependent Variable	Indemnity ratio		
Categories	Full samples	Buy-up	CAT
GD	-0.101***	-0.114***	-0.000
	(0.019)	(0.020)	(0.017)
SD	0.012***	0.012***	0.003**
	(0.001)	(0.001)	(0.001)
dry	0.739***	0.764***	0.375***
	(0.031)	(0.032)	(0.027)
wet	0.182***	0.187***	0.168***
	(0.019)	(0.020)	(0.017)
Year FE	Yes	Yes	Yes
Constant	0.240***	0.287***	0.046***
	(0.006)	(0.007)	(0.005)
Observations	11,392	11,391	10,116
R-squared	0.346	0.359	0.055
Number of counties	841	841	813

Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6 The second-step participation regression with FE for soybeans, equation (20)

Dependent Variables	Extensive margin Logit of insured acres percentage			Intensive margin Logit of WACL
Categories	Full samples	Buy-up	CAT	Full samples
L.IndemnityRatio	0.188***	0.229***	-0.271***	0.125***
	(0.052)	(0.044)	(0.070)	(0.006)
L.GD	0.060	0.066	0.009	0.009
	(0.101)	(0.089)	(0.111)	(0.011)
L.SD	0.014*	0.013**	-0.005	0.001
	(0.007)	(0.007)	(0.008)	(0.001)
L.dry	-0.215	0.011	-0.884***	0.111***
	(0.168)	(0.149)	(0.183)	(0.018)
L.wet	-0.324***	-0.285***	-0.232**	0.009
	(0.103)	(0.091)	(0.114)	(0.011)
Year FE	Yes	Yes	Yes	Yes
Constant	1.472***	0.799***	-2.418***	0.737***
	(0.036)	(0.033)	(0.036)	(0.004)
Observations	11,392	11,391	10,116	11,392
R-squared	0.128	0.249	0.492	0.659
Number of counties	841	841	813	841

Note: WACL represents weighted average level. Coverage level for the CAT contract is set equal to 0.5. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 7 How the logit transformation of buy-up contract participation, as measured by percent of insured acres in buy-up contracts, responds to a large disaster event for corn, equation (21)

	The indemnity ratio cut-off points				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of insured acres percentage				
5 years before event	-0.005	-0.005	-0.009	-0.001	-0.116**
	(0.021)	(0.020)	(0.025)	(0.040)	(0.054)
4 years before event	0.001	0.009	0.033	0.008	0.010
	(0.022)	(0.018)	(0.025)	(0.036)	(0.049)
3 years before event	-0.028	-0.006	0.008	0.007	0.101
	(0.021)	(0.018)	(0.023)	(0.036)	(0.082)
2 years before event	-0.002	0.025	0.015	-0.054	0.035
	(0.021)	(0.018)	(0.024)	(0.034)	(0.066)
1 year before event	-0.016	0.008	0.037	-0.006	-0.001
	(0.020)	(0.018)	(0.024)	(0.030)	(0.061)
Event year	0.013	0.059***	0.051*	0.029	-0.016
	(0.023)	(0.019)	(0.027)	(0.033)	(0.059)
1 year after event	-0.010	0.079***	0.140***	0.174***	0.232***
	(0.021)	(0.021)	(0.026)	(0.038)	(0.069)
2 years after event	-0.000	0.055***	0.142***	0.230***	0.160**
	(0.022)	(0.018)	(0.024)	(0.039)	(0.069)
3 years after event	0.014	0.059***	0.102***	0.195***	0.219***
	(0.022)	(0.018)	(0.023)	(0.035)	(0.064)
4 years after event	0.000	0.045**	0.055**	0.110***	0.218***
	(0.019)	(0.019)	(0.025)	(0.034)	(0.065)
5 years after event	-0.003	0.029	0.029	0.135***	0.203***
	(0.023)	(0.021)	(0.023)	(0.037)	(0.071)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.463***	0.391***	0.397***	0.439***	0.434***
	(0.073)	(0.038)	(0.033)	(0.027)	(0.021)
Observations	14,961	14,961	14,961	14,961	14,961
R-squared	0.402	0.405	0.409	0.412	0.406
Number of counties	973	973	973	973	973

Note: Robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.