Recent Events and Participation in U.S. Federal Crop Insurance Programs

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Recency Effects in Decision Making

- **Understanding the role of recency effects on the decision-making of individuals under uncertainty is a crucial question in behavioral economics.**

  - **Recency effects** refer to the strength of recent information on a decision-maker's working memory and probability judgement (Camerer and Loewenstein 2011).

  - The effect experienced at the last moments of an experiment has a privileged role in evaluations of subsequent choices (Fredrickson and Kahneman 1993; Schreiber and Kahneman 2000).

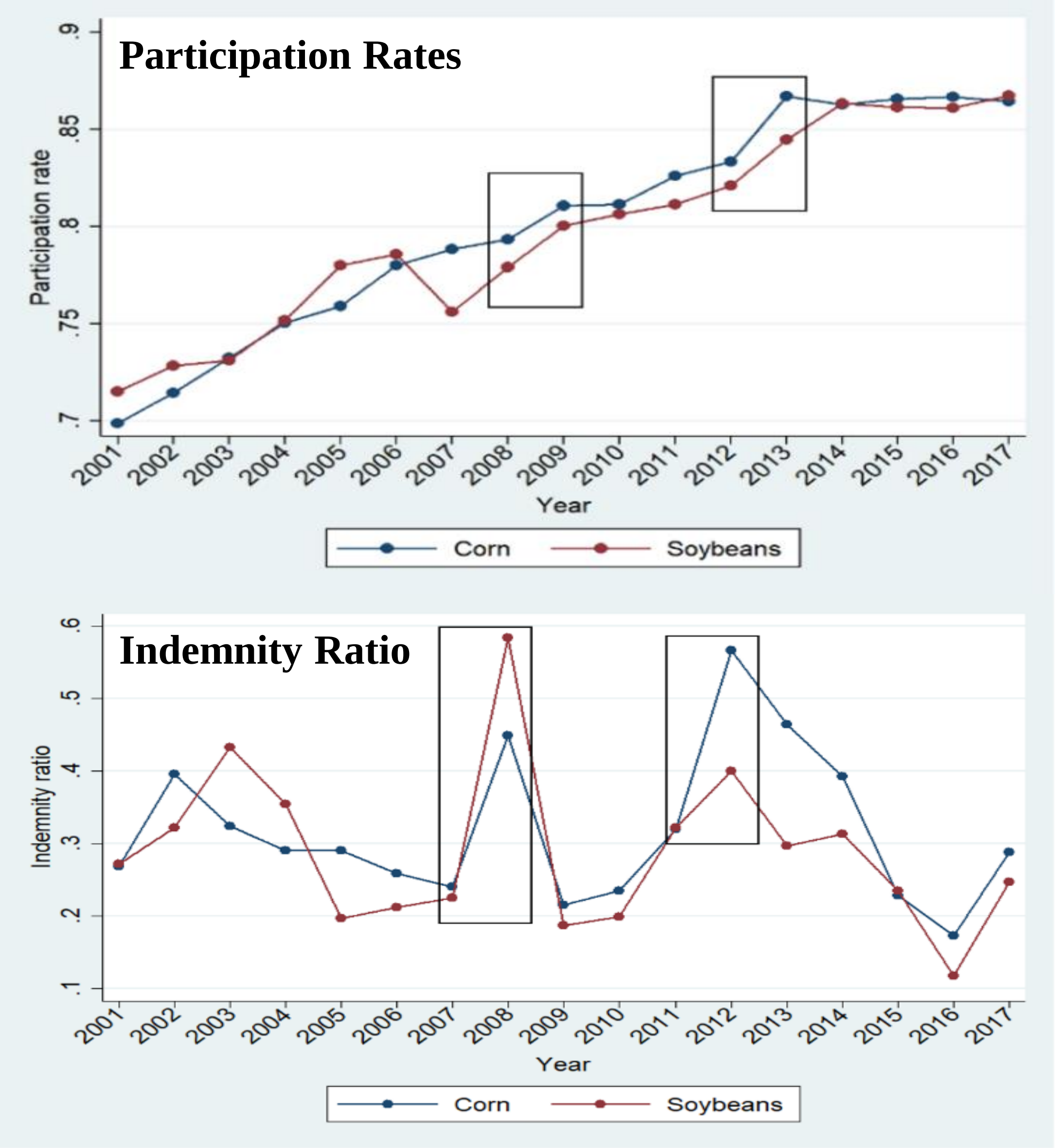
Recency Effects in Insurance Markets

- **Insurance participation increases after a natural event or a large loss.**
  - Rainfall Insurance in India (Stein, 2016)
  - Flood Insurance in US (Gallagher, 2014; Kousky, 2017)
  - Rice Insurance in China (Cai and Song, 2012; Cai et al., 2016)
- **There is limited research on recency effects in U.S. Federal Crop Insurance Program .**
  - Chong and Ifft's Powerpoint slides, 2016

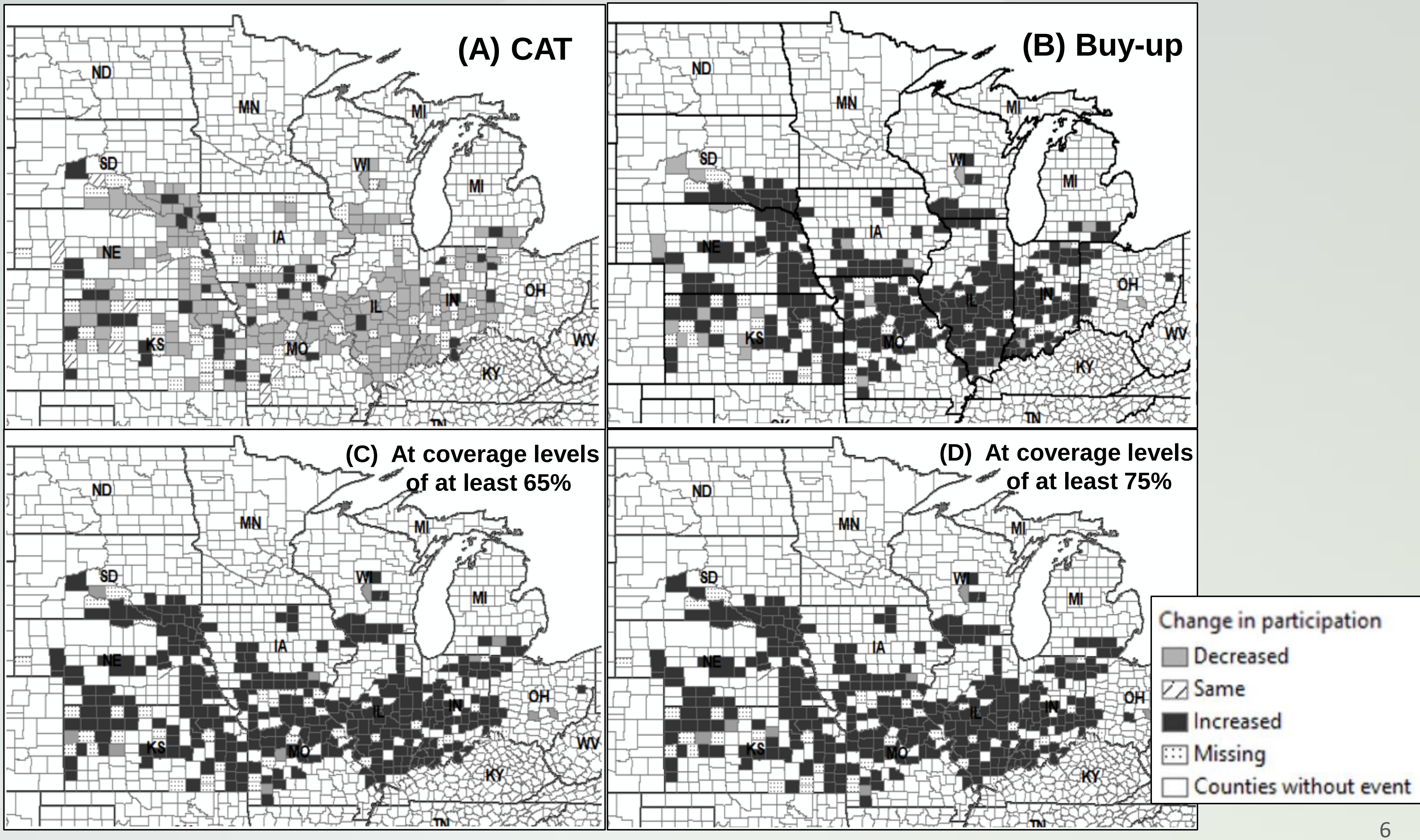
Research Question

- ❑ **Whether and how recent experience affects insurance choices with the U.S. Federal crop insurance program (FCIP)?**

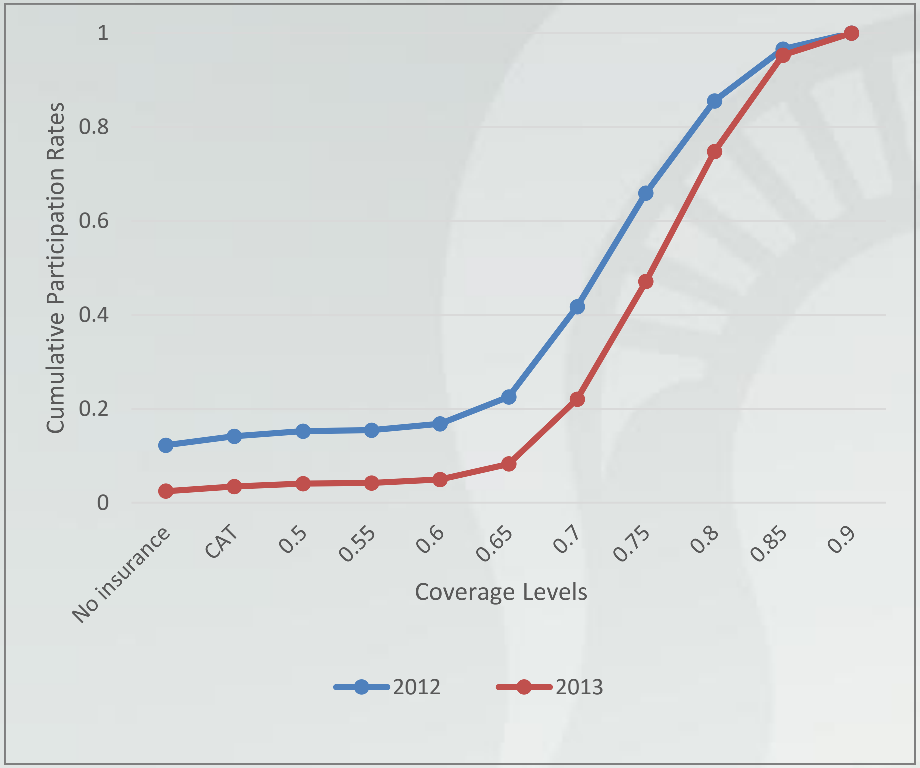
Average participation rates and indemnity ratio in US.



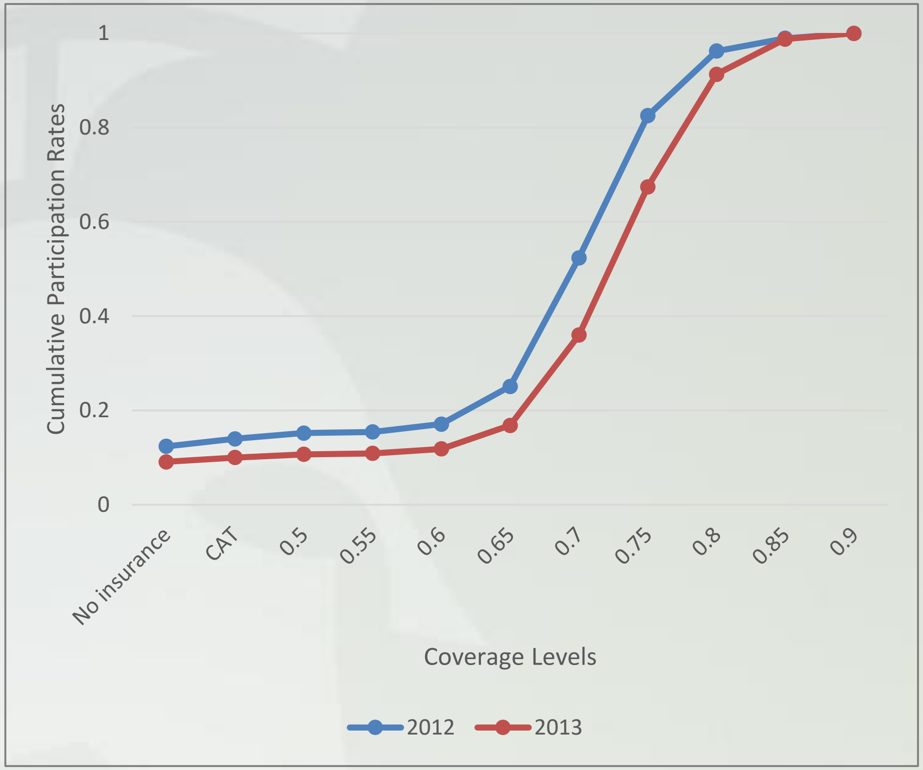
Changes in participation for event counties in 2013 compared with the drought year 2012.



Cumulative participation rates in drought year 2012 and the following year 2013.



(a) Corn

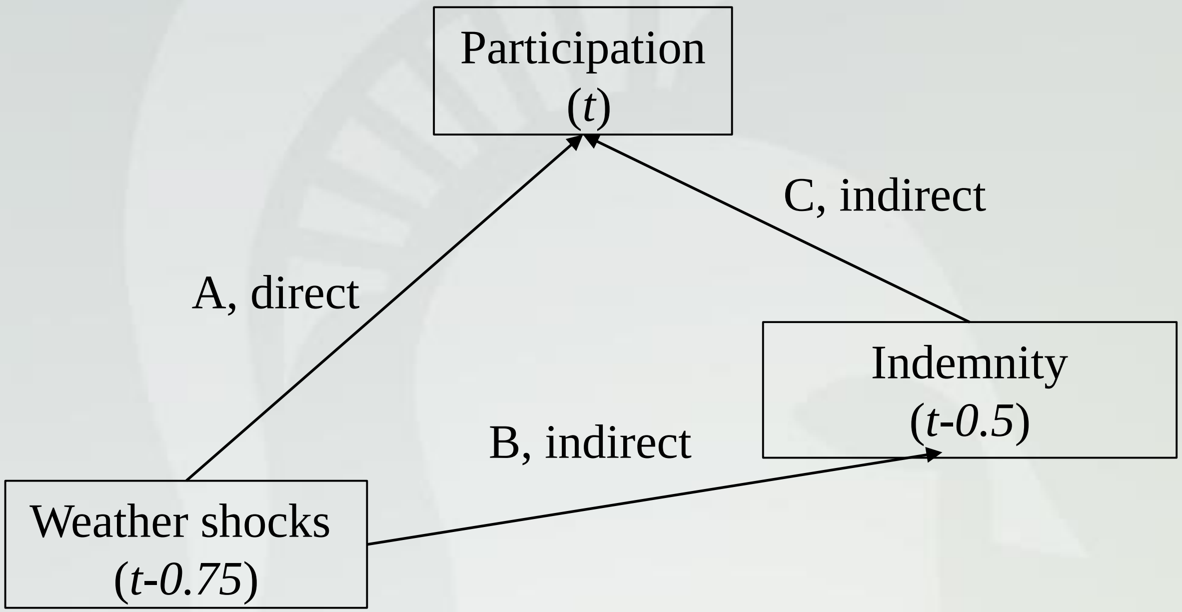


(b) Soybeans

Contributions

- ❑ The metrics of weather variables and indemnity.
- ❑ Decomposition into two channels through which recency effects can arise.
- ❑ Two estimation approaches: a two-step parametric approach and a flexible non-parametric approach.
- ❑ An illustration in theory incorporating recency effects.

Two Channels



Crop Insurance Variables

- Data Source: RMA and NASS
- Participation rates (P)= $\frac{\text{Net Insured Acres}}{\text{Planted Acres} + \text{Prevented Planting Acres}}$
- Indemnity ratio (R) = $\frac{\text{\# of Policies Indemnified}}{\text{\# of Policies Earning Premium}}$
- Time Period: 2001-2017
- County-level: Counties in 12 Midwest and Great Plains states (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI)
- Crops: Corn and soybeans

Weather Variables

- **Temperature**
  - Use daily maximum and minimum temperatures (T_d^{max}, T_d^{min}) (Source: NOAA)
  - Define cumulative heat based on temperature thresholds:

    Growing Degree Days (GDD)

    – **beneficial** temperature levels.

    Stress Degree Days (SDD)

    – **harmful** temperature levels.

  - ***GD***: Deviation from the average GDD over 1991-2000.

    SD: Deviation from the average SDD over 1991-2000.

Weather Variables

- **Moisture**
  - Use a monthly Palmer Z (***PZ***) index. (Source: NOAA)
  - Accounts for evapotranspiration, soil run-off.
  - Actual available moisture towards plant growth.
  - The value PZ=0 is to be expected, while PZ≤-2 represents drought and PZ≥5 represents flooding (Xu et al. 2013)
  - $\boldsymbol{dry} = -min(0, PZ)$.

    $\boldsymbol{wet} = max(0, PZ)$.

Two-Step Parametric Estimations

- $\mathrm{R}_{i,t}^{l} = \alpha_0^l + \alpha_1^l W_{i,t} + \delta_t^l + \varepsilon_{i,t}^l$ (7)
  - $\mathrm{R}_{i,t}^{l}$ - indemnity ratio
  - $W_{i,t} = (GD_{i,t}, SD_{i,t}, dry_{i,t}, wet_{i,t})'$ - weather vector
  - δ_t^l - year fixed effects
  - $\varepsilon_{i,t}^l$ - error item
  - i - county
  - t - year
  - $l \in \{corn, soybeans\}$

- $ln[P_{i,t}^l/(1 - P_{i,t}^l)] = \beta_0^l + \beta_1^l R_{i,t-1}^l + \beta_2^l W_{i,t-1} + \theta_t^l + u_{i,t}^l$ (8)
  - $P_{i,t}^l$- participation rate in current period
  - $R_{i,t-1}^l$ - indemnity ratio in past period
  - $W_{i,t-1}$ - weather vector in past period
  - θ_t^l- year fixed effects
  - $u_{i,t}^l$ - error item

Two-Step Parametric Estimations

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- A: β_2^l - direct effect of prior weather shocks on participation
  B: α_1^l - responses from weather shocks on indemnity
  C: β_1^l - responses from prior indemnity on participation
  B-C: $\beta_1^l\ \alpha_1^l$ - indirect effect of prior weather shocks on participation

- DE (share of direct effect in total effect): $\beta_2^l/(\beta_1^l\alpha_1^l + \beta_2^l)$
  IE (share of indirect effect in total effect): $\beta_1^l\alpha_1^l/(\beta_1^l\alpha_1^l + \beta_2^l)$

First Step Regression Results (Corn)

The indemnity regression with FE for corn.

	Full samples	Buyup	CAT	Coverage ≥65%	Coverage ≥75%
VARIABLES	Dependent Variable: R (Indemnity ratio)				
GD	-0.054**	-0.064***	-0.031*	-0.069***	-0.081***
	(0.021)	(0.022)	(0.018)	(0.024)	(0.026)
SD	0.023***	0.025***	0.011***	0.027***	0.026***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
dry	0.927***	0.958***	0.612***	0.975***	0.989***
	(0.031)	(0.032)	(0.025)	(0.035)	(0.039)
wet	0.249***	0.258***	0.200***	0.266***	0.279***
	(0.021)	(0.022)	(0.017)	(0.023)	(0.026)
Year FE	Yes	Yes	Yes	Yes	Yes
Constant	0.221***	0.262***	0.047***	0.320***	0.358***
	(0.007)	(0.008)	(0.006)	(0.008)	(0.009)
Observations	11,976	11,975	10,935	11,882	11,659
R-squared	0.290	0.283	0.134	0.275	0.264
Number of counties	892	892	877	888	881

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

Second Step Regression Results (Corn)

The participation regression with FE for corn.

VARIABLES	Full samples	Buyup	CAT	Coverage≥ 65%	Coverage ≥75%
	Dependent variable: $\ln[P/(1-P)]$				
L.R	0.357***	0.393***	-0.548***	0.236***	0.288***
	(0.041)	(0.034)	(0.059)	(0.024)	(0.026)
L.GD	0.090	0.057	0.033	-0.012	-0.100
	(0.093)	(0.080)	(0.105)	(0.061)	(0.069)
L.SD	0.010	0.006	-0.012	-0.014***	-0.035***
	(0.007)	(0.006)	(0.008)	(0.005)	(0.005)
L.dry	-0.059	0.154	-0.588***	0.374***	0.558***
	(0.139)	(0.120)	(0.150)	(0.092)	(0.106)
L.wet	-0.326***	-0.243***	0.011	-0.027	0.099
	(0.091)	(0.078)	(0.100)	(0.060)	(0.068)
Year FE	Yes	Yes	Yes	Yes	Yes
Constant	1.170***	0.524***	-2.378***	-0.549***	-1.585***
	(0.033)	(0.028)	(0.033)	(0.022)	(0.026)
Observations	11,976	11,975	10,935	11,882	11,659
R-squared	0.153	0.302	0.503	0.608	0.656
Number of counties	892	892	877	888	881

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

Results (Corn)

The direct and indirect effects of past weather shocks on participation for corn.

Variables	Effects	Full samples	Buyup	CAT	Coverage ≥65%	Coverage ≥75%
L.GD	DE	1.273	1.790	0.660	0.424	0.811
	IE	-0.273	-0.790	0.340	0.576	0.189
L.SD	DE	0.549	0.379	0.666	1.835	1.272
	IE	0.451	0.621	0.334	-0.835	-0.272
L.dry	DE	-0.217	0.290	0.637	0.619	0.662
	IE	1.217	0.710	0.363	0.381	0.338
L.wet	DE	1.375	1.716	-0.112	-0.755	0.552
	IE	-0.375	-0.716	1.112	1.755	0.448

Findings

- Higher indemnity in the recent past directly encourages subsequent participation.
- Prior adverse weather shocks work through the channel of indemnity to increase participation.
- The direct effects of prior adverse weather on participation are not consistent.

Lasting effects on participation of large indemnities

Flexible Event Study Model (Gallagher, 2014)

- $ln[P_{i,t}^{l}/(1-P_{i,t}^{l})] = \sum_{\tau=-T}^{T} \phi_{\tau}^{l} D_{i,t,\tau}^{l} + \eta_{s,t}^{l} + \sigma_{c}^{l} + \xi_{i,t}^{l}$ (9)

- $P_{i,t}^{l}$ - participation rate.
- $D_{i,t,\tau}^{l}$ - event time indicator variable, which tracks the year of large indemnity and the years before and after a large loss.
  For a calendar year *t* and crop *l*,
  $D_{i,t,0}^{l} = 1$ if a large loss appears in county *i* in year *t*;
  $D_{i,t,\tau}^{l} = 1$ if a large loss appears in county *i* in year *t* - τ.
- $\eta_{s,t}^{l}$ - state-by-year fixed effects.
- σ_{c}^{l} - crop reporting district fixed effects.
- $\xi_{i,t}^{l}$ - error term.

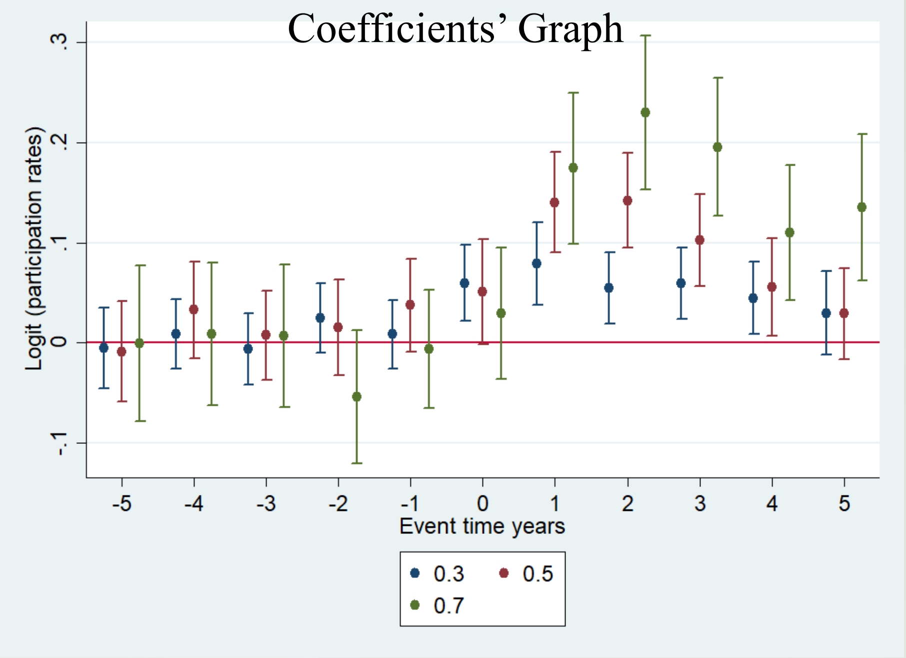
- Define **a large loss** occurs in one county when the county's indemnity ratio is greater than a specific cutoff point such as 0.1, …, 0.9.

Lasting effects on participation of large indemnities

Indemnity ratio cutoff points	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of participation rates				
Year-5	-0.005	-0.005	-0.009	-0.001	-0.116**
Year-4	0.001	0.009	0.033	0.008	0.01
Year-3	-0.028	-0.006	0.008	0.007	0.101
Year-2	-0.002	0.025	0.015	-0.054	0.035
Year-1	-0.016	0.008	0.037	-0.006	-0.001
Year of Event	0.013	0.059***	0.051*	0.029	-0.016
Year+1	-0.01	0.079***	0.140***	0.174***	0.232***
Year+2	0	0.055***	0.142***	0.230***	0.160**
Year+3	0.014	0.059***	0.102***	0.195***	0.219***
Year+4	0	0.045**	0.055**	0.110***	0.218***
Year+5	-0.003	0.029	0.029	0.135***	0.203***
state-by- year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
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 county	973	973	973	973	973

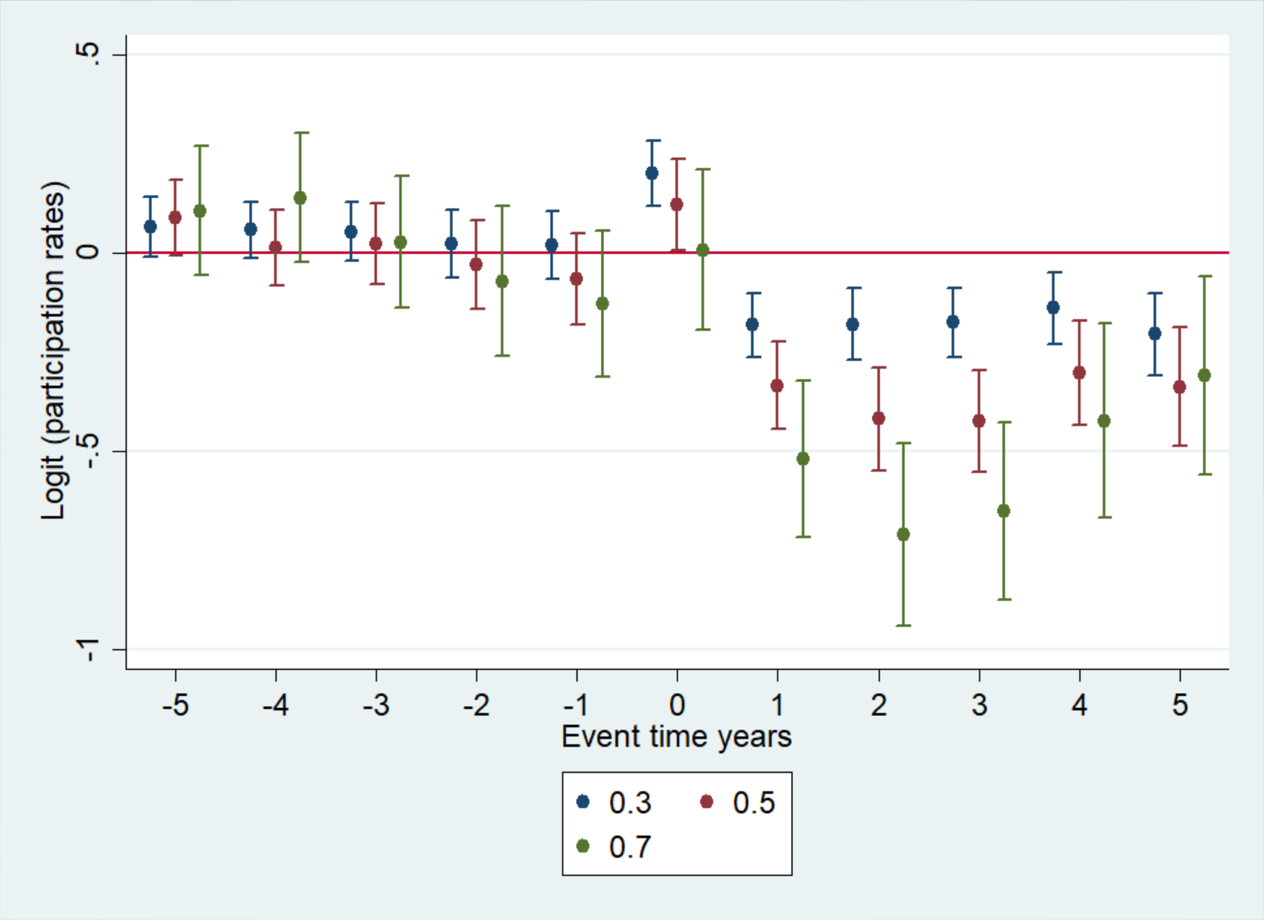
***p<0.01, ** p<0.05, * p<0.1

Regression results (Corn; Buy-up)



Lasting effects on participation of large indemnities

Coefficients' Graph (Corn; CAT)



Conclusions and Discussions

- Participation increases after a large loss or a natural disaster except CAT. Further studies may explore how long the increasing effects will last and whether they will approach to zero or some positive constants in the end.

- County-level data may lose the detail of heterogeneity among individual farmers within one county by treating all farmers in one county the same as the representative county average. But the county-level findings predict a similar incentive for an individual farmer making crop insurance purchase decisions.

Conclusions and Discussions

- Future research may explore whether the recency effects are from the change in individuals' preference and distribution or from psychological bias.

- If the recency effects are mainly caused by psychological bias, then policy makers can utilize the opportunities to take attractive measures when severe weather events occur, and further take advantage of human psychological inertia to keep the higher participation levels.

Thank you!