Homa Taheri
5 N Oakley Blvd Apt 1W
Chicago, IL, 60612
htaheri@iu.edu
857-285-0102
August 7, 2025

Admissions Committee
NBER PhD Student Workshop on Climate Finance

Dear Members of the Admissions Committee,

I am a PhD candidate in Economics at Indiana University in Bloomington, expected to complete my degree by May 2026. I am writing to apply for the NBER PhD Student Workshop on Climate Finance. My research is on insurance as a public policy tool, and I currently focus on agricultural insurance for my two papers at hand.

In my Job Market Paper, I study the US crop insurance policies in the 1990s and how they formed crop insurance adoption in the United States. My second paper is an impact evaluation of bundling drought-tolerant seeds and picture-based insurance for Ethiopian farmers. This is part of my work as a researcher at the International Food Policy Research Institute (IFPRI).

I have a 70 percent complete draft of my Job Market Paper and am seeking feedback to improve its rigor and policy relevance. My work aligns closely with the workshop themes, including how the impact of social insurance policies is affected by the occurrence of extreme weather incidents.

My faculty advisor is Professor Ahmad Lashkaripour, who I hope would support my application and can provide a reference. I look forward to the opportunity to engage with fellow researchers and leading experts, and to advance my research and career in this important field.

I appreciate your consideration.

Sincerely,
Homa Taheri
PhD Candidate, Department of Economics
Indiana University in Bloomington

Homa Taheri

Chicago, IL
homataheri1@gmail.com | 857-285-0102 | homataheri.com

Education

Indiana University
Bloomington, IN
Ph.D. Candidate of Economics

Harvard University, Kennedy School of Government
Cambridge, MA Master's in Public Administration in International Development

Institute for Management and Planning Studies
Tehran, Iran
Master's in Economics, summa cum laude

University of Tehran
Tehran, Iran
Bachelor's in Electrical Engineering

Professional Experience

Sep 2025- **University of Chicago, Center for Spatial Data Science**
Chicago, IL
Visiting Scholar (forthcoming)

May 2025- **International Food Policy Research Institute**
Remote
Economic Researcher, Crop Insurance in Ethiopia

Sep 2024- **University of Chile**
Remote
March 2025 Economic Consultant

Conducted program evaluation for adoption of two sustainable cattle production practices in Chile- Regenerative Livestock Approaches (RLA) and Silvopastoral Systems (SPS) for the Inter-American Development Bank (IDB).

Aug 2024- **International Food Policy Research Institute**
Remote
Dec 2024 Economic Consultant

Developed a Course titled "Integrating Gender in Cost-Benefit Analysis of Innovations to Enhance Smallholder Farmers' Resilience and Climate Change Adaptation".

June 2023- **Indiana Resilience Funding Hub**
Bloomington, IN
Sep 2023- McKinney Climate Fellow

June 2019- **Secretariat of Economic Development** Aguascalientes, Mexico Economic Consultant

Conducted research on bottlenecks of economic growth in Aguascalientes using the Growth Diagnosis Framework developed by the Center for International Development at Harvard Kennedy School.

Aug 2016- **Ministry of Cooperatives, Labor and Social Welfare**
Tehran, Iran
July 2018- Economic Researcher at the Social Welfare Deputy

Conducted a qualitative and quantitative analysis of social and economic conditions of vulnerable communities in Iran, using the Core Diagnostic Instrument (CODI) developed by the Inter-Agency Social Protection Assessment (ISPA), in collaboration with UNICEF.

Directed a group of 22 employees for improving the processes of the deputy through "learning by doing" within the government body.

Led a data analysis project of the historical pattern of the household loan in Iran.

Developed a version of the Mexican Microfinance Program (NAFINSA) for rural farmers in Iran.

Apr 2013- **Tavan Sazan Iran**
Tehran, Iran
Sep 2016 Technical Engineer

Sep 2012- **Vina Intelligent Solutions**
Tehran, Iran
Jan. 2013 Design Engineer

Teaching Experience

Jan 2025 **Indiana University**
Bloomington, IN
Guest Lecturer

Presented about Public Program Evaluation to graduate students at O'Neill School of Public and Environmental Affairs.

Aug 2022- **Indiana University**
Bloomington, IN
May 2024 Associate Instructor

Full Teaching responsibility of Introductory Microeconomics (two semesters) and Industrial Organization (two semesters) for undergraduate students at the Kelley School of Business and College of Arts and Sciences.

Working Papers

Taheri, Homa. n.d. " Who Needed the Mandatory Enrolment Push in 1994: The Case of Midwestern Farmers." Job Market Paper. Working paper.

Lashkaripour, Ahmad, Farid Farrokhi, and **Homa Taheri**. n.d. "Effective Paths to Carbon Reduction: A Global Framework for Trade and Energy Policy Evaluation." Working paper.

Felipe Bravo-Peña, **Homa Taheri**, and Claus Köbrich. n.d. "Determinants of the adoption of Silvopastoralism and Regenerative Livestock Approaches: Evidence from Chile." Working paper, Inter-American Development Bank.

Publications and Policy Notes

Kramer, Berber, Melody Braun, Paulina Smith Ruiz, and **Homa Taheri**. *AICCRA Training Report: A Course on Gender and Cost-Benefit Analysis of Innovations to Enhance Smallholder Farmers' Climate Change Adaptation.* Accelerating Impacts of CGIAR Climate Research for Africa (AICCRA), 2024. https://hdl.handle.net/10568/163607

Taheri, Homa. *Federal Crop Insurance Data: Summary of Business.* Report. August 2024. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4928774

Taheri, Homa. *Justice40 Initiative: An Introduction.* Report. Indiana Resilience Funding Hub, August 2023. https://eri.iu.edu/documents/irfh_justice40_initiative_report.pdf.

Taheri, Homa. *An Analysis of Federal Crop Insurance in the 2018 Farm Bill.* Report. March 10, 2023. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4433809.

Taheri, Homa. *A Framework for Analyzing Safeguards at the World Trade Organization.* Report, January 27, 2022. https://ostromworkshop.indiana.edu/pdf/seriespapers/2022spr-res/taheri.pdf.

Nyarko, Edward, and **Homa Taheri**. "Towards a Design of an Effective Safeguard Mechanism for the World Trading System." Master's thesis, Harvard Kennedy School, 2020. https://www.researchgate.net/publication/341901645_TOWARDS_A_DESIGN_OF_AN_EFFECTIVE_SAFEGUARD_MECHANISM_FOR_THE_WORLD_TRADING_SYSTEM.

Amirzadeh, Ehsan, Fatemeh Najafi Ziarani, and **Homa Taheri**. "An Analysis of Access of Iranian Households to Micro Finance Using Data Mining (in Farsi)." *Job and Society*, December 2018. http://magiran.com/p1966576.

Sharifan, Golnoosh, Alireza Abdollah Zadeh, **Homa Taheri**, Mahya Jaberi Ansari, and Aliyeh Nazemi. "Evaluation of Universal Health Insurance in Iran (in Farsi)." *Job and Society* 222 (2018). http://magiran.com/p1931554.

Giahi, Maryam, **Homa Taheri**, and Aliyeh Nazemi. "An Analysis of Unequal Access of Social Groups to the Benefits of Economic Growth in Iran (in Farsi)." June 2018. http://magiran.com/p1986384.

Taheri, Homa, Aliyeh Nazemi, and Maryam Giahi. "Inclusive Growth Diagnosis of Iran (in Farsi)." *Iranian Labor Market Management* 25 (2018). http://magiran.com/p1986368.

Taheri, Homa, and Kowsar Yousefi. "The Impact of Countries' Previous Legal Disputes in WTO on Their Current Cases (in Farsi)." The Journal of Planning and Budgeting 22, no. 2 (2017): 109–136. https://econpapers.repec.org/article/auvjipbud/v_3a22_3ay_3a2017_3ai_3a2_3ap_3a109-136.htm

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Conference Presentations

May 2023 — 3rd Hoosier Economic Conference, Bloomington, IN

March 2025 — 89th Midwest Economic Association Conference, Kansas City, MO

Awards

Indiana University

Markets, Decarbonization, and Trade Meeting of the National Bureau of the Economic Research (NBER) Travel Award (June 2025),

Fernandus & Elizabeth J. Payne Fellowship as a College of Arts and Sciences Spring Travel Award (April 2025),

Frank T. Bachmura Award for an Outstanding Student in Development Economics or Comparative Systems (March 2024),

McKinney Climate Fellowship (Summer 2023),

Ostrom Workshop Fellowship (2021-2022)

Harvard Kennedy School

Raymond Vernon Award for Commitment to International Development (May 2020)

John F. Kennedy Memorial Fellowship to fully cover cost of education (2018-2020)

Skills R, Stata, Latex

Languages Farsi (Native speaker), Urdu (Limited Proficiency) and Arabic (Limited Proficiency)

Role of Extreme Weather in Sensitivity of the Crop Acreage to the Crop Insurance Premium Subsidies

Job Market Paper of Homa Taheri

Abstract

How does the sensitivity of the crop acreage to the insurance premium subsidies as established by Yu et al (2017)[1] vary by changes in the occurance of extreme weather? In order to answer to this question, we studied corn and soybeans production in the Midwest during the 1989-2013 period.

Stylized facts

During this period, weather has been relative more condusive for producing soybeans, as captured by number of moderate days and extremely hot days below.

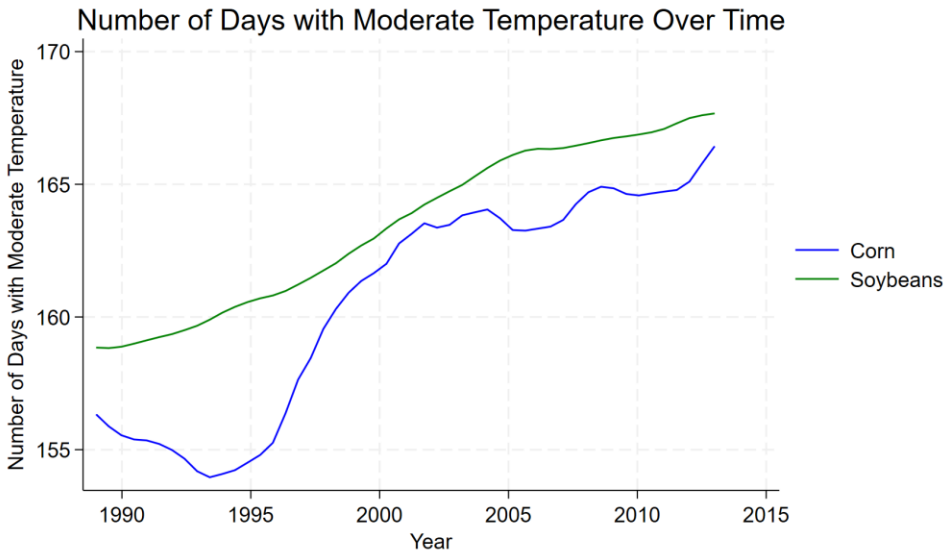


Figure 1- Number of days with moderate temperature over time

[1] Yu, Jisang, Aaron Smith, and Daniel A. Sumner. "Effects of crop insurance premium subsidies on crop acreage." *American Journal of Agricultural Economics* 100, no. 1 (2018): 91-114.

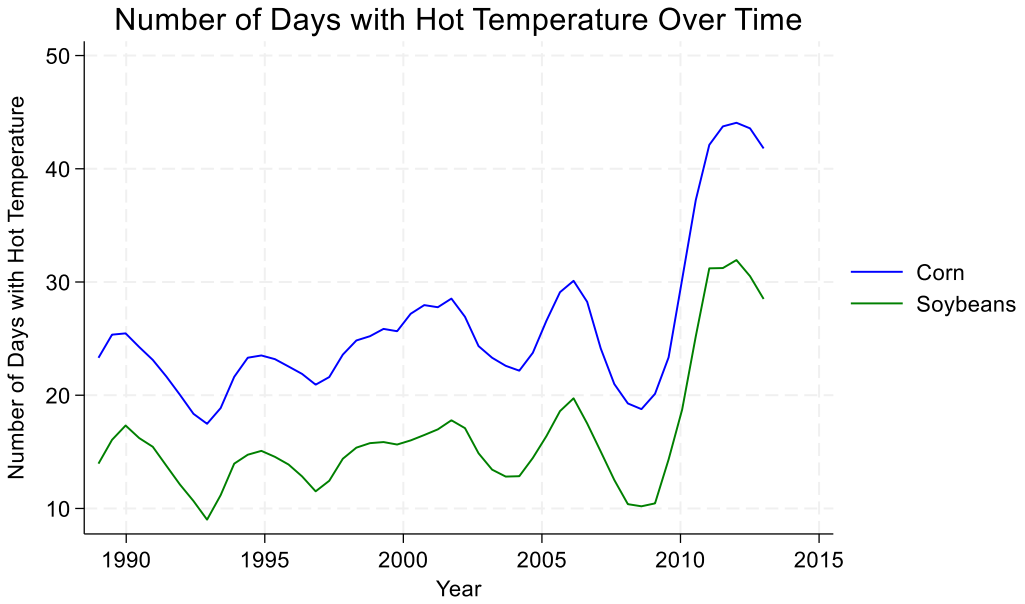


Figure 2- Number of days with extreme temperature over time.

A rule of thumb method for farmers to decide on whether to grow corn or soybeans is to check the relative size of soybeans price to corn price and grow soybeans when this ratio is higher than 2.5[2].

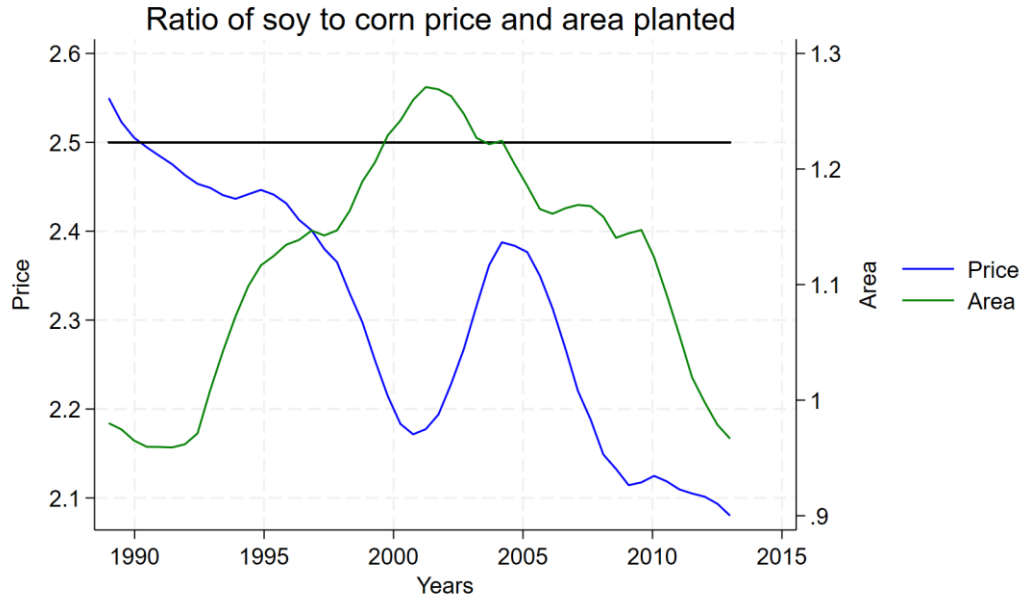


Figure 3- Left axis: Received price of farmers (blue) for soybeans relative to corn. Right axis: Relative area planted for soybeans relative to corn (green). The black horizontal line shows the rule of thumb threshold of switching from corn to soybeans, as known in the farming community.

[2] https://www.canr.msu.edu/news/the-corn-soybean-ratio-and-its-potential-impact-on-farm-profits

One observation is that yield of corn has been higher in level and variability compared to soybeans, which suggests corn to be a higher risk-higher return crop compared to soybeans.

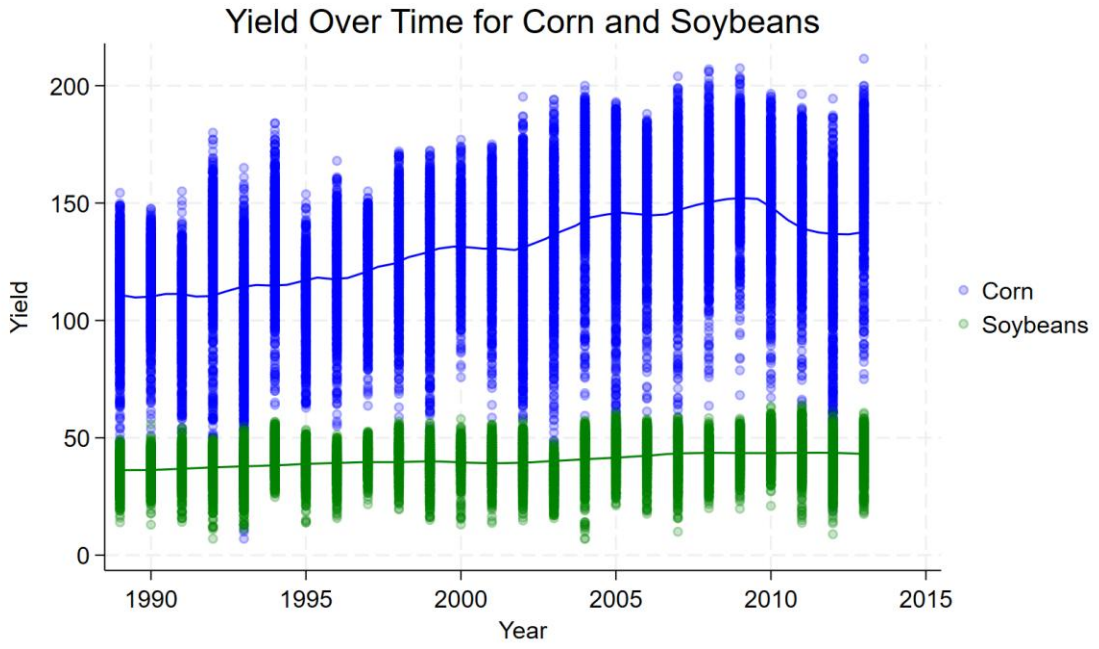


Figure 4- Corn yield is higher and has higher variance compared to soybeans.

Share of subsidy in premium for corn and soybeans over years

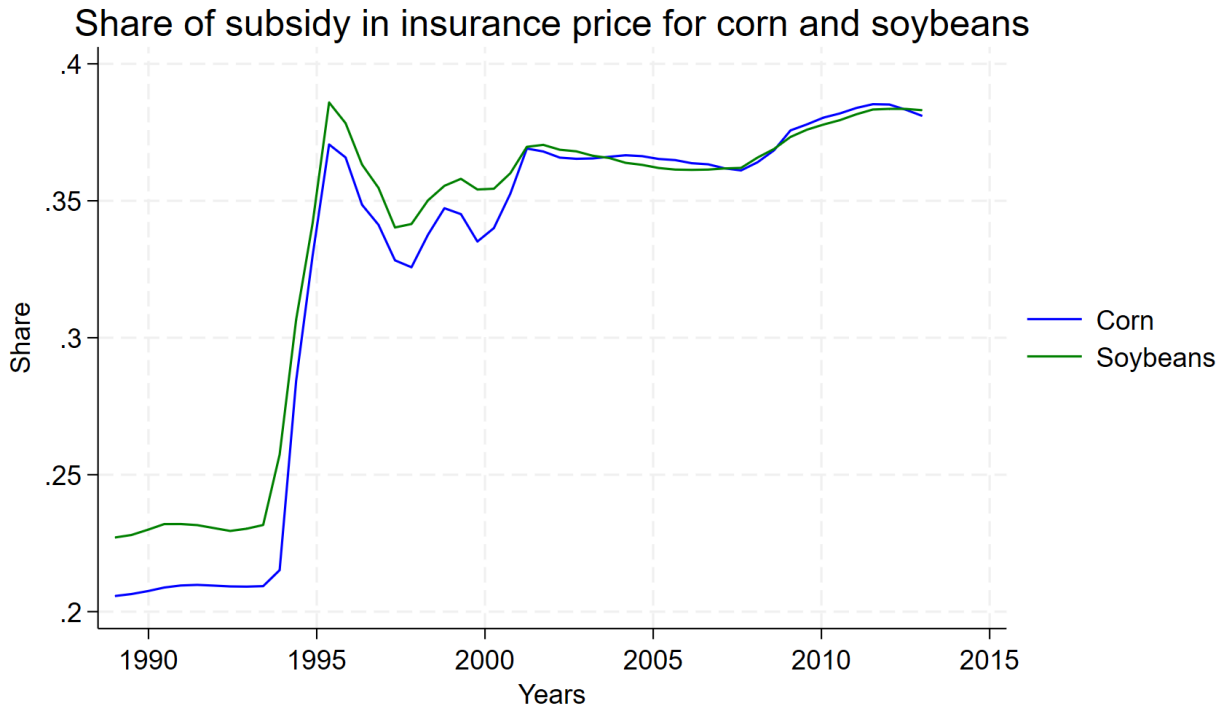


Figure 5- In the first half of the study period, there is a gap between percentage of insurance price covered by subsidy for two crops. It enables us to study the differential impact of subsidies on crop choice.

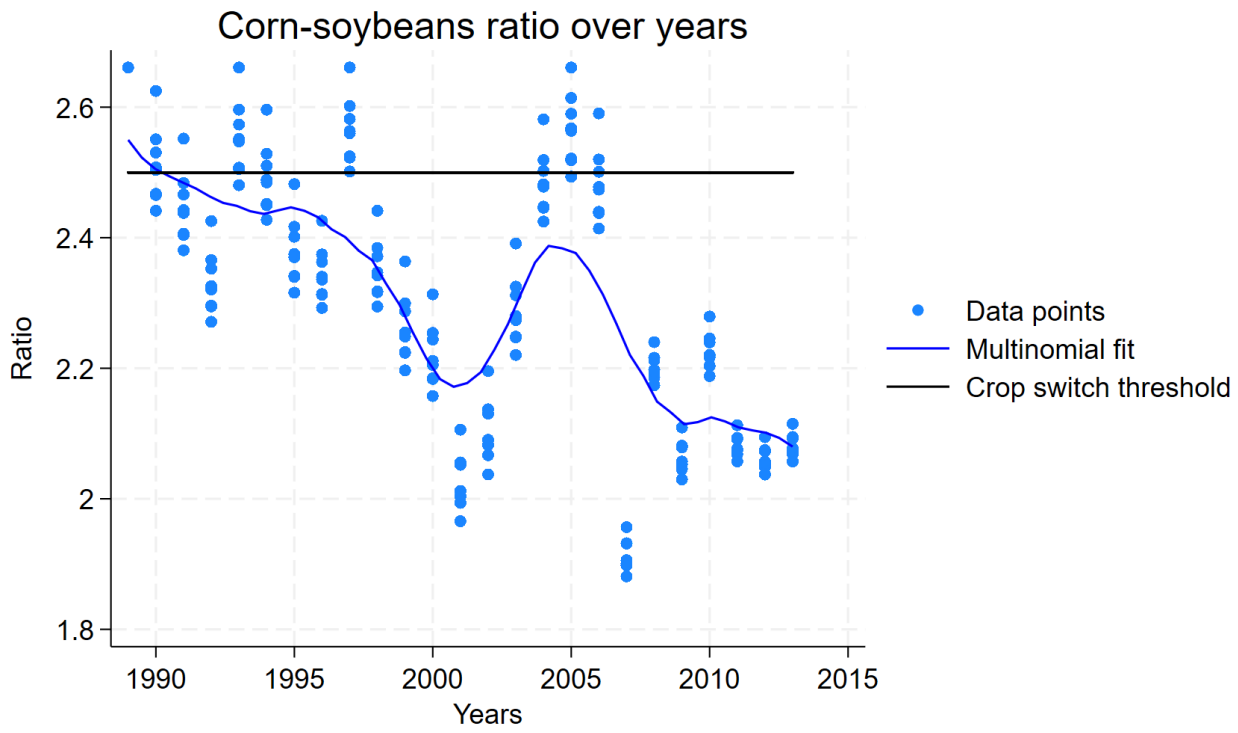


Figure 6- Relative price of soybeans to corn in eight Midwest states and the crop switching threshold.

Federal Crop Insurance Program

The federal crop insurance program underwent significant reforms in 1994, 2000, and 2008, each driven by distinct policy goals rather than direct responses to changes in acreage planted. The 1994 Federal Crop Insurance Reform Act, implemented in the aftermath of costly ad hoc disaster payments, introduced Catastrophic (CAT) coverage and mandated insurance participation for eligibility in other farm programs (Glauber, 2004[3]). This reform aimed to institutionalize risk protection and reduce reliance on emergency aid, not to address acreage shifts. The 2000 Agricultural Risk Protection Act (ARPA) further expanded the program by increasing premium subsidies, especially for higher coverage levels, and enhancing delivery mechanisms. This was intended to boost participation and stabilize farm incomes following low prices and widespread crop losses in the late 1990s (Goodwin & Smith, 2013[4]; USDA RMA, 2006[5]). The 2008 Farm Bill marked a transition toward revenue-based insurance products, such as Revenue Protection (RP), reflecting the growing role of risk management in U.S. farm policy and concerns over the efficiency of direct payments (Glauber, 2013[6]). While these reforms indirectly influenced planting decisions, especially on marginal lands (Yu, Smith & Sumner, 2017), the laws themselves were primarily motivated by

[3] Glauber, J. W. (2004). Crop Insurance Reconsidered. AJAE, 86(5), 1179–1195.
[4] Goodwin, B. K., & Smith, V. H. (2013). What Harm is Done by Subsidizing Crop Insurance? AJAE, 95(2), 489–497.
[5] USDA RMA. (2006). 2000 Agricultural Risk Protection Act: Five-Year Review.
[6] Glauber, J. W. (2013). The Growth of the Federal Crop Insurance Program, 1990–2011. AJAE, 95(2), 482–488.

budgetary concerns, program uptake, and a desire for more comprehensive risk protection—not by observed changes in acreage planted.

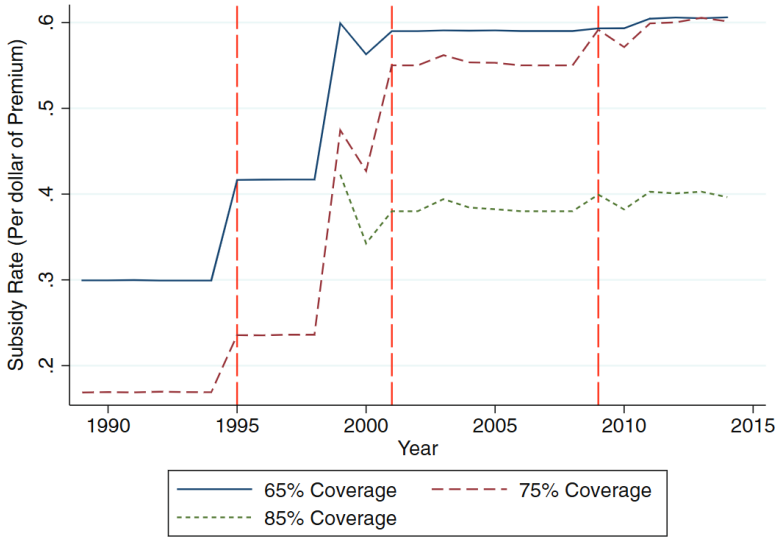


Figure 1. Subsidy rate by coverage level (1989–2014)

Note: The subsidy rates are computed by "National Total Subsidy" divided by "National Total Premium" for each coverage level. Subsidies and premiums for the group insurance products are excluded. Note that except for 1999 and 2000 and years after 2008, the subsidy rates are equal to the legislatively-determined subsidy rates.

Figure 7- Subsidy rate by coverage level over 1989-2014 (from Yu et al, 2017)

Conceptual framework on how premium subsidies and percentage of land insured affect the crop yield

In this paper, we build up on Yu et al (2017) by incorporating the economic damages associated with climate change in decision-making of the farmers in their purchase of crop insurance. Considering that the explicit effect of climate variables is important, most of the predicted damages from climate change in the US come from the increased frequency of extreme heat. Annan and Schlenker (2015) established that farmers with higher percentage of planted land insured have production yields that are more sensitive to extreme heat and precipitation. They suggest a moral hazard reasoning for this observation. In this section, we combine the insights of Annan and Schlenker (2015) paper about the additive and interactive effect of being a beneficiary of the FCIC on sensitivity of yield to extreme climate variables, with the model that Yu et al (2017) has developed.

Consider a representative farmer in a representative year who chooses to plant $A_j(w_j)$ acres of each crop j as a function of the extreme weather parameters of w_j. Let the premium rate (price) of insurance absent any subsidies for crop j and farmers-chosen coverage level θ_j, be $p_j(\theta_j(w_j))$. We assume that the farm insures all its planted acres at the same coverage level-

Let also the government subsidize insurance at a rate $s(\theta_j)$. $s(\theta_j)$ is constant across location and crops[7]. Then farmers pay a premium rate of $(1 - s(\theta_j))p_j(\theta_j)$ to insure crop j.

Let coverage level θ_j be the share of expected per acre revenue insured by crop insurance. For simplicity, we assume that climate parameters follow a normal distribution of $w_j \sim N(\overline{w_j}, \Sigma_j)$. We also-assume that the farm faces stochastic per acre crop revenue R_j, with mean $\bar{R}_j(\overline{w_j})$.

Assumption 1: Farmers are slow in their decision over changing acreage in response to extreme weather. It means the acreage is a function of the mean conditions of the weather: $A_j(w_j) = A_j(\overline{w_j})$.

Assumption 2: Revenue depends linearly on weather; $R_j(w_j) = \alpha_j + \xi_j w_j$; where α_j and ξ_j are constant. With this, we will have $\bar{R}_j = \alpha_j + \xi_j \overline{w_j}$.

Given the trigger for receiving insurance indemnity from the Government in case of crop damage, we write the crop revenue from an insured acre to be as follows:

$$\text{Crop revenue}_j = Max\left(R_j, \theta_j \bar{R}_j\right) \qquad (1)$$

In which, R_j is the realized market revenue in that year, and $\theta_j \bar{R}_j$ is the insured liability.

Farm profit in this case would be

$$\pi = \sum_{j=1}^{J} \Bigg\{ \underbrace{\max\left(R_j(w_j), \theta_j \bar{R}_j(\overline{w_j})\right) \times A_j(\overline{w_j})}_{Part1} - \underbrace{(1 - s(\theta_j))p_j(\theta_j) \times \theta_j \bar{R}_j(\overline{w_j}) A_j(\overline{w_j}) - C_j(A_j(\overline{w_j}))}_{Part\ 2} \Bigg\} \qquad (2)$$

Where $C_j(A_j)$ denotes the cost function of farmers. $R_j(w_j), \bar{R}_j(\overline{w_j})$ and $A_j(\overline{w_j})$ are all a function of climate conditions w_j or $\overline{w_j}$. For simplicity, we drop their index of these variables in the next lines.

Assumption 3: Farmers only care about the expected return and the risk of their profit and make choices accordingly.

Assumption 4: Farmers prefer higher expected returns to lower expected returns.

Assumption 5: Farmers prefer lower risk to higher risk.

Assumptions 3-5 would enable us to use a mean-variance utility function to model the decisions of farmers. Suppose the farmer maximizes the following mean-variance utility function.

[7] As it is currently in the United States.

$$\max_{\{A_j,\theta_j\}} U = \mu - \kappa\sigma \qquad (3)$$

Where μ is the expected profit, κ is the risk aversion parameter of the farmer, and σ denotes the standard deviation of profit. The standard deviation in this context only depends on part 1 of Equation (2), as it is the stochastic term.

We solve the optimization problem of the typical farmer by first finding the mean and variance of their profit. Let the weather variables w_j have a probability distribution function $f(w_j)$. Then the expected profit of the farmer would be

$$\mu = \int \left(\sum_{j=1}^{J} \left\{ \underbrace{\max(R_j, \theta_j \bar{R}_j) \times A_j}_{Part1} - \underbrace{\left(1 - s(\theta_j)\right) p_j(\theta_j) \times \theta_j \bar{R}_j A_j - C_j(A_j)}_{Part\ 2} \right\} \right) f(w_j) dw_j \qquad (4)$$

Part 2 is constant relative to w_j, so we can bring it out of the integral. To simplify Part 1, we rewrite the maximization term as

$$\max(R_j, \theta_j \bar{R}_j) = R_j + \max(0, \theta_j \bar{R}_j - R_j) = \alpha_j + \xi_j w_j + \max(0, \theta_j \bar{R}_j - R_j)$$

$$\mu = \int \left(\sum_{j=1}^{J} \left\{ \underbrace{\left[\alpha_j + \xi_j w_j + \max(0, \theta_j \bar{R}_j - R_j)\right] \times A_j}_{Part1} - \underbrace{\left(1 - s(\theta_j)\right) p_j(\theta_j) \times \theta_j \bar{R}_j\, A_j - C_j(A_j)}_{Part\ 2} \right\} \right) f(w_j) dw_j \qquad (5)$$

Part 2 are independent of the w_j, and we can take it out of the integral.

Before we proceed, we switch the order of summation and integration based on the linearity of expectation and the fact that the summation is taken over a finite number of units (crops). Since the integrand involves only measurable and bounded functions of weather shocks and includes non-negative components, Fubini's theorem (Billingsley, 1995[8], ch.18, p. 233) ensures that summation

[8] Billingsley, Partick. "Probability and measure. 3rd wiley." *New York* (1995). https://www.colorado.edu/amath/sites/default/files/attached-files/billingsley.pdf

and integration can be interchanged without loss of generality. This rearrangement allows us to interpret the expression as the sum of expected profits across units, each integrated over the distribution of weather realizations.

$$\mu = \sum_{j=1}^{J} \int_{-\infty}^{+\infty} \Big\{ \max\left(0, \theta_j \bar{R}_j - R_j\right) \times A_j f\left(w_j\right) dw_j + \left(\alpha_j + \xi_j \overline{w_j}\right) \times A_j - \Big(1 - s\left(\theta_j\right)\Big) p_j\left(\theta_j\right) \times \theta_j \bar{R}_j A_j - C_j\left(A_j\right) \Big\}$$

Given the expression inside the maximum function, we can establish that $0 \le R_j \le \theta_j \bar{R}_j$. This would yield $\max\left(0, \theta_j \bar{R}_j - R_j\right) = \theta_j \bar{R}_j - R_j$. Plugging in $R_j = \alpha_j + \xi_j w_j$ and $\bar{R}_j = \alpha_j + \xi_j \overline{w_j}$, we will have

$$\mu = \sum_{j=1}^{J} \Bigg\{ \underbrace{\int_{-\infty}^{+\infty} \left(\theta_j\left(\alpha_j + \xi_j \overline{w_j}\right) - \alpha_j - \xi_j w_j\right) \times A_j f\left(w_j\right) dw_j}_{revenue\ of\ farmers\ from\ insurance} + \underbrace{\left(\alpha_j + \xi_j \overline{w_j}\right) \times A_j}_{average\ crop\ revenue} - \underbrace{\Big(1 - s\left(\theta_j\right)\Big) p_j\left(\theta_j\right) \times \theta_j \left(\alpha_j + \xi_j \overline{w_j}\right) A_j}_{premium\ payment\ of\ farmers} - \underbrace{C_j\left(A_j\right)}_{production\ cost\ of\ farmers} \Bigg\} \qquad (6)$$

This further simplifies to

$$\mu = \sum_{j=1}^{J} \Bigg\{ \left(\theta_j\left(\alpha_j + \xi_j \overline{w_j}\right) - \alpha_j\right) \times A_j - \theta_j\, \xi_j \times A_j \int_{-\infty}^{+\infty} w_j f\left(w_j\right) dw_j + \underbrace{\left(\alpha_j + \xi_j \overline{w_j}\right) \times A_j}_{average\ crop\ revenue} - \underbrace{\Big(1 - s\left(\theta_j\right)\Big) p_j\left(\theta_j\right) \times \theta_j \left(\alpha_j + \xi_j \overline{w_j}\right) A_j}_{premium\ payment\ of\ farmers} - \underbrace{C_j\left(A_j\right)}_{production\ cost\ of\ farmers} \Bigg\}$$

Earlier we set $w_j \sim N(\overline{w_j}, \Sigma_j)$. This let us simplify this expression to

$$\mu = \sum_{j=1}^{J} \Big\{ \left(\theta_j\left(\alpha_j + \xi_j \overline{w_j}\right) - \alpha_j\right) \times A_j - \theta_j \xi_j \times A_j \overline{w_j} + \left(\alpha_j + \xi_j \overline{w_j}\right) \times A_j - \Big(1 - s\left(\theta_j\right)\Big) p_j\left(\theta_j\right) \times \theta_j \left(\alpha_j + \xi_j \overline{w_j}\right) A_j - C_j\left(A_j\right) \Big\} \qquad (6)$$

Simplify it to make the cancelling terms more clear

$$\mu = \sum_{j=1}^{J} \Big\{ \theta_j \alpha_j \times A_j + \theta_j \xi_j \overline{w_j} \times A_j \underbrace{-\alpha_j \times A_j + \alpha_j \times A_j}_{\textit{these two terms cancel out}} - \theta_j \xi_j \times A_j \overline{w_j} + \xi_j \overline{w_j} \times A_j - \Big(1 - s(\theta_j)\Big) p_j(\theta_j) \times \theta_j (\alpha_j + \xi_j \overline{w_j}) A_j - C_j(A_j) \Big\}$$

We eventually will have

$$\mu = \sum_{j=1}^{J} \Big\{ \theta_j \alpha_j \times A_j + \theta_j \xi_j \overline{w_j} \times A_j - \theta_j \xi_j \times A_j \overline{w_j} + \xi_j \overline{w_j} \times A_j - \Big(1 - s(\theta_j)\Big) p_j(\theta_j) \times \theta_j (\alpha_j + \xi_j \overline{w_j}) A_j - C_j(A_j) \Big\} \qquad (7)$$

Assumption 6: Absent the subsidies, the insurance premiums $p_j(\theta_j)$ are set at an actuarially fair level.

It is a simplifying assumption that would mean the premium would be equal to the expected value of loss of farmers. We borrow from the Equation (5), without the subsidy part to have:

$$p_j(\theta_j) \times \theta_j \bar{R}_j A_j = \theta_j \alpha_j \times A_j + \theta_j \xi_j \overline{w_j} \times A_j - \theta_j \xi_j \times A_j \overline{w_j} + \xi_j \overline{w_j} \times A_j$$

Rewrite it in terms of $p_j(\theta_j)$ to have

$$p_j(\theta_j) = \frac{\theta_j \alpha_j \times A_j + \theta_j \xi_j \overline{w_j} \times A_j - \theta_j \xi_j \times A_j \overline{w_j} + \xi_j \overline{w_j} \times A_j}{\theta_j \bar{R}_j A_j} = \frac{\theta_j \alpha_j + \xi_j \overline{w_j}}{\theta_j \bar{R}_j} \qquad (8)$$

To be completed.

Causal inference

The main challenge in identifying the response of acreage to premium subsidies is that farmer-received subsidies are endogenous to acreage. Farmers choose acreage and insurance coverage simultaneously. To overcome this endogeneity, as used the instrumental variable (IV) developed by (Yu, Smith and Sumner, 2017[9]). The IV is as follows: the US Congress or the USDA has increased the crop insurance subsidy rates per dollar of premium multiple times over the period of this study.

[9] Yu, Jisang, Aaron Smith, and Daniel A. Sumner. "Effects of crop insurance premium subsidies on crop acreage." *American Journal of Agricultural Economics* 100, no. 1 (2018): 91-114.

The 1994, the 2000 and the 2008 Farm Bill Acts changed the subsidy rates. We take these government policy changes as exogenous to acreage and use them in our regression to instrument for changes in the received premium subsidy.

Previous literature

Yu, Smith and Sumner, 2017[10]: Research on the acreage effects of U.S. crop insurance, which is directly relevant to the present article, is much more limited. Significant articles include Wu (1999), Young, Vandeveer, and Schnepf (2001), Goodwin, Vandeveer, and Deal (2004), and Goodwin and Smith (2013). Using data from Central Nebraska in 1991, Wu (1999) esti mates a system of equations of crop shares and crop insurance choices, and finds that making crop insurance available for corn leads to 5% to 27% increases in the share of corn acreage. The simulations of Young, Vandeveer, and Schnepf (2001) imply that the total acreage of eight major field crops would fall by about 0.4% as a response to the removal of all federal crop insurance subsidies. Goodwin, Vandeveer, and Deal (2004) empirically investigate the responses of acreage to U.S. federal crop insurance programs for corn, soybeans, and wheat. Based on data from the Corn Belt and the Northern Great Plains in 1985–1993, these authors find that premium subsidies increase crop insurance participation, and higher crop insurance participation rates induce acreage expansions. These authors' simulations imply that a 30% decrease in the farm-paid premium (an in crease in subsidy) for corn and soybeans would increase corn acreage by 0.28% to 0.49%. Goodwin and Smith (2013) present preliminary empirical estimates that also sug gest positive effects of premium subsidies on acreage.

Yu, Smith and Sumner, 2017[11]: standard expected utility theory suggests that farmers with any non-increasing absolute risk aversion preference would increase acreage of the crop as the riskiness decreases (Hennessy 1998). Goodwin (1993), Goodwin, Vandeveer, and Deal (2004) and O'Donoghue (2014) find empirical evidence on the positive effect of premium subsidies on the demand for crop insurance.

Data

We used the replication packages of two papers of 1- Annan and Schlenker (2015)[12] and Yu, Smith and Sumner (2018)[13] in this research. We limited the scope of paper to two crops of corn and

[10] Yu, Jisang, Aaron Smith, and Daniel A. Sumner. "Effects of crop insurance premium subsidies on crop acreage." *American Journal of Agricultural Economics* 100, no. 1 (2018): 91-114.
[11] Yu, Jisang, Aaron Smith, and Daniel A. Sumner. "Effects of crop insurance premium subsidies on crop acreage." *American Journal of Agricultural Economics* 100, no. 1 (2018): 91-114.
[12] Annan, Francis, and Wolfram Schlenker. "Federal crop insurance and the disincentive to adapt to extreme heat." *American Economic Review* 105, no. 5 (2015): 262-266.
[13] Yu, Jisang, Aaron Smith, and Daniel A. Sumner. "Effects of crop insurance premium subsidies on crop acreage." *American Journal of Agricultural Economics* 100, no. 1 (2018): 91-114.

soybeans, in eight Midwest States of Illinois (state code 17), Indiana (18), Iowa (19) and Michigan (26), Minnesota (27), Missouri (29), Ohio (39) and Wisconsin (55), over the years 1989 to 2013.

Annan and Schlenker (2015)[14] combines the publicly available data on county-level insurance coverage (RMA) with data on county-level acres planted and yields for corn and soybeans (NASS). The two data sources derive county aggregates in different ways: the RMA data is the sum of all actual contracts for a given year in the county. The NASS data on the other hand, uses a representative subsample of all farms in the June Agricultural Survey of each year to approximate the planting area in a county and hence has sampling noise. As a result, the fraction insured, the ratio of the insured planted area to the total planting area can be larger than one if the NASS estimate in the denominator is an underestimate of the actual planting area.

Yu et al (2018)[15] uses the annual county-level information on crop acreage and crop insurance characteristics for major field crops from surveys of the USDA National Agricultural Statistical Service (NASS) and the RMA's Summary of Business (SOB). For price data, the authors have used futures price data for corn, cotton, soybeans, rice, and wheat as reported by the Commodity Research Bureau (CRB, 2016) and then deflated each price by the Producer Price Index from the Bureau of Labor Statistics (BLS, 2016)[16].

There are observations without a specific county, recorded as "other" in the dataset. Since they are not tractable through years, we dropped those observations. It made the panel dataset unbalanced.

[14] Annan, Francis, and Wolfram Schlenker. "Federal crop insurance and the disincentive to adapt to extreme heat." *American Economic Review* 105, no. 5 (2015): 262-266.

[15] Yu, Jisang, Aaron Smith, and Daniel A. Sumner. "Effects of crop insurance premium subsidies on crop acreage." *American Journal of Agricultural Economics* 100, no. 1 (2018): 91-114.

[16] Further details from page 97 of the Yu et al (2018) paper: We construct each expected price variable using both futures prices and average prices received by farms. We regress the State-level annual prices received by farms on state dummies and futures prices for 1989-2014. We use the predicted values from this regression as the expected prices. We use similar futures prices as those used by the RMA in their price projection, and we use the average price from January to the signup deadline of crop insurance contracts. Due to the absence of relevant futures markets, the RMA uses CBOT corn futures prices to project prices of barley and sorghum (RMA, 2016). We follow the RMA's practice and use CBOT corn futures to construct farmers' price expectations of barley and sorghum. The underlying assumptions are: (a) the state-level basis relationships do not change, (b) the relationship between the realized prices and the futures prices do not change, and (c) the farms know these relationships.

Table 1- Summary of Statistics

	1989–1993	2010–2013	1989-2013
yield	74.354 (41.395)	92.684 (54.658)	86.337 (50.394)
areaPlanted	64801.054 (54860.524)	77085.560 (58295.910)	71705.231 (56463.097)
areaInsured	21388.701 (29829.906)	64330.863 (52459.897)	46947.015 (47008.809)
ddayMod	1.565 (0.295)	1.705 (0.273)	1.620 (0.278)
ddayHot	0.175 (0.186)	0.337 (0.308)	0.211 (0.217)
prec	0.622 (0.168)	0.604 (0.164)	0.598 (0.142)
premiumTotal	159618.796 (223581.631)	2808928.141 (2488180.487)	1069204.909 (1680648.733)
subsidy	38579.400 (52651.464)	1647175.454 (1412872.050)	584180.282 (948482.282)
price_received	138.334 (62.529)	159.380 (59.386)	131.017 (58.131)
crop_county_sublia	0.018 (0.011)	0.060 (0.028)	0.045 (0.031)
crop_insurance	0.145 (0.145)	0.571 (0.195)	0.373 (0.251)
crop_county_subrate	0.258 (0.037)	0.606 (0.063)	0.494 (0.161)
crop_county_premrate	0.069 (0.037)	0.097 (0.039)	0.086 (0.042)
fracInsured	26.943 (20.126)	80.150 (13.695)	59.987 (26.608)
N	6568	5007	32289

Estimation Strategy

Econometric Model Specification

We model the change in acreage as a dynamic panel model. The dependent variable is planted acreage, A_{ijt}, for county i, crop j and year t. The main explanatory variable is subsidy per dollar of liability, Γ_{ijt}. The main explanatory variables are subsidy per dollar of liability, Γ_{ijt}, percentage of land insured, P_{ijt}, and climate-related variables, number of heating degree days, and number of moderate days, amount of precipitation, and its squared value, all denoted collectively as $\mathcal{W}_{ijt}$. Control variables are acreage planted in the previous period, A_{ijt-1}, expected price, EP_{ijt}, crop-specific time trends, $Time_{jt}$, and county-crop fixed effects, ν_{ij}. The regression equation is

$$\ln(A_{ijt}) = \beta_0 + \beta_1\Gamma_{ijt} + \beta_2 EP_{ijt} + \beta_3 A_{ijt-1} + \sum_j \beta_{j4} Time_{jt} + \beta_5 P_{ijt} + \beta_{j6}\mathcal{W}_{ijt} + \beta_{jw7}\mathcal{W}_{ijt}(\Gamma_{ijt} - \overline{\Gamma_{\iota jt}}) + \beta_{jw8}\mathcal{W}_{ijt}(P_{ijt} - \overline{P_{\iota jt}}) + \nu_{ij} + u_{ijt} \quad (9)$$

u_{ijt} denotes random errors. The county-crop fixed effect captures unobserved heterogeneity across counties for each crop and across crops for each county. The crop-specific time trends capture unobserved heterogeneity across crops for each year. We include county-crop fixed effects (FE) in our models; hence, our identification comes from the correlation between the legislative changes in subsidy rates and county-level planted acreage of the crops.

Here, our main coefficient of interest are β_{j7}, but we have added the Γ_{ijt} as a single term, out of interaction as well, since according to Balli and Sørensen (2010[17], p. 2), in a regression with interaction terms, main terms should always be included; otherwise, excluding them would cause left-out variable bias. Moreover, we wrote the interaction term after demeaning the Γ_{ijt}, as according to Balli and Sørensen (2010[18], p. 3), it is easier to compare the models with and without the interaction terms.

Including the lag of dependent variable could cause a potential "Nickell bias" (Nickell, 1981[19]). Our study covers the span of 25 years, and has 32289 unique county-crop panel identifiers. Since the Nickell bias is proportional to the inverse of number of time periods, we expect the bias to be small,

[17] Balli, Hatice Ozer, and Bent E. Sørensen. "Interaction effects in econometrics." Empirical Economics 45, no. 1 (2013): 583-603. Earlier draft in 2010 that is reference in this paper: https://www.uh.edu/~bsorense/Ozer-Balli_Sorensen.pdf

[18] Balli, Hatice Ozer, and Bent E. Sørensen. "Interaction effects in econometrics." Empirical Economics 45, no. 1 (2013): 583-603. Earlier draft in 2010 that is reference in this paper: https://www.uh.edu/~bsorense/Ozer-Balli_Sorensen.pdf

[19] Nickell, Stephen. "Biases in dynamic models with fixed effects." Econometrica: Journal of the econometric society (1981): 1417-1426.

in the other of 4 percent. Also, our interest is to identify the causal relationship between the planted acreage and the crop insurance premium subsidy and percent of land insured; not the dynamic relationship between the current planted acreage and its lag. The bias in the coefficient of the premium subsidy is less problematic when the covariance of the demeaned premium subsidy variable and the demeaned lagged dependent variable is small.

Endogeneity of Γ_{ijt} and P_{ijt}

The subsidy per dollar of liability Γ_{ijt} is the weighted average of $\Gamma_i(\theta_j)$ defined in the Framework section across farms and coverage levels for each crop-county-year. Figure 8 illustrates the variation of the subsidy per dollar of liability over time and in the cross-section that stems from subsidy rates, riskiness, and choice of coverage level. Its dependence on both riskiness and coverage level makes Γ_{ijt} potentially endogenous to acreage (channels one and two of endogeneity, respectively). A more risky crop or a more risky county has a higher premium rate for a given crop insurance choice. As a result, all else equal, farmers tend to plant less riskier crops and plant less in riskier counties. Thus, omitting the "riskiness" variable that has a positive correlation with Γ_{ijt}, would cause an upward bias in OLS estimate for coefficient of Γ_{ijt}. Our model includes county-crop fixed effects, which control for any differences in riskiness that are constant over time, but differ by county or crop. The fixed effects cannot control for any changes in county-crop riskiness over time (like change in climate).

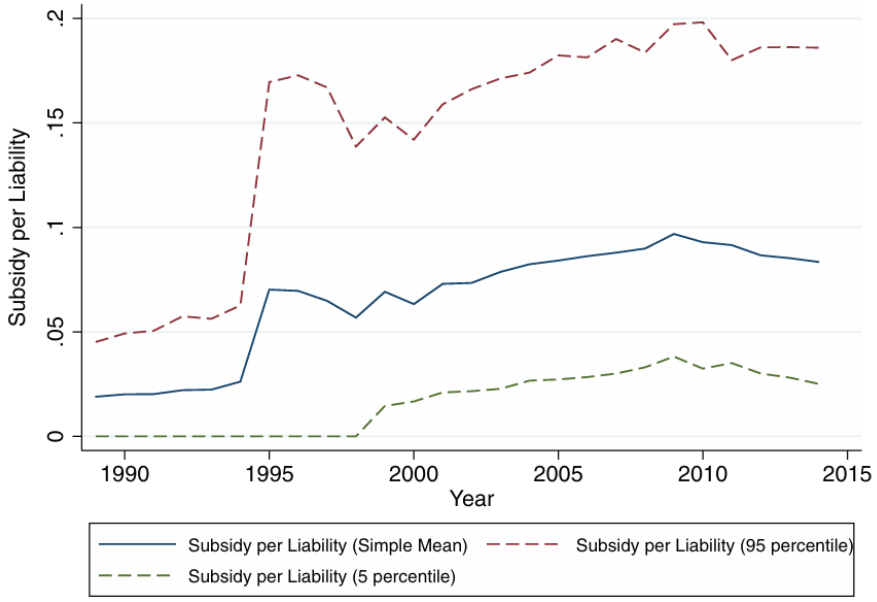


Figure 2. Subsidy per dollar of insured liability (1989–2014)

Note: The mean, 95 percentile, and 5 percentile are computed from unweighted distribution of the subsidy per dollar of insured liability. The figure represents the distribution of county-crop combination for each year and its change over time.

Figure 8- Subsidies per dollar of insured liability over the 1989-2014 period (from Yu et al (2017))

A second source of endogeneity is the dependence of Γ_{ijt} on the choice of coverage level. Although the sign of relationship is not determined. Recalling that we defined $\Gamma_j(\theta_j) = s(\theta_j)p_j(\theta_j)$, we have:

- An increase in the chosen coverage level for a crop may cause the subsidy rate to decrease because the subsidy rate is lower for the higher coverage levels ($s'^{(\theta_j)} < 0$).
- Also, the premium rate increases with the coverage level ($p'_j(\theta_j) > 0$).

So, the signed of $\Gamma'_j(\theta_j)$ is unknown. If Γ and θ are positively (negatively) correlated, and θ has a positive impact on crop acreage, the OLS would overestimate (underestimate) the impact of Γ on acreage.

Identification Strategy

We follow Yu et al (2017) and exploit the exogenous government-set variations in the subsidy rate that were illustrated in *Figure 7* to deal with the endogeneity of the premium subsidy. We instrument $\ln(\Gamma_{ijt})$ with subsidy rate for yield protection and revenue protection with 65 percent and 75 percent coverage levels. We choose these two particular coverage levels, as they are the most common converge levels and span the full 25 years of study. We define the variables $s65_t$ and $s75_t$ as the total subsidy paid for 65 and 75 percent coverage divided by the total premium paid for 65 and 75 percent coverage, respectively.

Discussion about the relevance and exclusion restriction of the instrumental variable

Assumption 7: The legislative changes in subsidy rates in Farm Bills of 1994, 2000 and 2008 was a response to factors separate from crop acreage.

With Assumption 7, we can establish that the IV is indeed exogenous and satisfies the exclusion restriction for valid instrumental variables. In terms of relevance of IVs, the IVs are coverage-specific.

Instrumental variable strength and validity

To verify the strength of the instrumental variables, I manually run the first stage of the IV as follows:

$$ln(\Gamma_{ijt}) = \alpha_0 + \alpha_1 s65_t + \alpha_2 s75_t + \alpha_3 \mathrm{EP}_{ijt} + \beta_5 \mathrm{P}_{ijt} + \beta_{j6} \mathcal{W}_{ijt} + \alpha_4 \mathrm{A}_{ijt-1} + \sum_j \alpha_{j4} Time_{jt} + \varepsilon_{ijt} \quad (10)$$

Fixed effects are at the county-crop level and the robust standard errors are clustered at the State-level. We clustered at the State-level, as according to Cameron, Gelbach, and Miller (2012)[20], for nested two-way or multiway clustering, one should cluster at the highest level of aggregation. For example, with individual-level data and clustering on both household and state one should cluster on state. The F-statistic for the Null hypothesis that the coefficients on the instrumental variables equals 0 is 521.4 which is far above the Stock-Yogo threshold[21] of thumb of ten for strong instruments.

Table 2- The first-Stage regression for log-log model

VARIABLES	(Yu et al - without climate) sublia	(This paper- with climate) sublia
nationalsubrate65	7.085***	7.126***
	(0.644)	(0.758)
nationalsubrate75	-3.072***	-3.121***
	(0.457)	(0.515)
L.lnacresplanted	-0.130***	-0.133***
	(0.0358)	(0.0353)
lnprice_received	-0.0145	-0.0516
	(0.0604)	(0.0597)
lnfracInsured		-0.00436
		(0.0226)
lddayMod		-0.261**
		(0.107)
lddayHot		-0.0110
		(0.0110)
lprec_cm		-0.867
		(4.567)
lprec2_cm		0.438
		(2.283)
corntime	0.0205***	0.0227***
	(0.00397)	(0.00370)
soybeantime	0.0302***	0.0323***
	(0.00276)	(0.00236)
Constant	-4.392***	-2.888***
	(0.617)	(0.599)
Observations	30,500	30,496
R-squared	0.839	0.841
Number of panelID	1,364	1,364

[20] Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. "Robust inference with multiway clustering." Journal of Business & Economic Statistics 29, no. 2 (2011): 238-249.
[21] Stock, James H., and Motohiro Yogo. "Testing for weak instruments in linear IV regression." (2002).

F-stat excluded instruments	521.4	279

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

In table 3, we used both instrumental variables for two endogenous variables separately: column 2 for sublia as the dependent variable and column 3 for fraction insured as the dependent variable. The F-statistic shows that IV is valid in both cases.

Table 3- Log-linear model for the first stage of the instrumental variable regression.

VARIABLES	(Yu et al, without climate) sublia	(This paper) sublia	(This paper) fracInsured
nationalsubrate65	7.148***	7.096***	332.0***
	(0.620)	(0.603)	(21.78)
nationalsubrate75	-3.082***	-3.074***	-176.8***
	(0.451)	(0.451)	(13.74)
L.acresplanted	-2.90e-06***	-3.00e-06***	-1.13e-06
	(4.33e-07)	(4.01e-07)	(3.62e-05)
price_received	7.58e-05	-0.000124	0.000845
	(0.000420)	(0.000418)	(0.0122)
ddayMod_100		-0.00130**	-0.0367
		(0.000512)	(0.0346)
ddayHot_100		-0.00152***	0.0833***
		(0.000376)	(0.0143)
prec_cm		-0.000393	0.459***
		(0.00192)	(0.0815)
prec2_cm		1.11e-06	-0.00287***
		(1.39e-05)	(0.000444)
corntime	0.0202***	0.0225***	1.288***
	(0.00360)	(0.00351)	(0.0641)
soybeantime	0.0283***	0.0304***	1.450***
	(0.00266)	(0.00235)	(0.0947)
Constant	-5.673***	-5.385***	-60.58***
	(0.139)	(0.150)	(5.019)
Observations	30,500	30,500	30,500
R-squared	0.838	0.842	0.755
Number of panelID	1,364	1,364	1,364
F-stat excluded instruments	420.3	468	133

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

Results

Next, we present the results of estimating Equation (11) with and without the use of IV in Table 3.

Table 4- Estimation of Equation 11- Effets of the premium subsidy on crop acreage

VARIABLES	(without IV) lnacresplanted	(with IV) lnacresplanted
sublia	-0.019	0.038**
	(0.012)	(0.015)
lnprice_received	0.033**	0.062***
	(0.0097)	(0.013)
lnacresplanted = L,	0.78***	0.80***
	(0.038)	(0.033)
corntime	0.0025	-0.0015
	(0.0013)	(0.0013)
soybeantime	0.0033*	-0.0011
	(0.0017)	(0.0016)
Constant	2.14***	
	(0.40)	
Observations	30,500	30,486
R-squared	0.699	0.695
Number of panelID	1,364	1,350

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

When I add the climate variables from Annan and Schlenker (2015).

Table 5- Re

VARIABLES	(1-without IV-Yu et al) lnacresplanted	(2-with IV-Yu et al) lnacresplanted	(3-without IV-this paper-loglog) lnacresplanted	(4-with IV-this paper-loglog) lnacresplanted
ln(Subsidy per Liability)	-0.019	0.038**	-0.018	0.036***
	(0.012)	(0.015)	(0.010)	(0.012)
lnprice_received	0.033**	0.062***	0.038***	0.068***
	(0.0097)	(0.013)	(0.0093)	(0.010)
lnacresplanted = L,	0.78***	0.80***	0.78***	0.80***
	(0.038)	(0.033)	(0.038)	(0.033)
lddayHot			-0.0038	-0.0019
			(0.0033)	(0.0028)
lprec2_cm			-0.041***	-0.038***
			(0.011)	(0.011)
corntime	0.0025	-0.0015	0.0023	-0.0016

	(0.0013)	(0.0013)	(0.0012)	(0.0011)
soybeantime	0.0033*	-0.0011	0.0031*	-0.00078
	(0.0017)	(0.0016)	(0.0016)	(0.0015)
Constant	2.14***		2.46***	
	(0.40)		(0.42)	
Observations	30,500	30,486	30,496	30,482
R-squared	0.699	0.695	0.703	0.700
Number of panelID	1,364	1,350	1,364	1,350

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

For the log-linear model, results are as follows:

We report results both with and without the interaction terms (in the log-linear model).

Sensitivity analysis

Subsets can be different years, states or crops

Different functional form

Table 3 shows that a 10 percent increase in the premium subsidy induces about 0.38 percent more planted acres. Absent use of IV, we would have estimated an effect with an insignificant coefficients with an opposite sign (row 1 in column 1). We estimate an own price elasticity of 0.062 (for lnprice_received). When looking at crop-specific behaviors, we see the following as in Table 3crop:

Table 3crop- Crop specific replication of table 3

VARIABLES	(IV-corn and soybeans) lnacresplanted	(IV-corn) lnacresplanted	(IV-soybeans) lnacresplanted
sublia	0.038**	-0.052***	0.086***
	(0.015)	(0.020)	(0.031)
lnacresplanted = L,	0.80***	0.56***	0.84***
	(0.033)	(0.043)	(0.015)
lnprice_received	0.062***	0.069***	0.084***
	(0.013)	(0.023)	(0.023)

corntime	-0.0015	0.0052***	
	(0.0013)	(0.0016)	
soybeantime	-0.0011		-0.0052*
	(0.0016)		(0.0028)
Observations	30,486	15,615	14,871
R-squared	0.695	0.386	0.826
Number of panelID	1,350	696	654

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

Appendix A

Add descriptive statistics (Table 1) by crop.

Appendix B

In case of using either of the log-log or log-linear model in the body of the paper, report the results for the other one in the appendix B.