On the Demand for Federal Crop Insurance

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Federal Crop Insurance

The United States Federal Crop Insurance Program (FCIP) has received signifcant attention as far as the United States food and agricultural policies are concerned. The program was created in the 1930s mainly as a risk management tool and has now become one of the major agricultural support programs in the United States. The coverage of the FCIP was initially limited but is currently characterized by a mix of many programs. The crop insurance programs have undergone many periodic modifications through the passage of various federal Acts and farm bills. [1]

The enactment of the 1980 Federal Crop Insurance Act significantly expanded crop insurance to many more crops and regions in the country. The Act greatly encouraged participation by offering farmers subsidized insurance premiums. Between 1988 and 1994, annual ad hoc disaster assistance programs were implemented to further provide relief to producers. Notably, the 1994 "Crop Insurance Reform Act" eliminated annual disaster programs, and made participation in crop insurance mandatory. This Act instituted catastrophic (CAT) coverage to protect producers against major losses at no cost to the producers including greater premium subsidy levels.

In recent years (e.g., the 2000 "Ag. Risk Protection Act"), Congress has even increased premium subsidy levels, while at the same time the role of the private sector in developing new insurance products has grown substantially. The current subsidies cover a significant fraction of insurance premiums. As a result of these changes, the program has experienced tremendous growth in participation, especially since the 1994 Act (Annan et al. 2014, and

[1] The various Acts reviewed for this paper were taken from the website of the Risk Management Agency (RMA) of the USDA (and Wang and Annan 2015): http://www.rma.usda.gov/aboutrma/what/history.html

Annan and Schlenker 2015). The major subsidy Acts centered on making insurance more affordable and improving the insurance program's compliance and integrity. These provide plausibly exogenous variation in insurance premiums. The construction of our instrument in the empirical exercise relies on these reforms following Annan (2015).

The FCIP contracts including premium subsidies are administed by the Federal Crop Insurance Corporation FCIC under the supervision of the Risk Management Agency (RMA) of the United State Department of Agriculture (USDA). The contracts which are designed by the RMA are sold and serviced through private insurance providers that are approved by the FCIC. The FCIC reinsure and approve the terms and conditons of the Federal contracts.

Insurance Plans

The Federal crop insurance program currently provides a mix of both yield-based coverage and revenue insurance. More generally, indemnity payments are triggered whenever yield or price realizations fall below certain guaranteed levels.[2] The plans may broadly exist occur either at the farm (individual-based) or county (area-based) levels. Examples of the policies include the actual production history (APH), actual revenue history (ARH), group risk income protection (GRIP), group risk plan (GRP) and etc. The most widely used yield based plan in the Federal crop insurance is the multiple peril crop insurance (MPCI). The MPCI, which is "individual based", provides comprehensive protection against various unavoidable perils including weather related causes.

Next, the GRP, also called area-yield insurance, is based on average county-yields. Introduced in 1993, the GRP had an insurance liability of about $2.5 million in its first year and is available for several crops. Together with its revenue insurance counterpart (that is, the GRIP), both covered a liability of about $8.5 billion on over 34 million acres insured

[2] The various insurance plans mentioned here were taken from the website of the Risk Management Agency of the USDA: http://www.rma.usda.gov/policies/. See this website for details.

by the year 2008 (Harri et al. 2011). Insured producers are paid indemnities when the average county yields fall below a county-yield guarantee, where the guarantee is simply the product of the expected county yields and a selected coverage level. In general, it is rare for producers to have access to better information about the overall county-yields than an insurance company. Asymmetric information: adverse selection and moral hazard which reduce the soundness of an actuarial process are therefore mitigated to a larger extent in the GRP compared to farm yield-based insurance counterparts. Another advantage is that insurers or rate makers are able to more accurately rate the county level plan since longer time series data is available.

The revenue insurance policies protects against revenue or gross income losses due to yield or price shortfalls. There are different revenue insurance policies which arise based on how “revenue” is defined and the way in which the coverage is provided. The group revenue insurance version (GRIP) pays indemnities when the average county revenue for the insured crop declines below the revenue level selected by the farmer. The adjusted gross revenue insurance (AGR) insures the revenue of the entire farm, not just the revenue derived from individual crops. This guarantees a percentage of the producers’ average gross revenue. The crop revenue coverage (CRC) protects against price and yield losses below a guarantee based on the higher of either an early season price or harvest price. Modifications of the definiton of “revenue” lead to other policies, including income protection (IP) and revenue assurance (RA). While the former protects producers against reductions in gross income when insured crop’s price or yield falls from early-season expectations, the latter permits farmers to select a dollar amount of target revenue from a range expressed in term of percentages of expected revenue. The empirical exercise derives the main outcome of interest by aggregating over all the various insurance plans. Future work will examine potential heterogeneity along the lines of individual versus area-based plans.

The remainder of this paper is organized as follows. Section 2 discusses the data used in the empirical analysis. Section 3 presents our empirical modelling framework and results. For illustration, these estimates are comapred with previous work. The final section concludes. All Tables and Figures are collected in the Appendix.

Data and Measurements

The data is an unbalance panel: covering over 673 counties in the Corn belt[3], and spanning 1989 through 2013. To be included in the main analysis, the county must have at least 23 years of available data. Our data come from multiple sources. The yields which are used to derive a measure of variabilty in production are constructed using data on total production and total planted acres. These two come from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA).[4] Particularly, the yield series are constructed as production per acre planted, rather than per acre harvested to better capture extreme productivity events that would typically trigger insurance payments.

The insurance variables which include: premiums, loss ratios, and total insured acres were obtained from the Risk Management Agency (RMA) of the USDA. These records are publicly available on the "summary of business" files of RMA. Premiums directly from the RMA include all Federally paid subsidies. We were careful to isolate the out-of-pocket premiums for our purposes. We constructed premium rates as out-of-pocket premiums per insured acreage.

Table 1 in the Appendix reports the moments, the smallest and largest order statistics of the main outcome variable *fraction of planted acreage insured*. The Table shows that considerable variation exist, even at the state level.[5] It is not surprising that the top-four major corn producing states which include Iowa, Illinois, Nebraska and Minnesota have the

[3]The empirical analysis reflect corn producers. We focus on the Corn belt: together, this region produces more than 90% of annual United States Corn output.

[4]Downloaded from http://quickstats.nass.usda.gov.

[5]This under-states the county level variation in our data.

largest mean insurance demand over the sample period. The total number of observations is 16,608, corresponding to the 673 counties.

To examine further the variation in fraction insured, Figure 2 plots the spatial distribution of average fraction insured while Figure 3 plots the standard deviation of fraction insured at the county level. To generate Figure 2, we compute the average taken over time realizations per county. These are then mapped over the entire United States. For Figure 3, we derive the standard deviation of the fraction of the land insured per county. Similarly, the county level standard deviations are mapped over the entire United States. Both figures suggest that there is significance variation in the average fraction insured (SD) across counties over the period. As in Table 1, large fractions acreage are insured in counties located in the major corn producing states. Figures 2 and 3 also suggest some positive correlation between the average fraction insured and the underlying variability (SD). This correlation is about 40% and it is statistically siginificant at 1%.

Figure 1 further displays the distribution of the *fraction of planted acreage insured* variable by year. The Figure demonstrates two major patterns. First, there is significant variation across counties in terms of the program's expansion. Second, there is tremendous variation across years and the expansion of the program has been higher in recent years. There are observable trends (see e.g., movement of the median) in insurance demand. Finally, our weather data come from Schlenker and Roberts 2009, which has been updated to include recent years. The weather variables include growing degree days (GDD)[6], precipation and precipation-squared. We briefly discuss Schlenker and Roberts 2009's data construction process here.

Schlenker and Roberts 2009 constructed a fine-scale weather data based on the following

[6]GDD are a measure of heat accumulation used by farmer to predict a crop will reach maturity. GDD are calculated by taking the average of the daily maximum and minimum temperatures compared to a base temperature, T_{base}, (usually 10 °C). As an equation, $GDD = (T_{MAX} + T_{MIN})/2 - T_{base}$. For example, a day with a high of 23 °C and a low of 12 °C (and a base of 10 °C) would contribute 7.5 GDDs.

procedure. They begin by developing daily predictions of minimum and maximum temperature on a 2.5X2.5-mile grid for the entire United States. Next, the time at which a crop (here, Corn) is exposed to each one-degree Celsius interval in each grid cell in each day is derived. The predictions are merged with satellite scan records to restrict attention to grid cells that has cropland. They derive county aggregates by aggregating the whole distribution of realizations for all days in the growing season per county. In our empirical exercise, we rely on cummulative growing degree days cGDD outcomes and precipation records from Schlenker and Roberts 2009 to control for weather.

Modelling and Estimates

We explore the *fraction of planted acreage insured*, or simply "insured area", as our main outcome of interest. Denote by i a county and t year. We directly follow Annan and Schlenker 2015 in constructing the "insured area" variable. This is simply given by

$$\equiv \frac{\text{Total Insured Acres}_{it}}{\text{Total Planted Acres}_{it}}$$

Notice that RMA's reported total insured area can strangely exceed that of NASS's reported total planted area in the data set. In practice, we drop all cases where the fraction of insured area is larger than 1.0 as these are likely to emanate from data reporting errors.[7] Although not reported here, we also fix this object to 1.0 or drop the counties in question entirely whenever it is larger than 1.0 in the sequel. These alternative constructions did not significantly change the main empirical results.

[7] Another hypothesis, aside data reporting errors, will be double cropping and replanted acreage. The latter is more likely to be the case for sounthern United States. Figure A3 in the online Appendix of Annan and Schlenker 2015 shows the areas/counties where the fraction is larger than 1. Most of this is however in the northern part of the United States, eg. North Dakota.

Panel Estimates

Throughout, our modelling is at the county level. We start by considering commonly used county panel specification (see e.g., Goodwin 1993). Here "insured area" (in logs) y_{it} is assumed to linearly depend on the out-of-pocket premium rate (in logs) p_{it}, county-level fixed effects λ_i, and potential unobserved idiosyncratic county-specific time-varying factors ε_{it},

$$y_{it} = \gamma p_{it} + \beta X_{it} + \alpha + \lambda_i + f(Time) + \varepsilon_{it}$$

This formulation also includes literature-relevant covariates X_{it}. The expected utility maximization is usually the assumed framework within which the determinants of insurance purchases are determined (see e.g., Borch 1990). Motivated by this framework and the related literature, we include the following controls: average loss ratios in past 3 years (e.g., Goodwin 1993 and recent others), and yields-squared/variabilty in the last year in the covariates vector X_{it}. The vector also includes important weather controls and their nonlinearities in the lagged one year. The burgeoning climate economics literature (e.g., see Schlenker and Roberts 2009; Emerick and Burke 2013, Annan and Schlenker 2015, and etc) have shown that weather is a strong predictor of ag. output – and thus crucial when thinking about how rational economic producers make insurance purchase decisions. While contempraneous weather may be of little importance, past/lagged weather can crucial in farmer insurance decision making processes, eg., via adaptive expectations. We restrict attention to the role previous weather realizations. Here, weather enters the specifications in different forms to capture both instantaneous and/or potential dynamic effects. The county-level fixed effects are important because they soak up potential unobserved heterogeneity (e.g., risk aversion) that is the same across years. Unlike most previous studies, we include flexible time controls $f(Time)$, as we believe these are essential. The time controls capture trends in the insurance program's expansion. In practice, we access the robustness of our main results to different specifications of $f(Time)$ including linear, quadratic and splines. Our main parameter of interest is γ. This is of important policy interest and provides a direct measure of insurance price elasticity, with our log-log specification. [8]All results are robust to potential heteroskedascity of any form. In particular, we report robust standard errors which deals with concerns about normality, heteroscedasticity and outliers.

Results

The first four columns of Figure 4 report parameter estimates and standard errors from a pooled version of the panel model (equivalent to ignoring the i subscript) –under varying controls. The first column includes all the variables in the model, including log form of the premium rate, yield square in one lag, average of the past three years loss ratio, growing degree days in one lag , growing degree days square in one lag, precipitation in one lag, precipitation square in one lag, time trends, and the cross effects by premium rate and loss ratio. The first two columns of Figure 4 report the implied results from the pooled OLS specification. The second column inculdes the cross effects by premium rate and loss ratio. [9] The insurance price elasticities are -0.222, and -0.216 respectively.[10] Next, the last two columns of Figure 4 report the implied results from the county panel specification. The last column includes the cross effects by premium rate and loss ratio. The estimated insurance price elasticities are -0.436, and -0.423 respectively and are statistically significant at the 1% level. As a point of comparison, Goodwin 1993 using county level data from Iowa for 1985-

[8]The dependent variable y_{it} is bounded between 0 and 1, so we are also reporting another result by using the logit transformation of it, which is $ln(y_{it}/1 - y_{it}) = \gamma p_{it} + \beta X_{it} + \alpha + \lambda_i + f(Time) + \varepsilon_{it}$.

[9]We stick to a lag length of 1 for parsimony; longer lags do not meaningfully change our γ estimates.

[10]Employing a Heckman-2-Step type approach and survey elicited cross-sectional farm data set, Smith and Baquet 1996 find an elasticity estimate of -0.59. A fundamental challenge with their study: inability to effectively control for unobserved heterogeneity, although *elicited* farm level data was used. For a mere point of comparison, our pooled regression which neither controls for time-invariant unobserved heterogenity "Colums 1-4 of Table 2" provides an average estimate of about -0.29

1990 and similar specification finds an elasticity of -0.32, which is not too much different from our panel estimate after controlling for potential sampling noise.

The effect of the other control variables including weather and average loss ratio are worth pointing out. In particular, degree days in levels is postive but insignificant in the pooled OLS model. The squared of which is negative and significant at 1% level. On the other hand, the panel model suggests the opposite. Growing degree days in levels is significantly negative, while the squared degree days is siginificantly positive. Precipitation in both models is negative but squared precipitation is positive. Another important variable is the average loss ratio which is taken over the lass three years. This variable is positive and significant in all cases. This suggests that more risky agents are likely to enroll land into insurance.

To clearly understand the contrast between the pooled and panel model estimates, we consider the key identifying assumptions. More formally, the pooled model requires the following orthogonality condition

$$\mathbb{E}(p_t \epsilon_t | X_{it}) = 0, \ \forall t$$

for consistent estimation. In words, this says that the pooled estimate is consistent if changes in premium p_t are uncorrelated with the unknown determinants of "insured area" ε_t. This condition is unlikely to hold due to standard premium endogeneity arguments: while the control vector X_{it} houses many premium determining variables that are observable, there exist unobservables which potentially correlate with premium. A false correlation is created between p_t and ε_t. This causes the pooled elasticity estimate to be biased toward zero, since all of the predicted change in "insured area" is incorrectly attributed to the change in premium. This is a primary challenge in the pooled model, just as in many cross-sectional studies.

The panel model may alleviate this standard premium endogeneity concerns to an extent through the county-fixed effects and time trends that control for unobserved changes in insurance demand –thereby explaining the increase in elasticity estimates in last two columns of Figure 4. It is worth pointing out that the panel approach, however, is an imperfect solution because the county-level premiums may still reflect county-specific differential changes in insurance demand. The next subsection addresses the endogenity problem of insurance premiums more directly using an instrumental variable estimation strategy. We aim to provide well identified elasticities using exogenous changes in premiums that are driven by major Federal subsidy reforms over the period.

Note that the Figure 6 reports the implied results of the pooled OLS estimation and Panel estimation by using the logit transformation of the dependent variable, as a result, if the premium rate increases by 1% then the odd of the fraction insured acres decrease by 0.292%, 0.282%, 0.679%, and 0.666% respectively. Under standard transformations, the results in Figures 6 and 4 coincide.

Panel IV Estimates

Moving forward, we instrument for premiums using episodes of major Federal subsidy Acts that took place over the period. Notable examples, as discussed in the introduction section, include the Federal "Crop Insurance Reform Act" (CIRA) of 1994 and the "Agricultural Risk Protection Act" (ARPA) of 2000. We exploit these exogenous changes to construct the instrument[11]. Denote by Z_{it}^1 an indicator that is equal to 1 whether the CIRA is force,

[11] An potential concern will be that the timing of these reforms/Acts may be correlated with current county-level macroeconomic conditions and other factors that influence insurance demand. We will address potential concerns about the exogeneity of these policy changes based on standard economic arguments: "exclusion" holds conditonal on $f(Time)$ controls which likely reflect the direct channels through which the timing of the Acts may correlate insurance demand. Also, while policy decisions likely reflect current economic conditions, delays in the implementation of proposed or approved Federal Acts may help alleviate these exogeneity concerns. These delays mean current economic and /or insurance demand conditions may not move with actual implementation of the approved reforms. The condition $cov(Z_{it}, \varepsilon_{it}) = 0$ required for

and similarly by Z_{it}^2 an indicator that is equal to 1 whether the ARPA is in force. Our instrumenting vector comprises Z_{it}^1 and Z_{it}^2 . Here the identifying variation is from a pre and post design because the instrument reflect episodes before and after the major policy changes.

Results

For the instrument Z_{it} to be credible it must be valid and strong. In particular, it is important that the instrument be correlated with the out-of-pocket insurance premiums. This will show the strength of the instrument. The instrument has to be relevant and strong. First we find evidence against irrelevance as the standard rule of thumb diagnostics: F-stat>10 in the first stage is satisfied. Furthermore, the Montiel-Olea and Pflueger test for weak instruments for case of non-iid errors (e.g., robust SEs, cluster SEs, etc) suggest no evidence of weak-instruments (p-values =0.00). Throughout we employ county fixed effect specifications, but not random fixed effects. The Hausman test rejects the random effect model in favor of the alternative fixed effect model (p-values¡0.01). One can reject the null hypothesis of a zero coefficient on Z_{it} in the first-stage regression. We are left with the conclusion of no potential weak instrument problem.

The Figure 5 reports the intrumental variable IV estimates of the baseline panel model by using the two-stage panel IV estimation method and one-step panel IV estimation method respectively. Both of the two estimation methods obtain the same insurance price elasticity which is -0.89 and statistically significant at 1% level. However, the one-step panel IV method gains efficiency compared to the two-stage panel IV method because the standard error of one-step panel IV estimate of insurance price elasticity is less. This parameter estimate is dramatically larger than estimates from the pooled and panel models reported in Figure 4: -0.216 and -0.423, respectively. It is worth highlighting that our panel IV estimate is

the validity of major policy swings as an instrument likely holds.

considerably larger than most previous estimates of the premium elasticity of "insured area" reported in the literature (see e.g., Goodwin 1993). As we found in earlier results, average loss ratio is postive and significant across in the panel IV model.

For comparison, Figure 7 also reports the implied results of the two-stage panel IV estimation method and one-step panel IV etimation method respectively by using the logit transformation. In Figure 7 the premium rate increases by 1% ,the odds of the fraction insured acres will decrease by 1.42%. This is the case for both one-step and two-step estimation procedures. To put results into context, we further evaluate what the implications of the different estimates are on the effect of a given change in Federal premium subsidies on crop insurance participation. We do this using some back-of-the door policy experiments.

Finally, we replicate our panel IV estimation using subsidy rate as an instrument[12] instead of the policy reform shocks. The results are reported in Figure 8. Quantitatively, the results are identical. The estimated price elasticity of demand is -0.776. The last column of Figure 8 also reports the logit transformation estimates. Average loss ratio is positive and statistically significant. The squared degree days is also significantly positive, similar to columns 3-4 of Figure 4 and columns 2-3 of Figure 7.

Conclusions

The US Federal crop insurance program has received signifcant attention as far as the United States food and agricultural policies (e.g., Federal support programs) are concerned. There are ongoing policy debates about why the Federal government subsidize crop insurance, which effectively rests on our understanding of the market context of insurance demand. Much concerns revolves around the indequate participation rates of the program. At the same time, there is mounting empirical evidence about how price sensitive producers in the

[12]Note that, Subsidy rate=Subsidy/Total Insured Acres

United States are to participating in crop insurance, generally suggesting a *wide* range of elasticities. Research challenges remain, however, and the existing evidence is relatively outdated. More importantly, most of these studies fail to address the potential endogenity of insurance premiums.

The aim of this study has been to address these challenges and attempt to provide well-identified elasticity estimates that reflect current state of the world of the Federal crop insurance program, using a variety of methods. The data which spans 1989-2013 is an unbalanced panel: covering over 673 counties in the Corn Belt of the United States. We explore the *fraction of planted acreage insured* as our main outcome of interest. Our preferred model which exploits exogenous variations from major Federal subsidy policy changes provides a demand elasticity of -0.89. This estimate imply larger effects than suggested by previous estimates (see e.g., Goodwin 1993; and Smith and Baquet 1996; among others) which are based on less desirable econometric methodologies. The overall results are crucial for ongoing debates and have important policy implications for the Federal crop insurance program.

Future research aims to quantify the implications of results from this paper using some back-of-the door policy experiments. This will build on the current empirical modelling framework. Next, while this paper combines all insurance plans, another line of research (Paper III) examines potential heterogeneity in crop insurance demand along two dimensions: individual versus area-based plans, and revenue versus non-revenue plans. The latter is especially crucial for evaluating the effectiveness of subsidy reforms, since the crop revenue insurance which was introduced in the 1990s now accounts for about 70% of the total liability in the Federal program (see e.g., Goodwin 2012).

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Appendix

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Figure 1: Outcome: distribution of “Insured Area”

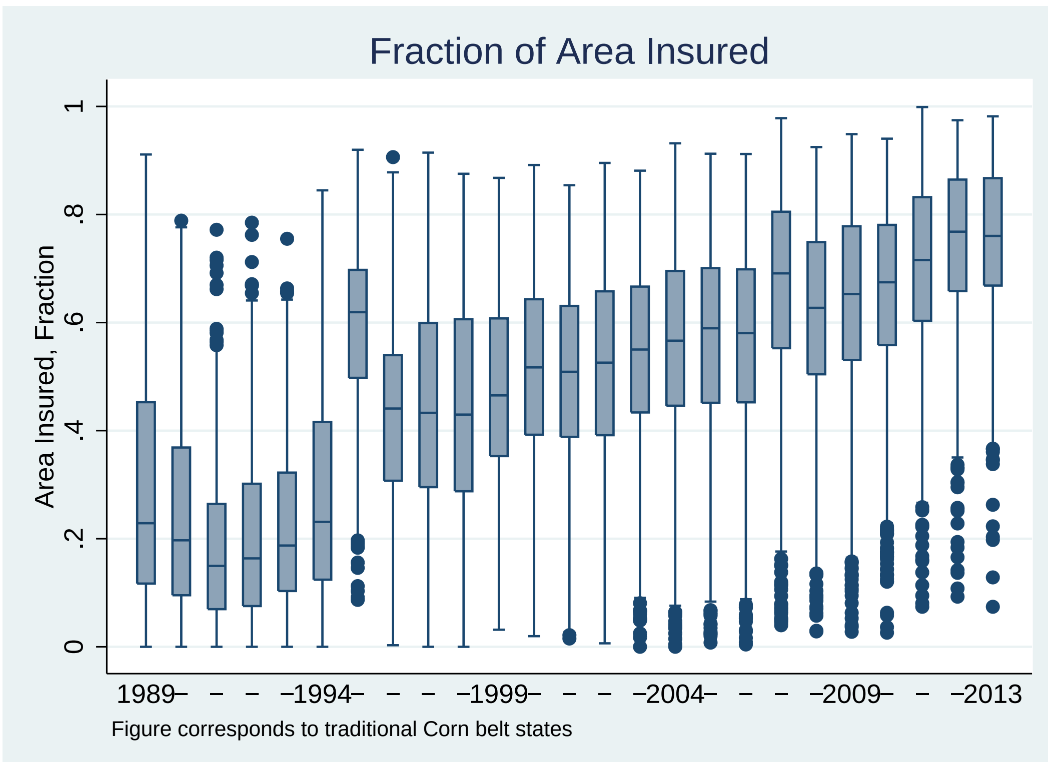


Table 1: Summary Statistics of “Insured Area”

State	*Mean*	*Std. Dev.,*	*Min.,*	*Max.,*	*# of Obs.,*
Illinois	0.51	0.21	0.01	0.91	2277
Indiana	0.45	0.21	0.01	0.89	2029
Iowa	0.67	0.18	0.06	0.97	2198
Kentucky	0.28	0.23	0.00	0.97	1748
Michigan	0.42	0.21	0.01	0.94	1158
Minnesota	0.59	0.24	0.02	0.98	1572
Nebraska	0.59	0.24	0.04	0.99	1828
N., Dakota	0.29	0.19	0.04	0.95	94
Ohio	0.40	0.21	0.01	0.89	1851
S., Dakota	0.56	0.26	0.00	0.96	379
Wisconsin	0.42	0.19	0.01	0.98	1468
Total	0.49	0.24	0.00	0.99	16608

Notes: Table reports the moments, the smallest and largest order statistics of “Fraction Insured” or simply “area insured” variable. For a county to be included in the sample, it must have at least 23 years of nonmissing data points.

Figure 2: Data set: corn-counties, average insured fraction

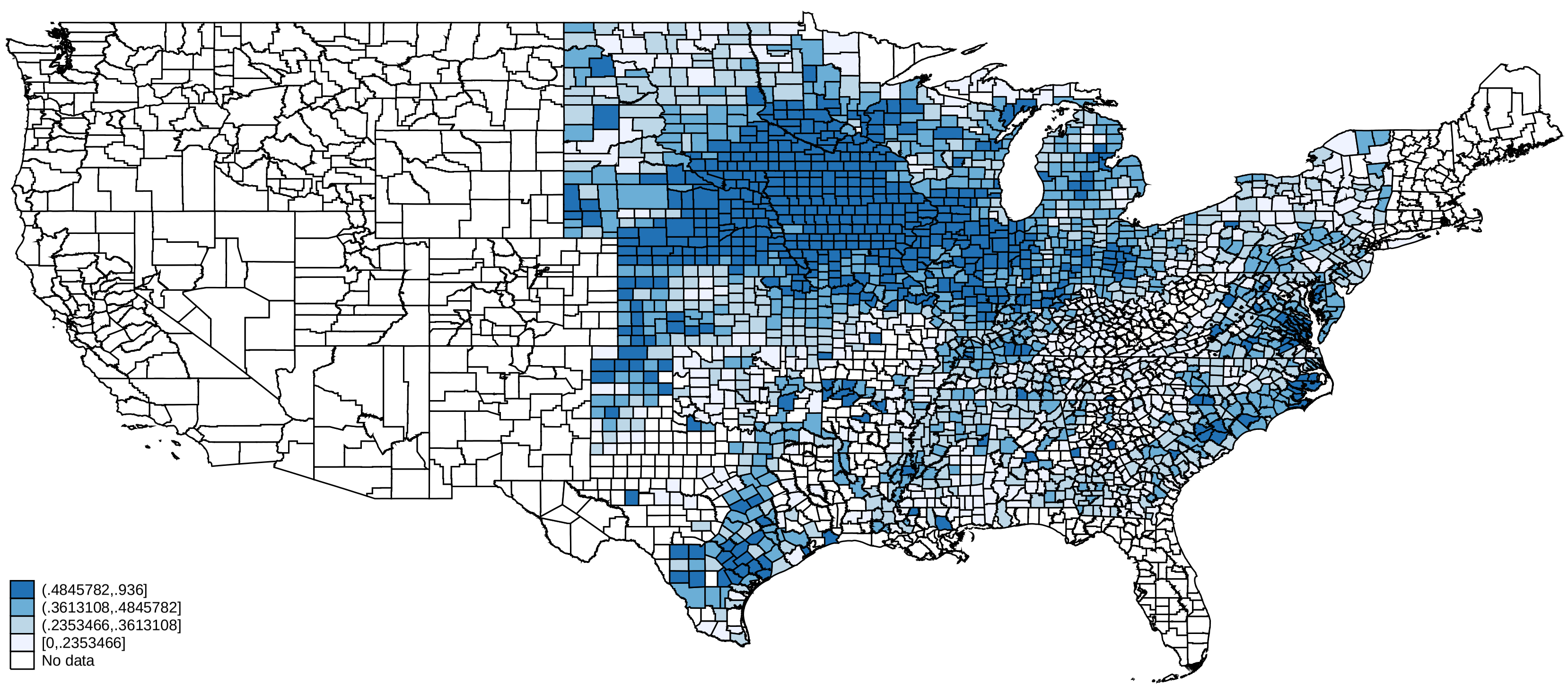
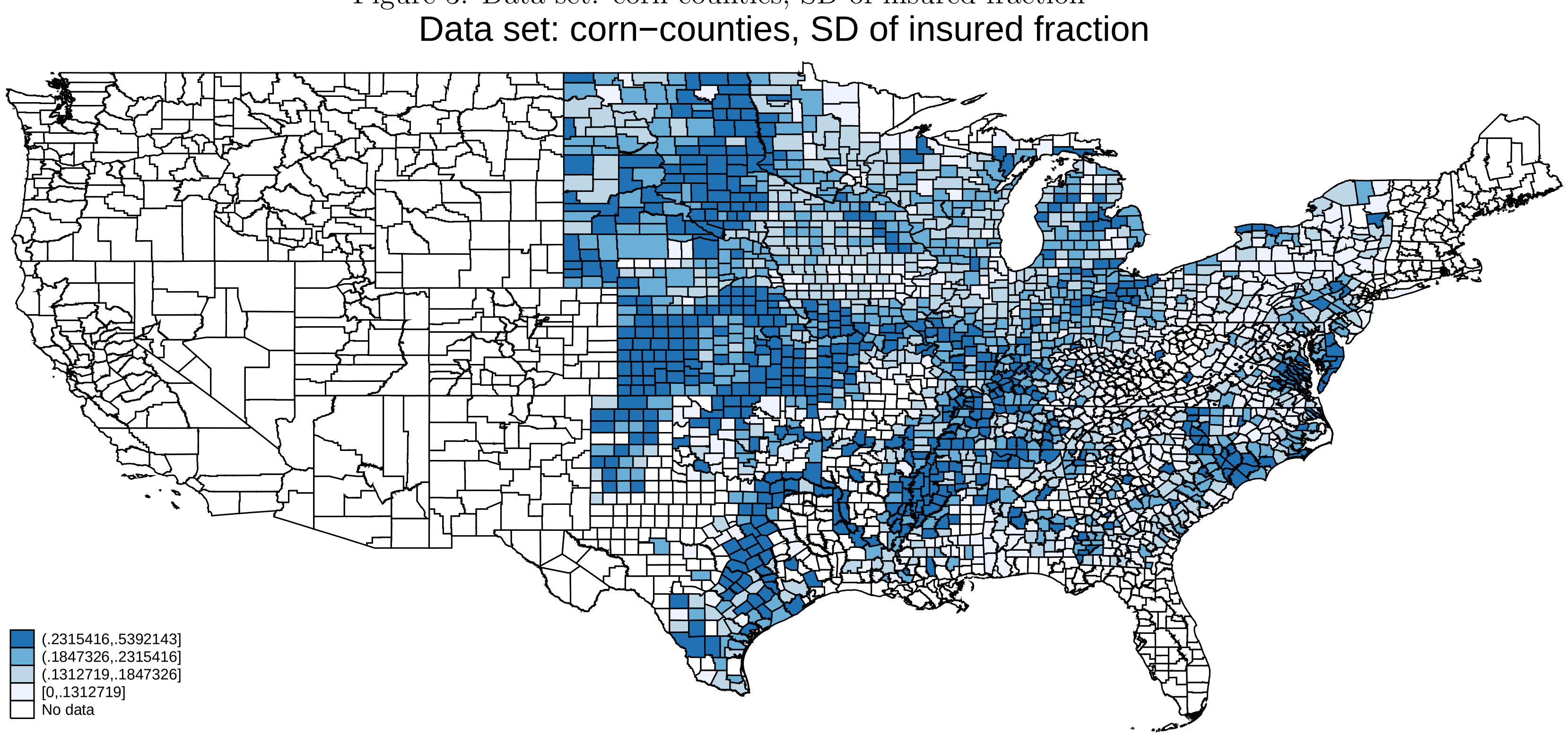


Figure 3: Data set: corn-counties, SD of insured fraction



Notes: SD denotes standard deviation. For each county this is derived over the temporal realizations.

Figure 4: OLS and Panel Estimates: under Alternative Specifications

ELASTICITY ESTIMATES UNDER ALTERNATIVE MODELS: OLS AND PANEL

	(1)	(2)	(3)	(4)
VARIABLES	logFracInsured	logFracInsured	logFracInsured	logFracInsured
logPremRate	-0.222***	-0.216***	-0.436***	-0.423***
	(0.0118)	(0.0117)	(0.0135)	(0.0132)
yieldSq_1lag	2.05e-05***	2.03e-05***	-3.53e-06***	-4.46e-06***
	(6.42e-07)	(6.45e-07)	(8.21e-07)	(8.59e-07)
avglossRatio3lags	0.0652***	0.0808***	0.0370***	0.0812***
	(0.00516)	(0.00832)	(0.00631)	(0.00913)
gdd_1Lag	0.173	0.172	-0.598***	-0.672***
	(0.151)	(0.151)	(0.197)	(0.198)
gdd2_1Lag	-0.158***	-0.155***	0.190***	0.224***
	(0.0516)	(0.0516)	(0.0712)	(0.0720)
prec_1Lag	-3.286***	-3.298***	-0.110	-0.135
	(0.156)	(0.156)	(0.113)	(0.113)
prec2_1Lag	2.345***	2.348***	0.146	0.144
	(0.132)	(0.132)	(0.0932)	(0.0932)
T	0.0661***	0.0666***	0.0949***	0.0969***
	(0.00165)	(0.00168)	(0.00222)	(0.00233)
premRateXavglossRatio3lags		-0.00142***		-0.00409***
		(0.000467)		(0.000645)
Constant	-131.6***	-132.7***	-189.2***	-193.1***
	(3.299)	(3.369)	(4.410)	(4.621)
Observations	14,544	14,544	14,544	14,544
R-squared	0.374	0.375	0.530	0.533
Model	Pooled OLS	Pooled OLS	Panel Model	Panel Model
Years	1989-2013	1989-2013	1989-2013	1989-2013
FEs	No	No	Yes	Yes
Number of fips			673	673

Robust standard errors in parentheses

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

Figure 5: OLS and Panel Estimates: under Alternative Specifications

ELASTICITY ESTIMATES UNDER ALTERNATIVE MODELS: OLS AND PANEL

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VARIABLES	logFracInsured	logFracInsured	logFracInsured	logFracInsured
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	(0.156)	(0.156)	(0.113)	(0.113)
prec2_1Lag	2.345***	2.348***	0.146	0.144
	(0.132)	(0.132)	(0.0932)	(0.0932)
T	0.0661***	0.0666***	0.0949***	0.0969***
	(0.00165)	(0.00168)	(0.00222)	(0.00233)
premRateXavglossRatio3lags		-0.00142***		-0.00409***
		(0.000467)		(0.000645)
Constant	-131.6***	-132.7***	-189.2***	-193.1***
	(3.299)	(3.369)	(4.410)	(4.621)
Observations	14,544	14,544	14,544	14,544
R-squared	0.374	0.375	0.530	0.533
Model	Pooled OLS	Pooled OLS	Panel Model	Panel Model
Years	1989-2013	1989-2013	1989-2013	1989-2013
FEs	No	No	Yes	Yes
Number of fips			673	673

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

Figure 6: OLS and Panel Estimates-logits: under Alternative Specifications

ELASTICITY ESTIMATES UNDER ALTERNATIVE MODELS: OLS AND PANEL-logits

	(1)	(2)	(3)	(4)
VARIABLES	logitFracInsured	logitFracInsured	logitFracInsured	logitFracInsured
logPremRate	-0.292***	-0.282***	-0.679***	-0.666***
	(0.0191)	(0.0194)	(0.0196)	(0.0197)
yieldSq_1lag	5.39e-05***	5.37e-05***	9.46e-06***	8.58e-06***
	(1.33e-06)	(1.34e-06)	(1.42e-06)	(1.45e-06)
avglossRatio3lags	0.169***	0.195***	0.117***	0.159***
	(0.0119)	(0.0186)	(0.0114)	(0.0170)
gdd_1Lag	0.852***	0.850***	-0.238	-0.309
	(0.307)	(0.307)	(0.339)	(0.340)
gdd2_1Lag	-0.450***	-0.445***	0.190	0.222*
	(0.104)	(0.104)	(0.119)	(0.120)
prec_1Lag	-9.422***	-9.442***	-0.888***	-0.911***
	(0.346)	(0.347)	(0.247)	(0.246)
prec2_1Lag	6.383***	6.387***	0.444**	0.441**
	(0.279)	(0.279)	(0.195)	(0.195)
T	0.126***	0.127***	0.177***	0.179***
	(0.00254)	(0.00260)	(0.00292)	(0.00304)
premRateXavglossRatio3lags		-0.00236**		-0.00387***
		(0.00113)		(0.000997)
Constant	-249.2***	-251.0***	-352.3***	-356.1***
	(5.103)	(5.223)	(5.852)	(6.082)
Observations	14,544	14,544	14,544	14,544
R-squared	0.429	0.429	0.615	0.615
Model	Pooled OLS-logits	Pooled OLS-logits	Panel Model-logits	Panel Model-logits
Years	1989-2013	1989-2013	1989-2013	1989-2013
FEs	No	No	Yes	Yes
Number of fips			673	673

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

Figure 7: Panel IV Estimates-logits: under Alternative Models

ELASTICITY ESTIMATES UNDER ALTERNATIVE MODELS-logits: PANEL IV

VARIABLES	(1) logPremRate	(2) logitFracInsured	(3) logitFracInsured
dum94	-1.071***		
	(0.0226)		
dum00	-0.0395***		
	(0.0127)		
yieldSq_1lag	-1.64e-06**	1.15e-05***	1.13e-05***
	(8.17e-07)	(1.23e-06)	(1.54e-06)
avglossRatio3lags	0.00477	0.151***	0.151***
	(0.00483)	(0.0115)	(0.00987)
gdd_1Lag	1.081***	-1.280***	-1.254***
	(0.170)	(0.276)	(0.349)
gdd2_1Lag	-0.247***	0.717***	0.705***
	(0.0620)	(0.0953)	(0.124)
prec_1Lag	0.857***	-0.782***	-0.780**
	(0.134)	(0.255)	(0.329)
prec2_1Lag	-0.743***	0.522***	0.519**
	(0.110)	(0.202)	(0.263)
T	0.126***	0.239***	0.239***
	(0.00123)	(0.00343)	(0.00248)
predlogPremRate_logit		-1.417***	
		(0.0284)	
logPremRate			-1.415***
			(0.0244)
Constant	-249.8***	-474.9***	
	(2.489)	(6.829)	
Observations	14,544	14,573	14,544
R-squared	0.747	0.666	0.509
Number of fips	673	673	673
Model	First Stage-Panel IV-logits	Second Stage-Panel IV-logits	One Step Panel IV-logits
Years	1989-2013	1989-2013	1989-2013
FEs	Yes	Yes	Yes
F Stat	1990		

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

Notes: We do not find evidence of weak-instruments, see e.g., Column 1 of Figure 5. The standard rule of thumb diagnostics: F-stat>10 in the first stage. Furthermore, the Montiel-Olea and Pflueger test for weak instruments for case of non-iid errors (e.g., robust SEs, cluster SEs, etc) suggest no evidence of weak-instruments (P-values =0.00). Overidentification tests provide evidence in favor of exogeneity of intruments (P-values ¿0.21). Hausman tests rejects the random effect model, so we are using fix effect model (P-values¡0.01).

Figure 8: Panel IV Estimates (Susbsidy Rate)

ELASTICITY ESTIMATES UNDER ALTERNATIVE MODELS: PANEL IV (Susbsidy Rate)

	(1)	(2)
VARIABLES	logFracInsured	logitFracInsured
logPremRate	-0.776***	-0.899***
	(0.0700)	(0.125)
yieldSq_1lag	-2.70e-06***	1.00e-05***
	(8.36e-07)	(1.42e-06)
avglossRatio3lags	0.0524***	0.127***
	(0.00579)	(0.0104)
gdd_1Lag	-1.066***	-0.541
	(0.221)	(0.357)
gdd2_1Lag	0.428***	0.344**
	(0.0863)	(0.141)
prec_1Lag	-0.0605	-0.856***
	(0.167)	(0.295)
prec2_1Lag	0.181	0.466**
	(0.136)	(0.232)
T	0.124***	0.196***
	(0.00604)	(0.0107)
Observations	14,544	14,544
R-squared	0.445	0.605
Number of fips	673	673
Model	One Step Panel IV	One Step Panel IV-logits
Years	1989-2013	1989-2013
FEs	Yes	Yes

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

Notes: We do not find evidence of weak-instruments, the standard rule of thumb diagnostics: F-stat>10 in the first stage. Furthermore, the Montiel-Olea and Pflueger test for weak instruments for case of non-iid errors (e.g., robust SEs, cluster SEs, etc) suggest no evidence of weak-instruments (P-values =0.00). Hausman tests rejects the random effect model, so we are using fix effect model (P-values¡0.01).