The Development of a Weather-based Crop Disaster Program

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Panel regressions are used to relate standardized county weather variables to yield outcomes in order to develop a crop disaster program for the top producing states of corn, soybeans, wheat, and cotton. Farm-level simulations are used to draw yield realizations and provide realistic consistency between county, district, and state yields and national prices. The proposed crop disaster program is estimated to save between $3 and $4 billion per year relative to the current crop insurance program, a reduction of approximately 30% compared to the $10.06 billion in federal expenditures on the crop insurance program in 2016. The savings are realized though two main mechanisms: (1) Focusing agricultural support on systemic weather risk and excluding idiosyncratic risk; and (2) Reducing the administrative cost of the program by eliminating underwriting gains accruing to private companies currently participating in the delivery of crop insurance. The disadvantage of the crop disaster product from the producers' perspective is the basis risk associated with the program being tied to a simulated and aggregate index rather than field-level yields, with a decrease in downside revenue risk protection relative to the current Revenue Protection (RP) policies available for crops with well-functioning futures markets.

Key words: agricultural policy, crop insurance, disaster aid, risk management, weather.

JEL codes: H20, Q18.

Major legislative initiatives in 1980, 1994, and 2000 expanded the role of federal crop insurance as the main federal safety net in protecting farmers from risk. During this period, the federal crop insurance program expanded its product offerings to farmers, increased subsidy rates, and as a consequence, overall participation increased substantially (Smith and Glauber 2012). By 2002, the adverse selection problem, where an insurance pool is overrepresented by relatively risky agents, was effectively eliminated by increasing participation rates through lowering the producers' cost of insurance with increases in subsidy rates (Goodwin and Smith 1995; Glauber 2013). One of the main rationales behind the dramatic shift in farm policy towards crop insurance was to replace ad hoc disaster programs, where payments were to a considerable extent based on congressional representation in agricultural committees and political power (Goodwin and Vado 2007). Federal crop insurance provides an approach to delivering farm safety nets that is based purely on the parameters of the program rather than requiring ad hoc legislation to trigger support payments.

However, the cost of crop insurance to taxpayers increased during the program's expansion. In order to deliver high participation rates and avoid adverse selection problems, large subsidies were necessary (Glauber 2013). To illustrate, the data in table 1 show that farmer-paid premiums accounted for an average of 38% of the total premium from 2012 to 2017. This is substantially lower than the average of 74% between 1990 and 1994 (Glauber 2013). Over the last six years,

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Table 1. Crop Year Government Cost of Federal Crop Insurance, 2007–2017

Year	Total Premium	Premium Subsidy	Farmer-paid Premium	Total Indemnities	A&O	Underwriting Gains	A&0/Total Premium	Underwriting Gains/Total Premium
2007	6,573	3,828	2,745	3,551	1,335	1,575	0.20	0.24
2008	9,867	5,696	4,171	8,691	2,011	1,095	0.20	0.11
2009	8,961	5,431	3,530	5,231	1,621	2,299	0.18	0.26
2010	7,607	4,715	2,892	4,258	1,371	1,918	0.18	0.25
2011	12,012	7,478	4,534	10,879	1,363	1,705	0.11	0.14
2012	11,152	6,992	4,160	17,490	1,405	(1,316)	0.13	–0.12
2013	11,837	7,308	4,529	12,108	1,398	644	0.12	0.05
2014	10,099	6,224	3,875	9,144	1,386	1,040	0.14	0.10
2015	9,804	6,102	3,702	6,339	1,434	1,816	0.15	0.19
2016	9,346	5,871	3,475	3,925	1,447	2,615	0.15	0.28
2017	10,092	6,360	3,732	5,158	1,483	2,685	0.15	0.27
Average								
2007–2017	9,759	6,000	3,759	7,889	1,478	1,461	0.16	0.16
2012–2017	10,388	6,476	3,912	9,027	1,426	1,247	0.14	0.13

Source: https://www.legacy.rma.usda.gov/aboutrma/budget/costsoutlays.html.

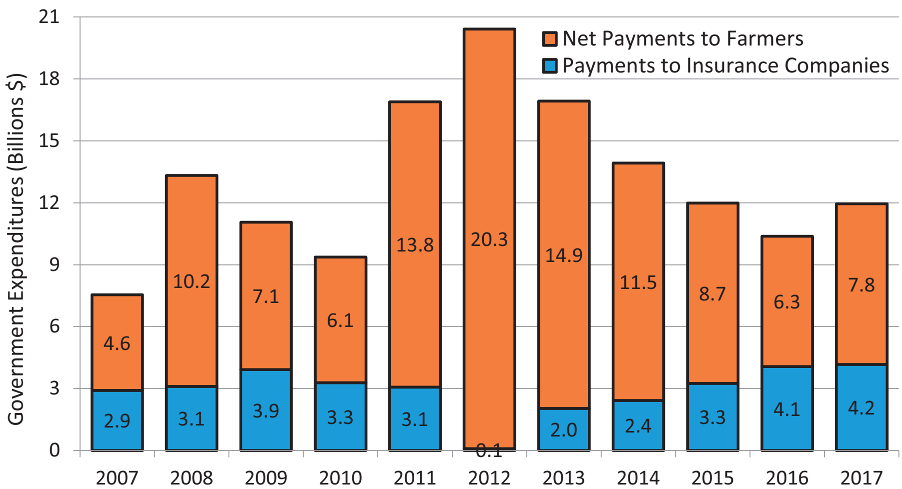

Figure 1. Annual crop insurance expenditures, separated by payments made to farmers and insurance companies.

Note: Net payments to farmers is computed by adding indemnities and premium subsidies, minus farmer-paid premiums. Payments to insurance companies include Administrative and Operating reimbursements and underwriting gains/losses

following the most recent 2011 Standard Reinsurance Agreement, annual payments to insurance companies in the form of underwriting gains and Administrative and Operating (A&O) costs have averaged \$2.7 Billion.[1] These payments, relative to net payments made directly to farmers, are shown in figure 1.

If the objective of farm policy is to provide a "safety net" that protects farmers against years in which yields are poor at a low cost to taxpayers, then there may be a more efficient option than the current crop insurance system. For example, Paulson and Babcock (2008) demonstrate that offering free access for agricultural producers to a current federally subsidized county yield-based plan, Group Risk Income Protection (GRIP), with

[1] This period includes 2012, which was the first year insurance companies did not receive an underwriting gain since 2004. If 2012 were excluded from the ten-year average, this average amount would increase to \$3.1 billion per year in underwriting gains and A&O expenditures.

a 93% coverage level could provide more direct benefits to agricultural producers for a lower taxpayer cost. The savings are obtained by eliminating the need for any role on the part of private insurance companies in product delivery. A formalized, permanent or standing disaster aid program would also provide more direct benefits to producers, as with the proposal in Paulson and Babcock (2008), and would also provide payments in a timelier manner. Under area-based crop insurance products, indemnities are realized once county yields are determined, which can often be only months before the next planting. In contrast, a weather-based disaster program that utilizes weather data throughout the growing season would provide indemnities once the publicly available weather data become available, which could result in payments within weeks of typical harvest months.

Starting with the 2008 farm bill, livestock safety net programs shifted to provide expanded disaster relief in the form of Livestock Forage Program (LFP), Livestock Indemnity Program (LIP), and Emergency Assistance for Livestock Honeybees, and Farm-Raised Fish (ELAP)—see ERS (2019) for a summary of safety net programs in the 2018 Farm Act.[2] While these are disaster aid programs, they function much differently than previous ad hoc disaster programs. These newer programs are triggered by well-defined adverse weather outcomes, rather than ad hoc legislation. Furthermore, the use of weather-based triggers, as opposed to individual production outcomes, may cut the cost of providing a farm safety net, albeit at the cost of production basis risk for the producer. Weather information is publicly available through the Drought Monitor Index, and payments are managed through the Farm Service Agency, rather than through a cooperation with private insurance companies. Payments are available as soon as drought thresholds are exceeded, even within the current growing season. For example, recent droughts that have occurred early in the grazing period have resulted in maximum payments being determined by early spring of the current year. Disaster payments can be made within season, enabling farmers to use the funds to stabilize production as well as providing a more efficient safety net by substantially reducing delays in payments.

This study examines the potential impacts of a similar disaster aid program for producers of major grain and fiber crops on the revenue distributions of farmers who raise those crops and on government costs. The analysis compares costs and coverages associated with existing crop insurance programs against a disaster program that would trigger payments based on weather outcomes from publicly available weather data that are used to predict county yields as reported by the National Agricultural Statistics Service (NASS).[3] While the proposed program is developed using NASS county yield and weather information provided by the National Oceanic and Atmospheric Administration (NOAA), the product could also be tailored to incorporate spatially interpolated weather data along with county-level regression models to more accurately estimate weather for a particular farm. Such programs would eliminate a number of the costs associated with insurance monitoring, administration, and underwriting gains, although other costs are likely to remain and may include education, marketing, acreage reports, issuing payments, and tracking coverage.

A disadvantage of moving from a system triggering indemnities at the field level to one at operating at the county level is that the shift will introduce basis risk for recipients.[4] In fact, basis risk is itself a major reason why area based insurance programs have lower budgetary costs than an insurance program using the same insurance coverage rate that targets the farmer's actual yield.[5] Using farm yield as the target, the farmer's downside revenue risk is effectively prevented from falling below the farmer's insured liability. Using an index that is not based on the famer's own yield lowers the contribution of the insurance

[2] The 2014 farm bill also created a mechanism for insurance companies to provide weather index coverage.

[3] County level yields are computed by NASS using producer surveys and sampling techniques that are detailed further in NASS (2012).

[4] While Miranda (1991) formally defined basis risk empirically as the gap between systemic and idiosyncratic deviations, Smith and Watts (2009) state the main problem of basis risk is whether a farm will actually receive an indemnity when they experience a loss. They define basis risk to be the central problem of all index products that are currently being developed in developing countries and estimate the correlation between local yields and regional weather to be less than 0.50 in most applications.

[5] While this discussion focuses on the potential savings from area-based insurance products by not insuring basis risk, it is notable that savings would also be realized through the elimination of requiring individual crop loss adjustment.

program to reducing downside revenue risk. We empirically examine this basis risk.

The weather index used for calculating the indemnity trigger and indemnity payment in our proposed crop disaster aid program would have some important advantages over those used in the current livestock disaster programs. First, in many of the more productive grain and fiber growing regions, weather stations are more intensively established than in regions where pasture and feed are grown for cattle. This concentration of weather stations provides sufficient data to estimate weather (temperature and rainfall) at a given point near the weather stations. This advantage is likely to diminish in regions outside of the plains and Midwest, where weather station coverage is less dense. Second, in regions across the plains and the Midwest, weather outcomes are relatively consistent across space because of limited changes in altitude and terrain (Glauber 2013). This also allows for the use of more accurate spatial interpolation in the absence of a weather station at a specific geographic location and a stronger correlation between regional weather and yields. Finally, the amount of land used for crop production and the higher amount of total liability, relative to livestock production, may lead to large savings when converting from the current crop insurance program to an index-based disaster program.

Weather and Yield Data

The two main components used in developing a crop disaster program include weather and yield data. Weather data are obtained from the NOAA's Daily Global Historical Climatology Network (GHCN) data set (Menne et al. 2012). These relationships are established at the county level, since that is the lowest level of production detail available on a consistent basis.[6] Yields are calculated from NASS data and computed as total production divided by total planted acres within a county.[7]

The analysis includes counties from the states ranked as the top five for corn and soybean production (Illinois, Indiana, Iowa, Minnesota, and Nebraska), wheat (Kansas, Montana, North Dakota, and South Dakota) and cotton (Arkansas, Georgia, Mississippi, North Carolina, and Texas). In 2015, federally subsidized crop insurance policies for corn, cotton, soybeans, and wheat comprised \$75.9 billion in total liability (74% of total liability across all commodities). In the states included in the analysis, the total liability from Risk Management Agency (RMA) policies for corn (\$25.9 billion), cotton (\$2.3 billion), soybeans (\$13.5 billion), and wheat (\$4.0 billion) accounts for 60.2% of the total liabilities across those four commodities (\$75.9 billion) and 44.6% of liability across all commodities (\$102.4 billion). The states and counties included in this study tend to be relatively dense production areas for the given crops and also represent a large proportion of overall crop production.[8]

In developing an index to predict yields, two main variables are typically used: temperature and precipitation. While temperature can be measured in many ways (e.g., daily maximum, daily minimum, mean temperature, etc.), the most commonly used indicator of the ability of plants to absorb heat from temperature is measured through the use of growing degree days (GDDs). GDDs are computed daily based on NOAAs methodology for computing the metric, which assumes that plant growth occurs only within the range of temperatures between 10 and 30 degrees Celsius (50° to 86° F) (NOAA 2017). A GDD is computed as the difference between the average of the daily minimum and maximum temperatures and the base temperature of 10° C (50° F). Minimum temperatures below 10° C are set to 10°, while maximum temperatures above 30° C are set to 30°. Other studies have also utilized

[6] Rejesus et al. (2015) provides a discussion of the trade-offs typically presented in the choice of weather variables. While past studies, such as Deschenes and Greenstone (2007), have focused on more disaggregated levels of analysis, this typically is restricted to using reported yields from the Census of Agriculture, which is done every 5 years. Thus, the establishment of relating weather to yields is accomplished at the county level.

[7] Past comparisons of using planted and harvested acres to calculate yields appeared to show little difference (Deschenes and Greenstone 2007). The main reason for deviation between these two measures is prevented planting, where, in effect, a crop is destroyed early in the planting season (typically due to unfavorable planting conditions) and a late season crop is planted. Hence, insurance commonly uses planted acres as its measure, although the Risk Management Agency (RMA) often allows for prevented planting provisions, whereby producers can be compensated for pre-planting costs.

[8] It would be reasonable to expand the analysis to more states and crops; however, the expansion into less representative regions and crops introduces additional empirical difficulties. This analysis is intended to be based on a representative population that covers the majority of production and current liability under existing agricultural crop insurance programs.

Table 2. Summary Statistics of Weather and Production Variables, 1980-2015

Variable	Min.	25th Percentile	50th Percentile	Mean	75th Percentile	Max.	Standard Deviation
Corn and Soybean Counties in IA, IL, IN, MN, and NE ($n = 426$)							
Detrended yield (corn)	17.7	142.5	163.8	158.8	180.1	234.1	29.8
Detrended yield (soybeans)	5.7	44.3	50.0	49.0	54.6	74.9	8.0
Growing degree days	867	1,549	1,696	1,693	1,839	2,386	214.5
Precipitation	3.1	20.6	28.7	31.6	40.0	140.0	14.3
Cotton Counties in AR, GA, MS, NC, and TX ($n = 159$)							
Detrended yield	0.0	1.1	1.6	1.6	2.0	3.9	0.6
Growing degree days	1,784	2,273	2,408	2,396	2,513	3,057	199.7
Precipitation	1.5	20.7	32.2	36.0	48.0	201.4	19.5
Wheat Counties in KS, MT, ND, and SD (n = 195)							
Detrended yield	2.1	30.5	38.7	39.1	46.8	109.9	13.0
Growing degree days	535	1,255	1,484	1,561	1,928	2,383	387.4
Precipitation	2.1	15.0	23.4	27.0	35.0	152.5	16.2

Note: Yields are measured in bushels per acre, except in the case of cotton, which is measured as 480-lb bales per acre. Growing degree days are computed based on the methodology described in NOAA and are measured in Celsius. Precipitation are aggregated between April 1 and September 30 and measured in inches.

cooling degree days (CDD) (Rejesus et al. 2015; Yu and Babcock 2010). However, the two measures are relatively similar with the slight distinction in using different bases, where CDD is relative to 65° and GDD is relative to 50°.

Daily GDDs are computed and aggregated on a monthly basis across a growing season starting April 1 through September 30. Total precipitation is also aggregated from the same weather stations, across the same time period. Thus, the total annual GDDs and precipitation (in inches) are computed for each county by taking daily averages from weather stations within the county. These two indicators are used as they jointly characterize the growing conditions necessary for plant growth (Payero et al. 2006).

Deviations from historical average precipitation and GDD levels are computed within each county. Historical averages are based on annual county-level calculations from 1950 to 2014. Deviations from the average are used to adjust the weather variables so that they are shown as deviations from "typical" weather in the county.

Yields are detrended at the county-level using a simple linear regression with time as the covariate (using the base year of 2014). This adjustment is made in order to eliminate the effects of increasing yields over time associated with technological improvements. The use of time trends is well documented and is currently recognized by the RMA with their offering of trend-adjusted APH yield guarantees. While RMA has not released the methods they use to compute trend adjustment factors for each county, a linear regression is relatively consistent for most yield series (Adhikari, Knight, and Belasco 2012).

Table 2 presents a summary of the weather and production variables utilized in this study. For example, within major corn producing counties, the average detrended yield is 158.8 bushels per acre. Those counties receive an annual average of 31.6 inches of rainfall and 1,693 GDDs.[9]

There are many reasons why precipitation and GDDs cannot simply be used as linear predictors of yield. First, the interaction between the two explanatory variables is important. For example, the impact of lower than normal rainfall largely depends on temperatures. A relatively cool summer may dampen the impact of lack of rainfall. Conversely, a relatively hot summer that is also relatively dry can result in summer drought conditions. Second, the timing of rainfall matters dry (as was the case in 2012 for much of the Midwest). For example, Westcott and Jewison (2013) found June precipitation along with July precipitation and temperature were the main determinants of yield shortfalls during the 2012 drought.[10] Third,

[9] Since growing degree days are calculated using the methods described earlier, the units for this measure are not days, but rather the accumulation of deviation between the average temperature and lower growing threshold, both measured in Celsius.

[10] Westcott and Jewison (2013) also include a binary variable that equals one when precipitation was in the lowest 10% of

the relationship between weather and yields may be different under normal or advantageous weather conditions as compared to adverse conditions. In developing safety net programs, such as crop insurance, the adverse part of the tail is most important for program sustainability and likely to be highly correlated with weather conditions.

Weather indicators are used to partially explain deviations in detrended yields for each county, using a fixed effects within estimator. Weather has been characterized in several different ways in previous studies to partially explain yields. Typically, the objective is to isolate the impact of technology or potential impacts from predicted changes in climate on agricultural production. Deschenes and Greenstone (2007), for example, compute monthly GDDs and precipitation during January, April, July, and October and use second-order polynomials on each indicator to estimate yields. Schlenker, Hanemann, and Fisher (2006) regress second-order polynomials for GDDs and precipitation on farmland values. Weather variables are aggregated for the growing season, which is assumed to be April through September. Schlenker and Roberts (2009) collect temperature and precipitation data in order to estimate nonlinear relationships between yields and weather.[11] Schlenker and Roberts also compute GDDs as a robustness check and find similar results. Cai, Yu, and Oppenheimer (2014) use a similar data series and assumption while utilizing spatial relationships in order to more accurately identify standard errors. Yu and Babcock (2010) compute CDDs, combine that information with precipitation on a monthly basis, and derive an index to focus on adverse weather and yield deviations. Their index consists of standardized deviations from average levels, truncated to include only adverse weather.[12] The benefit of using such an index is that it focuses on the impact of drought, which is particularly important for crop insurance and may provide a better fit given that the relationship between weather and yields are likely to be stronger during times of drought, relative to normal and wetter than normal years.

Modeling Yields

The model developed for this application uses an approach that addresses the issues raised in the last section, which include accounting for (1) the interaction between temperature and precipitation, (2) timing of weather, and (3) focus on adverse events. Two main questions have to be considered when relating weather to yields. First, what elements of weather provide insight into describing yield deviations from trend? More specifically, which weather variables are of significance? These variables may include monthly precipitation, mean temperature, GDDs, an index developed from weather variables, or an accumulation of weather variables during the growing season.[13]

Similar to the index developed in Yu and Babcock (2010), standardized values are computed by dividing each deviation from the predicted value by the standard deviation, so that standardized deviations are relative to the predicted value, rather than means. This is computed for $STDGDD_{it} = \max(0, GDD_{it}/std(GDD_i))$ and $STDPRCP_{it} = \min(0, PRCP_{it}/\ std(PRCP_i))$, where $std(.)$ is the standard deviation in yields for county i; $STDGDD_{it}$ is the standardized GDD for county i in time t; and $PRCP_{it}$ is the total precipitation (in inches) for county i and year t. Index values are computed as follows:

$$(1) \quad IP_{it} = STDGDD_{it} * (-STDPRCP_{it}).$$

Thus the index only takes a nonzero and positive value when temperatures are higher than normal ($GDD_{it} > 0$), and rainfall is less than normal ($PRCP_{it} < 0$). A second version of this index is computed that utilizes the sum of the two components, such that

$$(2) \quad IS_{it} = STDGDD_{it} - STDPRCP_{it}.$$

historical precipitation that was found to largely explain yield outcomes during the droughts of 1988 and 2012. Further descriptions regarding the timing of rainfall are described in Payero et al. (2006).

[11] Schlenker and Roberts (2009) assumed the growing season for corn and soybean production was March–August, while the growing season for cotton production was April – October.

[12] This particular index is nonzero and positive only when both rainfall is lower than average and heat, as measured by cooling degree days, is higher than average for the county. Otherwise, the index carries a zero value.

[13] Preliminary regressions were attempted based on previous models relating yields to weather (Schlenker, Hanemann, and Fisher 2006; Deschenes and Greenstone 2007; Schlenker and Roberts 2009; Yu and Babcock 2010; Westcott and Jewison 2013). While we estimated many of these regressions, they all had shortcomings that are addressed with the functional form utilized in this study.

While the index value defined in equation (2) was not used in the main results reported by Yu and Babcock (2010), they did report finding similar results when using an index based on equation (2). These indexes provide a standardized measure that places all counties within a similar scale. The index variables are computed at three aggregation levels, including the county, agricultural district, and state levels. While these variables may seem redundant, they work to smooth out weather outcomes throughout the affected region and distinguish between localized and more systemic or widespread weather events. This is important because there can be a substantial amount of noise in local weather outcomes, especially when regressed on yields. The index, *IP*, is also created for each agricultural district (*DIP*) and state (*SIP*).

Timing is also an important aspect of identifying the impact of adverse weather on production. For this reason, the indices described above are developed and related to particular periods during the growing period. Thus, we compute both IS_G and IP_G for each time period, $G = \{AM = April - May;\ JJ = June{-}July;\ AS = August - September;\ GS = April - September\}$. Thus, each variable accumulates two months that divide the growing season into three periods.

Using the above notation, the following model is used to characterize standardized detrended yield deviations as a function of standardized weather outcomes:

$$(3)\quad \begin{aligned} Y_{it} = {} & \beta_0 + \beta_1 IS\_G_{it} + \beta_2 IS\_G_{it}^2 \\ & + \beta_3 IP\_G_{it} + \beta_4 IP\_G_{it}^2 + \beta_7 DIP_{dt} \\ & + \beta_8 DIP_{dt}^2 + \beta_9 SIP_{st} + \beta_{10} SIP_{st}^2 \\ & + e_{it} \end{aligned}$$

where Y_{it} is the standardized yield deviations from trend for county i in year t. Data utilized for this study includes county-level data from 1980 to 2015. Regressions were run separately for each state and commodity combination so that each state includes a panel of counties within the state across time. Variables that were determined to be statistically insignificant in each regression were excluded from the final regressions.

Regression Results

Regression results are presented in tables 3–6. While the parameter estimates themselves assist in predicting yields, there are few noteworthy observations. First, the reported adjusted R-squared measure does not account for the variability that is captured through the use of detrending and using county-specific fixed effects. Thus, the reported fits are relative to the dependent variable, which is the standardized deviation from trend in yields. Second, there is considerable heterogeneity in the regression results by state, as noted by parameter significance and goodness-of-fit statistics. The variation in parameter estimates and gains in explanatory power across regressions highlight the importance of state-specific regressions, as opposed to a single regression for all states, particularly during extreme weather years.

Third, early weather conditions, including late spring and early summer, seem to be particularly important in explaining yields. Westcott and Jewison (2013), for example, discuss the predictive power of weather conditions through July in major corn producing states. Fourth, regional weather indicators at both the state and agricultural district levels are statistically significant in nearly all regressions. These results indicate that regional weather variables help to smooth local weather variations in order to more clearly determine the severity of weather conditions. The use of larger scale regional weather variables is particularly important if the focus is on insuring against systemic risk events. Fifth, the statistical significance of second-order polynomial terms show that the relationship between yields and other variables is nonlinear. This finding is consistent with previous research (Schlenker and Roberts 2009; Westcott and Jewison 2013; Cooper, Tran, and Wallander 2017).

It is particularly important for a disaster program to provide payments during adverse weather years. To illustrate, regression results are used to predict corn yields during the 2012 drought in major corn producing states. Figure 2 presents actual and predicted yields and standardized yields for counties within those five states, which were impacted by the drought by varying degrees.

Given the high degree of correlation between many of the covariates in the included regression, focusing on the marginal effect of a single covariate on predicted weather outcomes does not provide any particularly interesting insights. The primary use of the estimated regressions is to predict systemic weather events that adversely affect yields, so that the proposed insurance product provides an

Table 3. Fixed Effects Panel Estimation Results for Corn Yields, by State, 1980-2015

Variable	Illinois ($n = 94$)		Indiana ($n = 82$)		Iowa ($n = 99$)	
	Parameter Estimate	T-stat	Parameter Estimate	T-stat	Parameter Estimate	T-stat
Intercept	0.323	12.048***	0.277	9.977***	0.022	0.740
$IS_{AM,i}$	1.146	13.623***	1.481	16.577***	0.893	10.303***
$IS^2_{AM,i}$	−0.755	−10.459***	−0.990	−13.660***	−0.323	−6.731***
$IS_{JJ,i}$	−0.821	−11.192***	−0.533	−12.441***		
$IS^2_{JJ,i}$	0.265	4.743***			−0.125	−2.924**
$IS_{AS,i}$	−0.559	−8.286***	−0.498	−11.489***		
$IS^2_{AS,i}$	0.135	3.621***			−0.333	−10.990***
$IP_{AM,i}$	1.339	7.258***	1.486	7.509***		
$IP_{JJ,i}$	−1.016	−6.963***	−0.595	−5.990***	−1.248	−5.902***
$IP_{AS,i}$			0.806	7.328***	0.747	4.356***
IP_i	0.641	5.320***	0.342	4.423***	1.028	5.424***
IP^2_i	−0.213	−4.660***			−0.280	−4.430***
IP_D	−1.965	−8.726***	−2.458	−8.199***	−3.041	−6.981***
IP^2_D	1.055	7.460***	2.140	7.960***	1.200	3.277**
IP_S	3.323	7.304***	4.994	9.425***	3.639	3.776***
IP^2_S	−8.638	−11.565***	−11.983	−12.335***	−3.389	−2.877**
Adjusted R2	0.430		0.382		0.192	
	Minnesota ($n = 68$)		Nebraska ($n = 83$)		Top 5 states ($n = 426$)	
	Parameter Estimate	T-stat	Parameter Estimate	T-stat	Parameter Estimate	T-stat
Intercept	−0.295	−8.460***	0.108	3.088**	0.134	8.886***
$IS_{AM,i}$	0.746	9.227***	0.384	8.051***	0.758	21.599***
$IS^2_{AM,i}$	−0.209	−4.027***			−0.288	−15.731***
$IS_{JJ,i}$	0.901	11.471***	0.622	7.546***	−0.183	−8.389***
$IS^2_{JJ,i}$	−0.640	−16.542***	−0.510	−11.203***		
$IS_{AS,i}$			−0.356	−10.371***	−0.176	−4.243***
$IS^2_{AS,i}$	−0.085	−3.833***			−0.125	−4.141***
$IP_{AM,i}$	0.313	1.923.	−0.751	−6.278***		
$IP_{JJ,i}$					−1.191	−21.716***
$IP_{AS,i}$					0.345	4.214***
IP_i					0.719	10.077***
IP^2_i			0.163	4.882***	−0.174	−6.489***
IP_D	−2.424	−6.506***			−1.452	−12.205***
IP^2_D	1.767	4.730***			0.880	10.572***
IP_S	18.553	9.354***	−0.893	−8.547***	−0.384	−4.914***
IP^2_S	−31.194	−8.708***				
Adjusted R2	0.176		0.204		0.204	

Notation Key: ***, **, *, and . indicate statistical significance at the .001, .01, .05, and .10 level. IS = Index using summation. IP = Index using product. AM = April, May. JJ = June, July. AS = August, September. D = Agricultural district. S = State.

appropriate safety net level when an adverse event occurs. These regression results are used to establish triggers in the developed disaster program, which are the focus of the simulations that are conducted in the next section.

Farm-Level Simulations

To estimate the impact of the proposed crop disaster program at the farm-level, a simulation method is used that is similar to Cooper and Delbecq (2014), which is an extension of the technique used in Cooper (2010). This procedure addresses three main issues that arise in simulating farm-level yields. First, the correlation in deviations between yields and price has to be preserved. This assumption is particularly important when considering RP crop insurance policies within the Midwest corn growing region, which is one of the few regions where yield realizations correlate with prices. Adhikari, Belasco, and Knight (2010), for example, show that the estimated

Table 4. Fixed Effects Panel Estimation Results for Cotton Yields, by State, 1980–2015

Variables	Arkansas ($n = 14$)			Georgia ($n = 31$)			Mississippi (n=29)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
Intercept	0.174	0.065	2.689**	0.417	0.051	8.233***	0.131	0.046	2.866**
$IS_{AM,i}$	0.717	0.105	6.823***	−1.298	0.166	−7.798***			
$IS^2_{AM,i}$				0.999	0.113	8.817***			
$IS_{JJ,i}$	−0.642	0.071	−9.015***	−0.311	0.055	−5.650***	−0.369	0.059	−6.282***
$IS^2_{JJ,i}$									
$IS_{AS,i}$	0.167	0.083	2.009*	−0.338	0.142	−2.387*			
$IS^2_{AS,i}$				0.234	0.102	2.292*			
$IP_{AM,i}$				−0.883	0.278	−3.178**			
$IP_{JJ,i}$									
$IP_{AS,i}$				−0.557	0.322	−1.733.			
IP_i									
IP^2_i									
IP_D							0.558	0.122	4.589***
IP^2_D									
IP_S	−1.939	0.471	−4.120***	5.380	0.824	6.528***			
IP^2_S	1.485	0.387	3.842***	−8.195	1.214	−6.748***			
Adjusted R2	0.194			0.162			0.041		

	North Carolina (n=13)			Texas (n=72)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
Intercept	0.23422	0.08048	2.91**	0.236	0.036	6.555***
$IS_{AM,i}$				−0.639	0.095	−6.703***
$IS^2_{AM,i}$				0.148	0.057	2.578*
$IS_{JJ,i}$	0.27503	0.11431	2.406*			
$IS^2_{JJ,i}$						
$IS_{AS,i}$	−1.26267	0.2078	−6.076***	0.218	0.057	3.832***
$IS^2_{AS,i}$	0.4876	0.0981	4.971***			
$IP_{AM,i}$						
$IP_{JJ,i}$	−0.47667	0.22849	−2.086*	−0.781	0.089	−8.797***
$IP_{AS,i}$				−0.642	0.151	−4.244***
IP_i	0.85464	0.3948	2.165*	0.479	0.128	3.726***
IP^2_i	−0.69	0.23102	−2.987**			
IP_D				−0.674	0.191	−3.538***
IP^2_D				0.124	0.073	1.713.
IP_S	5.86591	1.49254	3.93***			
IP^2_S	−9.75127	2.17269	−4.488***			
Adjusted R2	0.142			0.142		

Notation Key: ***, **, *, and . indicate statistical significance at the .001, .01, .05, and .10 level. IS = Index using summation. IP = Index using product. AM = April, May. JJ = June, July. AS = August, September. D = Agricultural district. S = State.

Table 5. Fixed Effects Panel Estimation Results for Soybean Yields, by State, 1980–2015

Variables	Illinois ($n = 91$)			Indiana ($n = 65$)			Iowa (n=99)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
Intercept	0.049	0.030	1.633	0.096	0.033	2.952**	−0.193	0.027	−7.062***
$IS_{AM,i}$	1.037	0.079	13.077***	0.802	0.095	8.406***	1.056	0.080	13.250***
$IS^2_{AM,i}$	−0.444	0.047	−9.393***	−0.142	0.054	−2.648**	−0.428	0.044	−9.680***
$IS_{JJ,i}$	−0.327	0.084	−3.878***	−0.405	0.035	−11.557***			
$IS^2_{JJ,i}$	0.200	0.065	3.083**				0.127	0.040	3.206**
$IS_{AS,i}$	−0.204	0.076	−2.681**	−0.317	0.038	−8.352***			
$IS^2_{AS,i}$	−0.099	0.043	−2.299*				−0.050	0.028	−1.780.
$IP_{AM,i}$									
$IP_{JJ,i}$	−0.991	0.168	−5.901***				−1.476	0.195	−7.555***
$IP_{AS,i}$							−0.573	0.158	−3.618***
IP_i	0.233	0.073	3.208**				0.973	0.175	5.569***
IP^2_i							−0.292	0.058	−5.028***
IP_D	−1.753	0.180	−9.724***	−1.892	0.351	−5.393***	−0.535	0.122	−4.370***
IP^2_D	0.839	0.140	6.003***	1.341	0.311	4.316***			
IP_S				4.704	0.627	7.509***			
IP^2_S				−9.398	1.107	−8.492***			
Adjusted R2	0.190			0.192			0.101		

	Minnesota (= 65)			Nebraska ($n = 55$)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
Intercept	−0.331	0.036	−9.291***	0.104	0.036	2.869**
$IS_{AM,i}$	0.582	0.076	7.708***			
$IS^2_{AM,i}$	−0.133	0.033	−4.057***			
$IS_{JJ,i}$	1.013	0.081	12.553***	0.709	0.093	7.625***
$IS^2_{JJ,i}$	−0.570	0.039	−14.443***	−0.534	0.052	−10.227***
$IS_{AS,i}$				−0.363	0.042	−8.671***
$IS^2_{AS,i}$	−0.077	0.023	−3.287**			
$IP_{AM,i}$						
$IP_{JJ,i}$						
$IP_{AS,i}$						

Continued

Table 5. continued

Variables	Illinois ($n = 91$)			Indiana ($n = 65$)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
IP_i				0.538	0.107	5.035***
IP_i^2						
IP_D						
IP_D^2						
IP_S	21.241	3.184	6.672***	−0.505	0.135	−3.731***
IP_S^2	−36.412	5.481	−6.644***			
Adjusted R2	0.115			0.112		

Notation Key: ***, **, *, and . indicate statistical significance at the .001, .01, .05, and .10 level. IS = Index using summation. IP = Index using product. AM = April, May. JJ = June, July. AS = August, September. D = Agricultural district. S = State.

spearman yield price correlations throughout Illinois are statistically significant and negative with absolute values that exceed 0.12 in every county.

Second, spatial correlations need to be preserved. This is accomplished by matching historical correlations across national, state, and county yield deviations. Third, the relationship between farm level yield deviations and county deviations is preserved through a procedure originally developed in Coble and Dismukes (2008). This procedure assumes that differences between county and farm level yields are distributed according to a standard normal distribution with a variance inflation factor, where base county rates from the RMA are used to estimate the variance inflation factors and NASS county yields are assumed to be equivalent to county yields for producers who purchase crop insurance.

At the farm level, indemnities are received when predicted county yields are below the county-level yield trigger, where predicted yields arise from weather outcomes and the state-specific regressions presented above. In the proceeding analysis, this weather-based index disaster product is compared to RP at the 70% and 85% coverage levels. The base of comparison is the RMA's Revenue Protection (RP) product since that is the most commonly purchased product within most major grain agricultural production regions. The 70% coverage level is particularly appealing for the proposed disaster program from a multilateral standpoint as it would be consistent with the loss criteria established under Paragraphs 7 and 8 of the Agreement on Agriculture (Glauber 2016). To provide a contrast with current crop insurance coverage choices, the 85% coverage level is also evaluated because it is extensively used by farmers, particularly in the Midwest region.

Simulations are conducted for each county within the included states for each commodity. Distribution of yields are simulated for each county, agricultural district, state, and national price combination by taking 10,000 random yields draws. The main results from this simulation assuming a 70% coverage level are presented in table 7. For RP for corn, the average farmer-paid premium per acre is $15.17, which implies that the total per acre premium for the representative farm is $37.00, while the subsidized portion—the net expected benefit to the producer—is $21.83

Table 6. Fixed Effects Panel Estimation Results for Wheat Yields, by State, 1980–2015

Variables	Kansas ($n = 84$)			Montana ($n = 43$)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
Intercept	0.109	0.039	2.796**	0.376	0.039	9.640***
$IS_{AM,\,i}$	−0.661	0.122	−5.420***	−0.487	0.120	−4.045***
$IS^2_{AM,i}$	0.389	0.114	3.424***	0.232	0.068	3.390***
$IS_{JJ,\,i}$	0.216	0.101	2.129*	−0.841	0.056	−14.996***
$IS^2_{JJ,i}$	−0.411	0.093	−4.416***			
$IS_{AS,\,i}$	0.096	0.058	1.656.			
$IS^2_{AS,i}$						
$IP_{AM,\,i}$	−1.540	0.307	−5.022***	−0.964	0.215	−4.490***
$IP_{JJ,\,i}$	0.913	0.300	3.048**			
$IP_{AS,\,i}$	−0.355	0.144	−2.469*			
IP_i	0.600	0.118	5.087***	0.490	0.127	3.865***
IP^2_i						
IP_D				−0.892	0.256	−3.482***
IP^2_D						
IP_S	0.658	0.160	4.111***	2.384	0.365	6.526***
IP^2_S						
Adjusted R^2	0.057			0.208		
	North Dakota ($n = 43$)			South Dakota ($n = 25$)		
	Parameter Estimate	Standard Error	T-stat	Parameter Estimate	Standard Error	T-stat
Intercept	0.174	0.047	3.708***	0.393	0.053	7.428***
$IS_{AM,\,i}$	0.424	0.063	6.748***	−0.295	0.057	−5.132***
$IS^2_{AM,i}$						
$IS_{JJ,\,i}$	−0.466	0.123	−3.776***	−0.415	0.179	−2.320*
$IS^2_{JJ,i}$	−0.455	0.080	−5.716***	−0.574	0.132	−4.334***
$IS_{AS,\,i}$	−0.133	0.061	−2.201*			
$IS^2_{AS,i}$						
$IP_{AM,\,i}$	−1.778	0.131	−13.568***			
$IP_{JJ,\,i}$	1.126	0.285	3.953***	1.918	0.377	5.087***
$IP_{AS,\,i}$						
IP_i	0.646	0.173	3.737***			
IP^2_i						
IP_D						
IP^2_D						
IP_S	1.994	0.199	10.022***	3.481	0.512	6.803***
IP^2_S				−2.915	0.454	−6.424***
Adjusted R^2	0.271			0.279		

Notation Key: ***, **, *, and . indicate statistical significance at the .001, .01, .05, and .10 level. IS = Index using summation. IP = Index using product. AM = April, May. JJ = June, July. AS = August, September. D = Agricultural district. S = State.

per acre, as shown in the table.[14] Participation in RP insurance increases total revenue per acre for the participating farmer by an average of $22[15] and reduces the coefficient of variation of revenue per acre by 26.7%, relative to not purchasing crop insurance.[16]

Index insurance impacts are simulated using the out-of-sample portion, where the out-of-sample portion randomly excludes certain counties from the simulation as a robustness check to evaluate the sensitivity of rates

[14] With a 70% coverage level, the subsidized portion, based on RMA's subsidy schedule, of an RP policy is 59%.

[15] The increase in revenue is equal to the amount of subsidies in the premium because the assumption is made that crop insurance products are rated accurately.

[16] The decrease in revenue coefficient of variable is shown in the drop under no insurance to RP insurance as falling from 0.30 to 0.22.

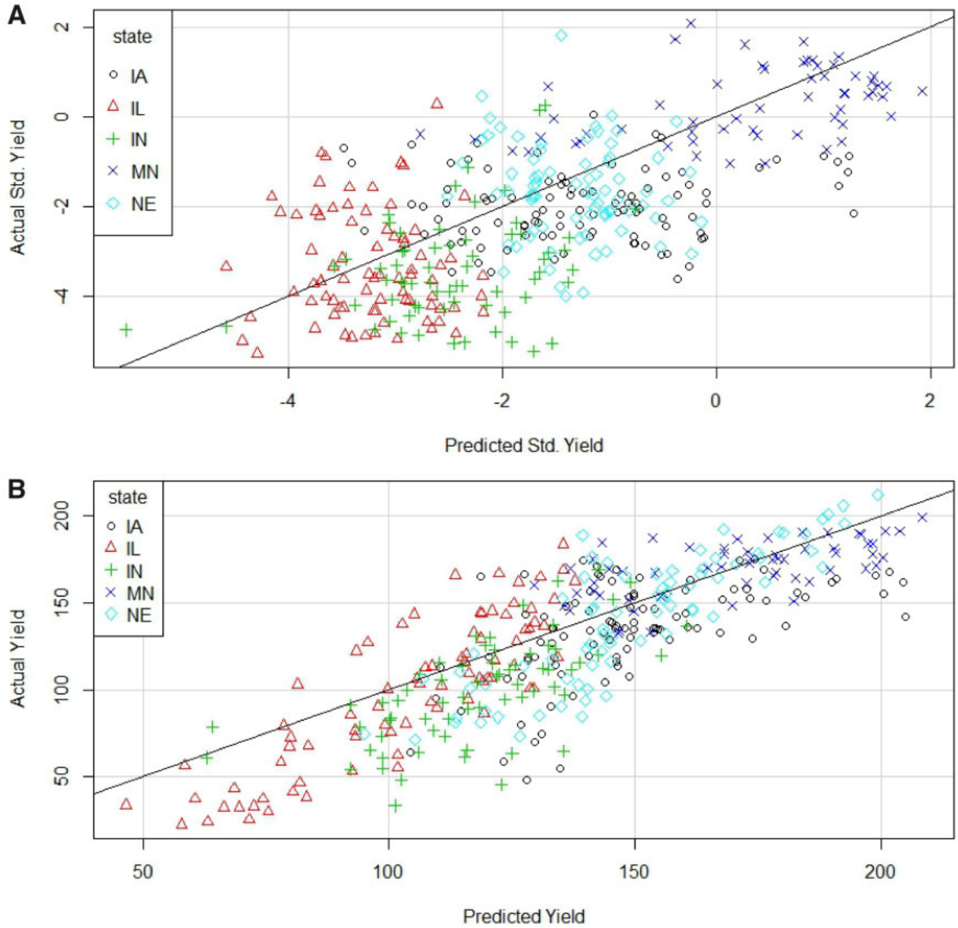

Figure 2. a. Plot of actual versus predicted standardized yields for major corn producing counties during the drought of 2012. b. Plot of actual versus predicted yields for major corn producing counties during the drought of 2012.

to exclusions. Specifically, out-of-sample yield predictions are generated for each county by making that county's yield predictions based on state yield regressions that did not include that county.[17] Based on the results presented in table 7, the Index product for corn costs an average $10.14 per acre. Given that the index product is part of a disaster aid program, the premium cost would be fully subsidized through government expenditures. Participation in the index program would increase revenue per acre by an average of $10 from the base scenario of $720 to $730. This should not be surprising given that the program would be rated to be actuarially fair, that is, indemnities would, on average, equal premiums. Under the disaster aid program, the coefficient of variation would decrease from 0.30 to 0.28, providing a reduction of 6.7%. This is less than half of the reduction that comes from the use of RP participation, which is likely the difference between idiosyncratic and systematic risk components, and due to regression error in predicting county yield.

Basis risk is an important consideration when comparing individual and index insurance products. Thus Type I and Type II errors associated with the developed index insurance product are also included in table 7. In this context, a Type I error is defined as the likelihood of receiving no indemnity when a loss is experienced, which is estimated

[17] In-sample predictions (not included here) were consistent with the out-of-sample predictions, albeit with a slightly higher variance with the latter.

Table 7. Summary of Per-Acre Government Paid Portion of the Insurance Premium and Farm-level Revenue per Acre Statistics under Alternative RP Scenarios Using a 70% Coverage Rate Choice (Average across All Counties in Sample)

	Premium Subsidy / Acre	Avg Total Revenue/ Acre	95% Confidence Interval of Revenue/Acre	Coefficient of Variation of Total Revenue/Acre	Loss & no indemnity paid (%)	Gain & indemnity paid (%)
Corn						
No insurance	...	720	[242; 1139]	0.30		
RP insurance[a]	21.83	742	[522; 1123]	0.22		
Index-RP[ab]	10.14	730	[295; 1146]	0.28	10.41	5.58
Soybeans						
No insurance	...	553	[211; 954]	0.34		
RP insurance[a]	12.54	566	[382; 945]	0.29		
Index-RP[ab]	3.53	557	[258; 953]	0.33	11.48	1.40
Winter Wheat						
No insurance	...	275	[15; 580]	0.52		
RP insurance[a]	16.10	291	[165; 569]	0.38		
Index-RP[ab]	7.80	283	[75; 575]	0.45	9.96	2.84
Upland Cotton						
No insurance	...	425	[26; 1045]	0.73		
RP insurance[a]	36.75	462	[267; 1020]	0.52		
Index-RP[ab]	27.77	451	[94; 1028]	0.58	9.82	5.59

Note: Analysis assumes the 2016 RMA base price. *RP insurance* is the standard RP insurance calculated over farm level yields while *Index-RP* is the same except calculated over county level yields. The simulations comprise a representative farmer in each of 379 corn, 351 soybean, 123 winter wheat, and 100 cotton counties. The results are weighed by the number of acres of the crop enrolled in federal crop insurance in the county. [a]Premium assumes a 70% coverage rate on the RP policy. [b]Estimate based on the out-of-sample Index.

to be 10.41% for a corn farmer under a 70% index product. The Type II error, defined as the likelihood of receiving a payment when no loss is experienced, is estimated to 5.58% for a corn farmer under a 70% Index product. These Type I and Type II error estimates are based on the assumption that an RP policy results in no Type I or Type II.[18]

The procedure described above was repeated for soybeans, wheat, and cotton. For each of these commodities, the free index RP premium is less than half of the subsidized portion of the RP insurance. These savings come from the index product insuring systemic risk and not insuring idiosyncratic risk events.

This process was repeated for each crop assuming an 85% coverage level and reported results are provided in table 8. While a higher coverage level increases the likelihood of an indemnity payment and the total premium, it also results in a decrease in the subsidy rate from 59% at the 70% coverage level to 38% at the 85% coverage level. The net effect of these two changes leads to higher subsidies per acre for the RP Index product in all cases except for cotton. The index insurance benefit increases across all commodities due to the 100% subsidized nature of the product. The likelihood of underpaying decreases as the coverage level increases, except in the case of corn. Additionally, higher coverage levels lead to an increase in the likelihood of overpayment.

Table 9 shows the estimated cost of each program. To compute total taxpayer costs of federal agricultural insurance for each of the simulated scenarios, we first add the cost of the premium subsidy and the net of premium and indemnity payments to the producer. For RP insurance, under 70% coverage the cost would include an average premium subsidy of $21.83 for corn. Since our simulations assume that each representative farmer is rated fairly, indemnities will equal total premium (including subsidies), so that the total taxpayer cost is equal to the premium subsidy. Based on simulations, the estimated subsidy premiums per acre are $12.54 for soybeans, $16.10 for wheat, and $36.75 for cotton.

The second component required to compute the total cost of crop insurance program consists of the costs associated with

[18] While the price received by the farmer is likely to deviate from the futures price at harvest, these deviations persist in both individual and area products and do not represent an area of risk that is unique to index products.

Table 8. Summary of Per-Acre Government Paid Portion of the Insurance Premium and Farm-Level Revenue per Acre Statistics under Alternative RP Scenarios Using a 85% Coverage Rate Choice (Average across All Counties in Sample)

	Premium Subsidy / Acre	Avg Total Revenue/ Acre	95% Confidence Interval of Revenue/Acre	Coefficient of Variation of Total Revenue/Acre	Loss & no indemnity paid (%)	Gain & indemnity paid (%)
Corn						
No insurance	. . .	720	[242; 1139]	0.30		
RP insurance[a]	26.65	747	[609; 1095]	0.19		
Index-RP[ab]	17.41	737	[330; 1148]	0.26	12.05	12.36
Soybeans						
No insurance	. . .	553	[211; 954]	0.34		
RP insurance[a]	17.90	571	[445; 925]	0.25		
Index-RP[ab]	9.24	563	[310; 939]	0.29	10.16	5.31
Winter Wheat						
No insurance	. . .	275	[15; 580]	0.52		
RP insurance[a]	16.58	292	[205; 553]	0.34		
Index-RP[ab]	10.33	286	[115; 575]	0.41	7.85	5.32
Upland Cotton						
No insurance	. . .	425	[26; 1045]	0.73		
RP insurance[a]	34.15	459	[299; 989]	0.48		
Index-RP[ab]	26.28	451	[114; 1004]	0.55	8.72	7.07

Table 9. Estimated Insurance Savings Based on Simulated Insurance Premium and Revenue Results

Indicator	Corn	Soybeans	Wheat	Cotton
2016 RMA enrolled acres (M)	82.15	73.26	42.81	9.44
Average premium subsidy per acre (70% coverage level)[a]				
RP insurance	21.83	12.54	16.10	36.75
Free index RP	10.14	3.53	7.80	27.77
% Reduction with free index RP	53.55	71.85	51.55	24.44
Estimated cost of RMA RP ($B)[b]	2.97	1.52	1.14	0.58
Cost of free index RP ($B)[c]	1.06	0.33	0.42	0.33
Savings ($B)	1.92	1.20	0.72	0.24
Change in downside risk protection (%)	−43	−32	−55	−65
Average premium subsidy per acre (85% coverage level)[a]				
RP Insurance	26.65	17.9	16.58	34.15
Free Index RP	17.41	9.24	10.33	26.28
% Reduction with free index RP	34.67	48.38	37.70	23.05
Estimated cost of RMA RP ($B)[b]	3.14	1.88	1.02	0.46
Cost of free index RP ($B)[c]	1.82	0.86	0.56	0.32
Savings ($B)	1.33	1.02	0.46	0.15
Change in downside risk protection (%)	−46	−30	−44	−62

Note: 2016 RMA Base prices are assumed. [a]Simulations are based on a representative farmer in each included county/crop combination. [b]Figures based on simulated RP premium rates applied to all enrolled acres and include average administrative and operating expenses (A&O) and underwriting gains as a percent of total premium. Average A&O and underwriting gains, as a percentage of total premium, are based on historical averages following the most recent 2011 Standard Reinsurance Agreement, shown in table 1 and are, respectively, 14% and 13%. [c]Figures based on simulated Free Index RP premium rates applied to all enrolled acres and include average A&O expenses as a percent of total premium.

administering the program. Based on the results shown in table 1, administrative and operating (A&O) cost have averaged 16% of total premium since 2007, while underwriting gains have also averaged 16% of total premium over the same time period. More recently, average A&O and underwriting gains over the last six years (2012–2017) have been 14% and 13%, respectively. These recent figures provide a more accurate assessment of recent payments to insurance companies as they reflect experience following the most recent 2011 Standard Reinsurance Agreement.[19] Using these values, the average A&O cost per acre for corn policies would be around \$5.18 [=37.00 × 0.14] and underwriting gains are expected to be around \$4.81 [=37.00 × 0.13]. These two administrative cost components are added to the producer subsidies to obtain the total costs incurred by taxpayers. Thus, when administrative costs are added to premium subsidies, the average tax payer cost per acre for corn is \$31.82[=21.83 + 5.18 + 4.81] under the current RP program. Total per acre taxpayer costs can also be computed using a similar method for soybeans (\$18.28), wheat (\$23.47), and cotton (\$53.57).

The total taxpayer cost of the index-based disaster aid program would account for the price of the premium and indemnity under a disaster program. If we include the full cost of the A&O portion of the current crop insurance program and simply took out the underwriting gains and added the premiums associated with index insurance,[20] the per acre index program cost would be approximately \$10.14 for corn, \$3.53 for soybeans, \$7.80 for wheat, and \$27.77 for cotton. It is worth mentioning that the farmer has paid no direct premiums to participate in the disaster aid program and the program would still cost the federal government less per acre for corn (\$18.94), soybeans (\$13.80), wheat (\$13.56), and cotton (\$18.30).

Given that the index program would be provided for all farms, federal expenditures would be spread across more producers. For example, in the top five corn states, over 48 million acres were planted, of which 91% were insured under a federal crop insurance product and 83% were insured under the RP policy. If all 82.15 million enrolled acres of corn were converted into the proposed index insurance program, the cost of the index program would be \$1.06 Billion. This amount implies that expenditures under the index program are \$1.92 billion less than the estimated cost of the RMA RP program (\$2.97 billion). When these savings are spread across the four major commodities, total estimated savings in federal expenditures amount to \$4.08 Billion. Under the 85% coverage level scenario, total savings are reduced to \$2.95 billion. This reduction in savings is the result of a more generous index program that has a higher coverage level and costs \$3.55 billion, which is \$1.41 billion more than under a 70% coverage level. The RP program costs are about the same under both scenarios since the lower subsidies associated with the higher coverage level offset the higher premiums.

The disadvantage of the disaster product from the producers' perspective is that it provides less coverage than the current RP insurance policy. This is due to the basis risk associated with the index program being tied to a simulated aggregated index rather than field-level yields. In fact, it is this basis risk that accounts for premiums for the Index product being less expensive than for traditional RP – there is simply less yield risk at the county level.[21] The increase in basis risk is manifested through an increase in downside revenue risk, and not in mean revenue, which changes little in the shift from RP insurance to the index product. If we measure the change in downside risk as the percent change in the lower bound of the 95% confidence interval on farm revenue reported in table 7, for 70% coverage, then the downside risk of the index plan over RP is 43, 32, 55, and 65% higher for corn, soybeans, winter wheat, and upland cotton, respectively. These reductions in downside risk are similar to those obtained when considering a higher 85% coverage level, as shown in table 8. Much of the lower downside risk loss of corn and soybeans relative to wheat and cotton is likely attributable to idiosyncratic risk being a larger portion of total yield volatility for wheat and cotton relative to corn and

[19] While figures above are quoted at the national level, underwriting gains are actually computed at the state level over the entire book of business in that state. Since state-level underwriting gains information are not available, we use national averages as a proxy.

[20] This is likely to be a conservative estimate regarding the administrative cost of administering such an index program as there are likely to be savings from current insurance administrative and operating costs for two main reasons: (1) Since weather data are used to determine indemnities, no insurance adjuster is needed to validate losses and; (2) Enrollment in the program could be done online, reducing the administrative cost of enrollment. However, these potential cost savings are ignored in the present study.

[21] One way to compensate for the basis risk in the index plan would be to allow producers to opt for a multiple on coverage of greater than the 1.0 that we assume (Miranda 1991). In the Group Risk Plan in the early 1990s, this was achieved by allowing producers to choose a scaling factor on acreage of greater than 1.0 (Skees, Black, and Barnett 1997). Miranda (1991) found the optimal scale factor on area planted from a hedging standpoint was 1.6. Subsidy rates are currently much higher than back in the early 1990s, and allowing scaling factors greater than 1 could substantially increase government costs.

soybeans. Differences in the price-yield correlations among these crops could also play a role, with a negative correlation between yields and price being stronger for corn and soybeans.

Concluding Comments

The proposed crop disaster program would provide revenue protection to farmers of major commodities at a cost significantly reduced from existing crop insurance programs. These savings are realized largely though two mechanisms: (1) Focusing agricultural support on systemic weather risk, rather than idiosyncratic risk, and (2) delivering more direct benefits to producers by eliminating the need for insurance companies to participate in the delivery of insurance.

The disadvantage of the proposed crop disaster product from the producers' perspective is the basis risk associated with the program's simulated and aggregate index rather than field-level yields, thus providing less coverage under the index product. Regressions were developed for major producing states that relate weather outcomes to county-level yields. The regression parameters provide the backbone of the proposed disaster program, which uses farm-level simulations in order to evaluate the relative cost of implementation. The proposed index-based disaster aid program would substantially lower the cost of the federal safety net program and take advantage of weather data to write insurance contracts in a more cost-effective manner. The disaster aid program would result in estimated savings of approximately $4.08 billion across the four major commodities considered in the analysis when a 70% coverage level is considered. Savings are reduced to $2.95 billion when an 85% coverage level is considered.

Over the three-year period 2014–2016, the cost of the federal crop insurance program averaged $9.7 billion per year. The proposed disaster aid program is estimated to save a substantial amount by reducing or eliminating payments made to insurance companies and eliminating the coverage of idiosyncratic risk that is currently part of individual crop insurance policies.[22]

In 2015, the average acre-weighted insurance coverage levels for RP corn crop insurance in Iowa (80.94), Illinois (79.38), and Indiana (79.65) were all far above the 70% coverage level. Thus it is likely that the magnitude of subsidies on a per acre basis are going to be higher than anticipated in this analysis.

The disadvantage of lowering the participation of insurance companies is the associated increase in yield basis risk for producers and the reduction in protection against revenue risk. At the 70% coverage rate, the change in downside risk protection for the producer of the disaster aid program compared to RP insurance ranges from -32% for soybeans to -65% for cotton. At the 85% coverage rate, relative to the protection provided by an 85% RP insurance product, the increase in downside risk protection increases relatively modestly for corn, soybeans, and cotton, but increases by 20% for winter wheat, which is likely a reflection of the relatively low ratio of idiosyncratic to area yield variability for this crop.

Beyond decreasing the downside revenue protection of the producer, a potential consequence of the increase in basis risk associated with the disaster aid program over traditional crop insurance—which may lower the cost of credit (Ifft, Kuethe, and Morehart 2013) although data are not publically available to test this relationship—is that bank loans could become more costly for farmers using insurance based on aggregate yield. Measuring the social welfare implications of the increased basis risk requires specification of a social welfare function for federal crop insurance, or at least social welfare weights, could be a good subject for future research.

The crop disaster program examined in this study has been presented as a free crop insurance option since there are zero farmer-paid premiums. However, it is likely that some farmers would be willing to pay a premium to insure basis risk. The additional coverage could be added through a wrapper product. Two current examples of wrapper

[22] The proposed savings are likely to be conservatively stated and are likely to increase when considering the expansion of the proposed product into additional states that produce corn. Slight reductions are also likely when considering the low proportion of corn producers who do not currently purchase federal crop insurance but will participate in the crop disaster program. However, it is worth noting that participation in existing livestock disaster program are lower than 100% as many ranchers do not submit claims even when residing in counties declared for full payments under the LFP program.

types of products tied to individual farm based insurance include RMA's Margin Protection plan and Harvest Price Option. By utilizing the proposed index product as a base layer of insurance, for example, the buy-up portion of a Yield Protection or RP policy could be sold with or without a subsidy. Such an option may provide a producer with downside risk protection similar to the current program, but depending on the subsidy rate, at potentially lower government cost.

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