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ARTICLE

Systemic risk, relative subsidy rates, and area yield insurance choice

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Abstract

We investigate the nature of crop yield systemic risk and its implications for farmers' area yield insurance choices. A theory-grounded, normalized measure of systemic risk, R^2, is developed and made amenable to empirical analysis through the logit link. The measure is estimated on a large-scale, unit-level corn yield dataset. We find that systemic risk explains less than half of total unit yield variability on average, suggesting that the risk management effectiveness of area yield insurance is low. By relating natural resource endowments with systemic risk, we find that more excessive heat and drought events lead to larger while more excessive precipitation events lead to smaller systemic risk. We then study whether current area yield insurance subsidy rates provide farmers with sufficient subsidy transfers to compensate for the uncovered risk exposure associated with area yield insurance. A new concept, the threshold relative area subsidy rate (TRASR), quantifies a lower bound on the ratio of area yield insurance subsidy rate over individual yield insurance subsidy rate below which risk-averse farmers should always prefer individual yield insurance to area yield insurance. The calibrated TRASR values indicate that current area yield insurance subsidy rates discourage farmers from choosing area yield insurance over individual yield insurance, especially at low area yield insurance coverage levels. We also find that TRASR is positively correlated with systemic risk at the unit-level of analysis, suggesting that farmers who like area yield insurance's risk management features will dislike its transfer implications and vice versa.

KEYWORDS
basis risk, climate change, idiosyncratic risk, individual yield insurance, natural resource endowments, risk management, transfer seeking

JEL CLASSIFICATION
D81, Q12, Q18

1 | INTRODUCTION

Systemic yield risk exists because yields tend to be strongly and positively correlated in a region. This risk can lead to substantial indemnity payments in catastrophic weather years, which is considered a major reason why private crop insurance providers would be unwilling to take on the risk (Miranda & Glauber, 1997). The U.S. Federal Crop Insurance Program (FCIP) has evolved into a public–private partnership in which the federal government shares risks with private providers. Systemic risk has also encouraged the federal government to promote area insurance contracts, which pay indemnity based on average yield or revenue loss in an area rather than on individuals' losses. To the extent that area yield or revenue outcomes correspond with farm-level outcomes, indemnification based on pertinent area statistics can meet farmer financial shortfalls when needed. In addition, compared to individual insurance plans, area insurance plans have the advantages of lower information requirements and less potential for moral hazards (Barnett et al., 2005; Miranda, 1991; Skees et al., 1997). However, as shown in Figure 1, the share of area insurance insured acres in total

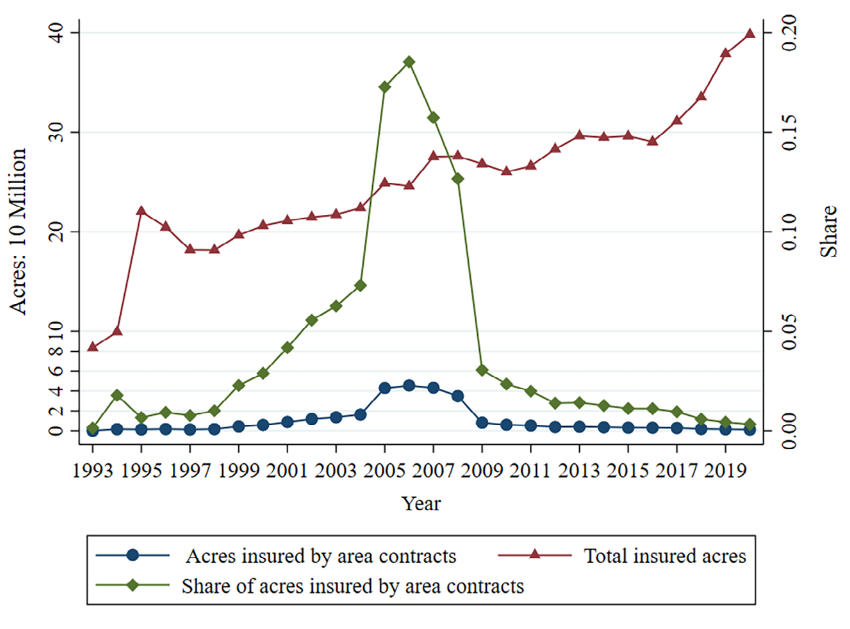

FIGURE 1 Share of acres insured by area insurance contracts for all crops, 1993–2020
Notes: 1. Source: Summary of Business (SOB), 1993–2020, Risk Management Agency (RMA). 2. This figure plots acres insured by area insurance contracts and acres insured by any kind of crop insurance contract for all crops over 1993–2020 (left y-axis), and the share of area insurance insured acres in total insured acres for all crops over 1993–2020 (right y-axis). 3. Area insurance programs before 2014 are Group Risk Plan, Group Risk Income Protection, and Group Risk Income Protection with Harvest Revenue Option. Area insurance programs starting in 2014 are Area Yield Protection, Area Revenue Protection, and Area Revenue Protection with Harvest Price Exclusion.

insured acres has never exceeded 20% ever since its inception. This observation poses questions regarding the extent to which systemic risk can account for individual farmers' risks and whether farmers view area insurance plans as competitive alternatives to individual plans. In this paper, we seek to answer these questions by first modeling, measuring, and decomposing systemic risk in corn yield across the Greater Midwest. We then apply findings in systemic risk, together with the current FCIP premium subsidy features, to understand low area insurance demand in the United States and likely impacts of climate change for systemic risk.

Following Miranda (1991), we use a linear additive model (LAM) to decompose unit yield into a systemic component that is correlated with area yield and an idiosyncratic component that is uncorrelated with area yield. We then measure systemic yield risk as the proportion of unit yield variation explained by area yield variation. Bounded between 0 and 1, this index provides a unitless measure of the proportion of yield risk that AYP can potentially cover. We also show how LAM enables a further decomposition of systemic risk into three more fundamental components: sensitivity of unit yield to area yield, area yield variance, and a unit's idiosyncratic yield variance. By relating each systemic risk component to climate and land variables, we further explore how systemic yield risk is determined by natural resource endowments.

Using a large-scale, unit-level dataset, we estimate systemic risk for corn yield across 12 major corn production states in the Midwest. We find that the proportion of unit yield risk that is systemic to county yield is 46% on average, suggesting that AYP can provide only modest risk protection. Systemic risk is highest at the southern and western fringes of the Corn Belt but comparatively low in much of Iowa and surrounding areas, indicating a mismatch between major corn production areas and high systemic risk areas. Regions with high systemic yield risk are characterized by large county yield variances and strong unit-to-county yield sensitivities. These regions typically experienced more drought and excessive heat events in the sample years, suggesting that the common downward shift of individual yields in these catastrophic events is the primary cause of high systemic risk.

Given AYP's limited risk management effectiveness, we then turn to investigating whether the current AYP subsidy level delivers sufficient transfers to compete with YP. Although FCIP is mainly intended to provide farmers with risk management tools, it is widely accepted that subsidy transfers at least partly motivate farmers to insure (Du et al., 2017; Goodwin & Smith, 2013). We introduce a novel concept, the Threshold Relative Area Subsidy Rate or TRASR, which is defined as the ratio of the AYP subsidy rate over the YP subsidy rate such that the two insurance plans provide equal expected net returns. As YP provides better risk protection, TRASR constitutes a lower bound on the relative subsidy level needed to entice risk-averse farmers to choose AYP over YP. By calibrating TRASR values for corn farmers in the 12 chosen Midwest states and comparing these values to current relative subsidy rates for AYP over YP, we find that the current premium subsidy schedule discourages corn farmers from choosing AYP over YP, especially at low AYP contract coverage levels. We also find that TRASR is positively correlated with systemic risk at the unit level of analysis, suggesting a decision dilemma: Farmers who enjoy good risk protection from AYP are more likely to find current AYP subsidy rates financially unrewarding, whereas those who find current AYP subsidy rates financially rewarding are less likely to be well protected by AYP.

This paper makes several significant and practical contributions to the literature. First, it adds to the measurement and conceptual understanding of systemic risk. Previous studies generally measure systemic risk in terms of correlations within insurers' portfolios (Goodwin & Hungerford, 2015; Hayes et al., 2003; Miranda & Glauber, 1997) or yield correlations within a given region (Du et al., 2018; Tack & Holt, 2016; Wang & Zhang, 2003). Insurer portfolio analyses are functions of pertaining crop insurance plans and choices, and so are limited and indirect in shedding light on the underlying nature of systemic yield risk. Yield correlation analyses hew closer to the problem primitives. However, using a long panel dataset for Illinois and Kansas farms, Zulauf et al. (2013) finds that farm-to-county yield correlation has limited ability to explain the share of a farm's loss that is systemic with county yield. Our systemic risk measure is more structural in that it considers both how closely unit yield varies with county yield and what that means for total yield variation. The study closest to ours in modeling systemic risk is Claassen and Just (2011), which uses a sample of unit yields together with ANOVA methods to break down unit yield variance into systemic, random, and interaction components. Our paper departs from Claassen and Just (2011) by decomposing systemic risk into more fundamental components, a distinction that enables us to study how changes in unit yield and county yield variability affect systemic risk.

Second, this paper provides new perspectives on farmers' apparently low demand for area insurance plans in the United States. The existing literature generally compares AYP with YP in effects on yield variance (Barnett et al., 2005; Miranda, 1991; Stigler & Lobell, 2021) or certainty equivalent revenues (Awondo & Datta, 2018; Deng et al., 2007). These methods depend on assumptions about the yield distribution or the utility function and underestimate the effect of basis risk on farmers' AYP choices. Basis risk exists for AYP buyers because they will not receive any indemnity when individual yield loss occurs but area yield performs well. This type of risk is generally considered a major cause of low participation in weather index insurance worldwide (Clarke, 2016; Hill et al., 2016; Keller & Saitone, 2022). This paper circumvents the limitations of the existing literature by directly studying AYP's risk management effectiveness and premium subsidy transfers. Our systemic yield risk estimates suggest limited risk management effectiveness for AYP contracts and thus a high level of basis risk, whereas the calibrated TRASR values demonstrate that the current premium subsidy schedule favors YP over AYP in general. This paper further advances the literature by revealing a positive correlation between systemic yield risk and TRASR, suggesting that, in the presence of subsidized YP, AYP is typically unable to simultaneously meet farmers' risk management and transfer-seeking needs.

Third, this paper provides opportunities for projecting future systemic risk patterns and area insurance demand. Recent studies have found that climate change would likely increase yield variability, crop insurance demand, and FCIP costs (Annan & Schlenker, 2015; Ray et al., 2015; Tack et al., 2018), but little is known about how systemic risk will evolve and what role area insurance could play in the presence of climate change. Previous studies have found that yield correlations will be higher in extreme weather years (Du et al., 2018; Tack & Holt, 2016). Our results confirm earlier findings that more excessive heat and drought events will lead to higher systemic risk. However, we also find that more excessive precipitation events will lead to lower systemic risk, perhaps because floods are localized to low-lying land. As of 2020, the Federal National Climate Assessments for both the Midwest and the Great Plains project a hotter climate with more drought and more flooding events.[1] Thus, our findings suggest that climate change implications for future systemic risk patterns depend on the specific extreme weather events that an area is likely to incur. Given this and the finding of a positive correlation between systemic yield risk and TRASR, how climate change affects future AYP demand patterns will also be area specific.

The remainder of this paper proceeds by first presenting our conceptual framework for modeling systemic risk and TRASR. Some propositions and conjectures are then developed, and these inferences are examined in the empirical sections. We conclude with a summary of major findings as well as some discussions on policy implications and items for future research.

2 | CONCEPTUAL FRAMEWORK

Our focus is on yield risk so we assume throughout that price is non-random. To avoid unnecessary notation, we set output price equal to 1 and ignore it henceforth. All yield, premium, subsidy, and indemnity variables used in this paper are on a per-acre basis.

[1]See https://nca2018.globalchange.gov/chapter/21/ and https://nca2018.globalchange.gov/chapter/22/.

2.1 | Modeling systemic risk

Following Miranda (1991), we apply LAM to characterize the relationship between unit yield and county yield,[2]

$$\tilde{y}_i = \mu_i + \beta_i(\tilde{y}_c - \mu_c) + \varepsilon_i. \tag{1}$$

Here $\tilde{y}_i \in [0, y_i^u]$ and $\tilde{y}_c \in [0, y_c^u]$ are, respectively, unit yield and county yield variables, where subscript i denotes insurance unit and c denotes county. The two yield variables are continuously distributed over the associated yield range with respective expected values $\mu_i = \mathrm{E}(\tilde{y}_i)$ and $\mu_c = \mathrm{E}(\tilde{y}_c)$, where $\mathrm{E}(\cdot)$ is the expectation operator. The error term has mean zero, $\mathrm{E}(\varepsilon_i) = 0$, and is uncorrelated with county yield, $\mathrm{Cov}(\tilde{y}_c, \varepsilon_i) = 0$, where $\mathrm{Cov}(\cdot)$ is the covariance operator. LAM has been widely used in crop insurance analysis and farm-level policy studies to simulate farm yield from county yield when farm-level data are unavailable (Carriquiry et al., 2008; Coble & Dismukes, 2008). Ramaswami and Roe (2004) show that whenever systemic and idiosyncratic risks are additive in individual yields then LAM can be obtained by applying the law of large numbers.

By way of Equation (1), we decompose unit yield deviation from expectation into a systemic component, $\beta_i(\tilde{y}_c - \mu_c)$, which is correlated with county yield, and an idiosyncratic part, ε_i, which is uncorrelated with county yield. Coefficient β_i measures the sensitivity of unit yield to county yield. Because $\beta_i \leq 0$ is rare for crop production, we assume that $\beta_i > 0$ throughout the paper. Letting $\sigma_i^2 = \mathrm{Var}(\tilde{y}_i)$, $\sigma_c^2 = \mathrm{Var}(\tilde{y}_c)$ and $\sigma_{\varepsilon_i}^2 = \mathrm{Var}(\varepsilon_i)$, where $\mathrm{Var}(\cdot)$ is the variance operator, we have $\sigma_i^2 = \mathrm{Var}(\tilde{y}_i - \mu_i) = \beta_i^2 \mathrm{Var}(\tilde{y}_c - \mu_c) + \mathrm{Var}(\varepsilon_i) = \beta_i^2\sigma_c^2 + \sigma_{\varepsilon_i}^2$.

Systemic risk, labeled as R_i^2, is then modeled as the fraction of unit yield variation that can be explained by county yield variation,

$$R_i^2 = \frac{\mathrm{Var}[\beta_i(\tilde{y}_c - \mu_c)]}{\mathrm{Var}(\tilde{y}_i - \mu_i)} = \frac{\beta_i^2\sigma_c^2}{\beta_i^2\sigma_c^2 + \sigma_{\varepsilon_i}^2} = \frac{1}{1 + \sigma_{\varepsilon_i}^2/(\beta_i^2\sigma_c^2)}. \tag{2}$$

As $R_i^2 \in [0, 1]$, it provides a straightforward absolute measurement of systemic risk. Values $R_i^2 > 0.5$ indicate that systemic risk is the dominant yield risk source faced by the farmer so that AYP has the potential to remove the majority of total risk.

Equation (2) also shows that our systemic risk measure can be decomposed into three more fundamental components: (i) the square of unit yield's sensitivity to county yield, β_i^2; (ii) county yield variance, σ_c^2; and (iii) idiosyncratic yield variance, $\sigma_{\varepsilon_i}^2$. Proposition 1 provides simple inferences that can be extracted from the equation.

Proposition 1. Ceteris paribus, R_i^2 increases with (i) an increase in unit yield's sensitivity to county yield, β_i; (ii) an increase in county yield variance, σ_c^2; and (iii) a decrease in idiosyncratic yield variance, $\sigma_{\varepsilon_i}^2$.

Proposition 1 provides indications on which counties and insurance units are likely to have high systemic risk. The most discernible is that, ceteris paribus, systemic risk will be higher in counties with larger county yield variances. We can readily identify these counties because county yield data can be accessed from the National Agricultural Statistical Service (NASS). In addition, although idiosyncratic yield variance is not observable, we might in general expect that units in regions where

[2]Here, we use "unit" as a general concept. There are several insurance unit types, such as optional unit and enterprise unit. See Bulut (2020) for more information.

heterogeneous approaches to production are taken are more likely to display large idiosyncratic yield variance and so low systemic risk. Were AYP the only insurance choice, farmers would tend to adopt practices common in an area to align their risks with area risk and obtain better protection from AYP (Chambers & Quiggin, 2002).

A common notion about area insurance is that it should work best in homogenous areas where yield correlations are strong (Barnett et al., 2005). We comment next on the relationship between systemic risk and the correlation coefficient between unit yield and county yield. Denoting $\theta_i = \mathrm{Cov}(\tilde{y}_i, \tilde{y}_c)/(\sigma_i\sigma_c)$ as the correlation coefficient between $\tilde{y}_i$ and $\tilde{y}_c$, we can rewrite the beta coefficient as $\beta_i = \mathrm{Cov}(\tilde{y}_i, \tilde{y}_c)/\mathrm{Var}(\tilde{y}_c) = \theta_i\sigma_i\sigma_c/\sigma_c^2 = \theta_i\sigma_i/\sigma_c$.[3] Defining $\chi_i = \sigma_{\varepsilon_i}^2/\sigma_i^2$ as the share of idiosyncratic yield variation in total unit yield variation, we obtain.

$$R_i^2 = \frac{1}{1 + (1/\theta_i^2)\chi_i}. \tag{3}$$

Proposition 2. Ceteris paribus, R_i^2 increases with (i) an increase in the correlation between unit yield and county yield, θ_i; and (ii) a decrease in the share of total unit yield variation that is accounted for by idiosyncratic yield variation, χ_i.

Proposition 2 implies that a strong unit-to-county yield correlation may not lead to high systemic risk when the share of idiosyncratic yield variation in total unit yield variation is large. Were county yield variation small but unit yield variation large then AYP only removes a small proportion of yield risk even when unit yield is highly correlated with county yield.

2.2 | Systemic risk and natural resource endowments

In this subsection we investigate how systemic risk varies with natural resource endowments. This information will allow us to develop insights on the roles of land quality and weather conditions in determining systemic risk and on how the risk protection function of area insurance will evolve in the presence of climate change.

Rather than directly model systemic risk as a function of natural resource endowment variables, labeled as Z_c, we allow each of the three systemic risk components to be a function of Z_c. The aggregate effect of natural resource endowments on systemic risk can be obtained as follows. Letting $\tau_i^2 = \sigma_{\varepsilon_i}^2/(\beta_i^2\sigma_c^2)$, then $R_i^2 = 1/(1+\tau_i^2)$ and $R_i^2/(1-R_i^2) = 1/\tau_i^2$. Taking the natural log of both sides of the last equation generates.

$$\ln\left(\frac{R_i^2}{1-R_i^2}\right) = -2\ln(\tau_i) = 2\ln[\beta_i(Z_c)] + 2\ln[\sigma_c(Z_c)] - 2\ln[\sigma_{\varepsilon_i}(Z_c)]. \tag{4}$$

Because the logistic transformation is monotonic, the effect of Z_c on R_i^2 is qualitatively the same as the effect of Z_c on $\ln[R_i^2/(1-R_i^2)]$. Equation (4) shows that the effects of natural resource endowments on systemic risk pass through $\beta_i(\cdot)$, $\sigma_c(\cdot)$, and $\sigma_{\varepsilon_i}(\cdot)$. Thus, if a given natural resource endowment variable has the same effect on $\beta_i(\cdot)$ and $\sigma_c(\cdot)$, then these two effects are concordant with each other. However, were a natural resource endowment variable to have the same effects on $\sigma_{\varepsilon_i}(\cdot)$ and either one of $\beta_i(\cdot)$ and $\sigma_c(\cdot)$, then these two effects would offset.

[3]See Part I of online Supplementary Appendix (Appendix S1) on how to derive $\beta_i = \theta_i\sigma_i/\sigma_c$. This expression is also derived in Miranda (1991). See its Equation (13), p. 235.

2.3 | Modeling YP and AYP contracts

Before introducing our definition of TRASR, we first outline how YP and AYP work. We choose Yield Protection and Area Yield Protection as, respectively, our generic YP and AYP plans. These are the two major yield insurance plans currently available in the United States.

Unit i in county c with random yield $\widetilde{y}_i$ and choosing to purchase YP will receive indemnity payments in the form,

$$\widetilde{n}_i = \max\left(\phi_i \overline{y}_i - \widetilde{y}_i, 0\right), \tag{5}$$

where $\widetilde{n}_i$ is realized YP indemnity payment, $\overline{y}_i$ is the insurer's reference "expected" unit yield, as established by Risk Management Agency (RMA),[4] and ϕ_i is the YP coverage level chosen by the farmer with $\phi_i \in \{0.5, \ldots, 0.85\}$ where evaluations are in 5% increments. Thus, YP pays indemnities whenever $\widetilde{y}_i$ falls below the policy protection amount, $\phi_i \overline{y}_i$.

Similarly, AYP pays indemnities whenever the county average yield is lower than the policy-protected county yield level. Compared with the YP indemnity function, the AYP indemnity function takes a more complicated form,

$$\widetilde{n}_c = \rho \max\left[\min\left(\frac{\overline{y}_c \phi_c - \widetilde{y}_c}{\phi_c - l}, \overline{y}_c\right), 0\right], \tag{6}$$

where $\widetilde{n}_c$ is the realized AYP indemnity payment, $\overline{y}_c$ is the reference expected county average yield, and ϕ_c is the AYP coverage level with $\phi_c \in \{0.7, \ldots, 0.9\}$ also available in 5% increments. Protection factor ρ, with $\rho \in [0.8, 1.2]$, allows the insured to adjust the AYP liability to better match expected individual losses. The loss limit factor, l, with fixed value 0.18, allows the insured's entire loss to be paid when the county loss equals 82% of the expected county yield, but no additional indemnity is payable when the county loss exceeds 82% of the expected county yield (see Bulut and Collins (2014), p. 415, note 1).

2.4 | Deriving TRASR

This subsection illustrates the importance of relative premium subsidy rates in encouraging farmers to choose AYP over YP. Because YP provides better risk protection than AYP, under the actuarially fair premium assumption, it follows that risk-averse farmers will always choose YP over AYP whenever no premium subsidy is provided.

To see this, let π_i and π_c denote, respectively, YP and AYP premiums, whereas s_i and s_c denote respective subsidy rates. Under the actuarial fairness assumption, that is, $\pi_i = \mathrm{E}(\widetilde{n}_i)$ and $\pi_c = \mathrm{E}(\widetilde{n}_c)$, then the expected net returns from purchasing YP and AYP are

$$\begin{aligned}\mathrm{E}\left(\widetilde{y}_i^i\right) &= \mathrm{E}\left[\widetilde{y}_i + \widetilde{n}_i - (1 - s_i)\pi_i\right] = \mathrm{E}\left(\widetilde{y}_i\right) + s_i \mathrm{E}(\widetilde{n}_i) \text{ and} \\ \mathrm{E}\left(\widetilde{y}_i^c\right) &= \mathrm{E}\left[\widetilde{y}_i + \widetilde{n}_c - (1 - s_c)\pi_c\right] = \mathrm{E}\left(\widetilde{y}_i\right) + s_c \mathrm{E}(\widetilde{n}_c),\end{aligned} \tag{7}$$

respectively. Thus, when no premium subsidy is offered, that is, when $s_i = s_c = 0$, then the expected net returns from purchasing YP and AYP are the same and equal $\mathrm{E}\left(\widetilde{y}_i\right)$. Risk-averse farmers then will never choose AYP over YP as YP provides better risk protection.

[4]RMA establishes each unit's expected yield based on its actual production history (APH) yield, which is a simple average of 4–10 years of verified yield history on the insured unit. See Plastina and Edwards (2017) for more details on calculating APH yields. Also see Skees et al. (1997) for how RMA sets up county yield expectation.

Only when premium subsidies are introduced and the condition $s_c\mathrm{E}(\widetilde{n}_c) > s_i\mathrm{E}(\widetilde{n}_i)$ is satisfied will risk-averse farmers have incentives to choose AYP over YP. Then, the ratio

$$s^*_{c|i} = s_c/s_i = \mathrm{E}(\widetilde{n}_i)/\mathrm{E}(\widetilde{n}_c) \tag{8}$$

provides an intuitive lower bound on the relative subsidy rate at which a risk-averse or risk-neutral farmer will be indifferent between the two subsidized contracts. We call $s^*_{c|i}$ the threshold relative area subsidy rate (TRASR), the relative subsidy rate of AYP over YP at which the expected net returns from purchasing YP and AYP are the same.[5] Figure A1 in Part II of Appendix S1 illustrates how TRASR is related to a farmer's insurance choice. When the relative subsidy rate is below TRASR, then YP dominates AYP as YP provides better risk protection and higher expected net return; risk-averse or risk-neutral farmers should always prefer YP over AYP. When the relative subsidy rate is above TRASR, then AYP provides higher expected net returns and may dominate. In this case, farmers' insurance choices depend on their risk aversion levels.

By substituting in YP and AYP indemnity functions, we can develop an explicit form for $s^*_{c|i}$. First note that by assuming that yield expectations established by RMA perfectly match actual expectations, that is, $\overline{y}_i = \mu_i$ and $\overline{y}_c = \mu_c$, Equations (1) and (5) then jointly imply $\widetilde{n}_i = \max\left[\beta_i\left(\mu_c - \widetilde{y}_c\right) - \mu_i(1-\phi_i) - \varepsilon_i, 0\right]$. This new equation presents YP indemnities as a function of county yield and idiosyncratic yield. The YP indemnity function can be rewritten as

$$\widetilde{n}_i = \begin{cases} \beta_i\left(\mu_c - \widetilde{y}_c\right) - \mu_i(1-\phi_i) - \varepsilon_i, & \text{whenever } \widetilde{y}_c < \mathrm{M}_i(\varepsilon_i); \\ 0, & \text{whenever } \widetilde{y}_c \geq \mathrm{M}_i(\varepsilon_i), \end{cases} \tag{9}$$

where we use $\mathrm{M}_i(\varepsilon_i) = \mu_c - [\mu_i(1-\phi_i) + \varepsilon_i]/\beta_i$ to denote the trigger value of $\widetilde{y}_c$, given ε_i, below which YP pays strictly positive indemnities.

Similarly, the AYP indemnity function can be rewritten as

$$\widetilde{n}_c = \begin{cases} \mu_c\rho, & \text{whenever } \widetilde{y}_c < \mathrm{M}^{\mathrm{l}}_c; \\ \alpha_c\left(\mu_c\phi_c - \widetilde{y}_c\right), & \text{whenever } \mathrm{M}^{\mathrm{l}}_c \leq \widetilde{y}_c < \mathrm{M}_c; \\ 0, & \text{whenever } \widetilde{y}_c \geq \mathrm{M}_c, \end{cases} \tag{10}$$

where we use $\mathrm{M}_c = \mu_c\phi_c$ to denote the trigger value of $\widetilde{y}_c$ below which AYP pays strictly positive indemnities, and we use $\mathrm{M}^l_c = \mu_c l$ to denote the lower bound on $\widetilde{y}_c$ below which AYP always pays its maximum indemnity level, $\mu_c\rho$. We further use $\alpha_c = \rho/(\phi_c - l)$ to denote the inverse of the slope of the AYP indemnity function's middle component given in Equation (10). Because $0.8 \leq \rho \leq 1.2$, $0.7 \leq \phi_c \leq 0.9$ and $l = 0.18$, it follows that $\alpha_c \geq 0.8/0.72$, so $\alpha_c > 1$ always holds and α_c scales up AYP payments.

As demonstrated in Part III of Appendix S1, some transformations provide an explicit form for $s^*_{c|i}$:

$$s^*_{c|i} = \frac{\beta_i \int_{\underline{\varepsilon}_i}^{\overline{\varepsilon}_i} \int_0^{\mathrm{M}_i(\varepsilon_i)} F\left(\widetilde{y}_c\right) d\widetilde{y}_c dG(\varepsilon_i)}{\alpha_c \int_{\mathrm{M}^l_c}^{\mathrm{M}_c} F\left(\widetilde{y}_c\right) d\widetilde{y}_c}, \tag{11}$$

[5]TRASR also constitutes a lower bound on the relative subsidy rate needed to induce loss-averse farmers to choose AYP over YP. Loss aversion is found to be an important factor affecting agricultural producers' choices over risky outcomes (Feng et al., 2020; Liu, 2013; Lampe & Würtenberger, 2020). Losses of equal size outweigh gains for loss-averse farmers. Due to basis risk, loss-averse farmers would avoid AYP when YP provides the same expected net return as AYP.

where $F(\cdot)$ is the cumulative density function (CDF) for $\tilde{y}_c$, $G(\cdot)$ is the CDF for ε_i, $\overline{\varepsilon}_i = y_i^u - \mu_i + \beta_i \mu_c$ is the upper bound on ε_i and $\underline{\varepsilon}_i = -\mu_i - \beta_i(y_c^u - \mu_c)$ is the lower bound on ε_i. Thus, $s_{c|i}^*$ is a function of two random variables, $\tilde{y}_c$ and ε_i, as well as a parameter set. In the following subsection we seek to understand how $s_{c|i}^*$ is affected by systemic risk variables.

2.5 | TRASR and systemic risk

Although $s_{c|i}^*$ is not a direct function of R_i^2, it is a function of β_i. It also depends on metrics related to $\sigma_{\varepsilon_i}^2$ and σ_c^2 because both $\int_{\underline{\varepsilon}_i}^{\overline{\varepsilon}_i} \int_0^{\mathrm{M}_i(\varepsilon_i)} F(\tilde{y}_c) d\tilde{y}_c dG(\varepsilon_i)$ and $\int_{\mathrm{M}_c^l}^{\mathrm{M}_c} F(\tilde{y}_c) d\tilde{y}_c$ are formed from integrations of CDFs where we can study the effect of an increase in $\sigma_{\varepsilon_i}^2$ or σ_c^2 in terms of a mean-preserving spread (m.p.s.) of $G(\varepsilon_i)$ or $F(\tilde{y}_c)$. Although variance itself is widely used as a measure of risk, m.p.s. provides a more general way to study increased risk (Rothschild & Stiglitz, 1970). Proposition 3 provides relationships between $s_{c|i}^*$ and systemic risk components, where the mathematical proof can be found in Part IV of Appendix S1.[6]

Proposition 3. Ceteris paribus, $s_{c|i}^*$ increases with a m.p.s. in $G(\varepsilon_i)$. Signing the effects of a m.p.s. in $F(\tilde{y}_c)$ and an increase in β_i on $s_{c|i}^*$ requires additional information or conditions. However, when $\varepsilon_i \equiv 0$ then $s_{c|i}^*$ is strictly increasing in β_i.

The finding that $s_{c|i}^*$ increases with a m.p.s. in $G(\varepsilon_i)$ is intuitive because under the assumption that no single unit has an impact on county yield, an increase in idiosyncratic risk increases $\mathrm{E}(\tilde{n}_i)$ but has no effect on $\mathrm{E}(\tilde{n}_c)$. By Equation (8), $s_{c|i}^*$ increases as a result.

As for the effect of a m.p.s. in $F(\tilde{y}_c)$ on $s_{c|i}^*$, intuition might suggest that a m.p.s. in $F(\tilde{y}_c)$ increases $\mathrm{E}(\tilde{n}_c)$ because AYP pays more frequently as county yield risk increases. However, the existence of the loss limit factor complicates the effect of a m.p.s. in $F(\tilde{y}_c)$ on $\mathrm{E}(\tilde{n}_c)$. For example, if the left spread of a m.p.s. in $F(\tilde{y}_c)$ works only on the range $[0, \mu_c l]$ and the right spread of the m.p.s. only shifts some $\tilde{y}_c$ values smaller than $\mu_c \phi_c$ to be greater than $\mu_c \phi_c$, then $\mathrm{E}(\tilde{n}_c)$ decreases with the m.p.s. operation. In addition, $\mathrm{E}(\tilde{n}_i)$ increases with a m.p.s. in $F(\tilde{y}_c)$ because unit yield risk increases with an increase in the county yield risk given that idiosyncratic yield risk is unaffected by county yield risk. Thus, even if $\mathrm{E}(\tilde{n}_c)$ increases with a m.p.s. in $F(\tilde{y}_c)$, determining the overall effects of a m.p.s. in $F(\tilde{y}_c)$ on $s_{c|i}^*$ requires additional information or conditions. However, because the distribution of average unit yield approaches that of average county yield, it might be reasonable to expect that on average, a m.p.s. in $F(\tilde{y}_c)$ has similar effects on $\mathrm{E}(\tilde{n}_i)$ and $\mathrm{E}(\tilde{n}_c)$, and so the overall effect on $s_{c|i}^*$ would then be small. Conjecture 1 follows.

Conjecture 1. On average, the effect of a m.p.s. in $F(\tilde{y}_c)$ on $s_{c|i}^*$ is small.

Finally, although an increase in β_i only affects $\mathrm{E}(\tilde{n}_i)$, the effect on TRASR is ambiguous. Intuition suggests that $s_{c|i}^*$ increases with an increase in β_i because as unit yield becomes more sensitive to county yield, unit yield variation increases for a given level of county yield variation. As a result, $\mathrm{E}(\tilde{n}_i)$ increases while $\mathrm{E}(\tilde{n}_c)$ does not change. This is exactly the case when $\varepsilon_i \equiv 0$, that is, when there is no idiosyncratic risk. In this case, $\tilde{y}_i - \mu_i$ is solely determined by $\tilde{y}_c - \mu_c$ and always has the sign of $\tilde{y}_c - \mu_c$. Given $F(\tilde{y}_c)$, an increase in β_i thus increases the probability of receiving a YP payment but has no effect on the probability of receiving an AYP payment. But suppose instead that $\varepsilon_i \not\equiv 0$. In this case, when $\tilde{y}_i - \mu_i < 0$, $\varepsilon_i < 0$ and $\tilde{y}_c - \mu_c > 0$, then $\tilde{y}_i - \mu_i$ will be less negative as β_i increases, which in turn means fewer YP indemnities (if any). As a result, $\mathrm{E}(\tilde{n}_i)$ may decrease with an increase in β_i. However, we should expect $s_{c|i}^*$ to increase with an increase in β_i when the lower bound of ε_i, $\underline{\varepsilon}_i$, is

[6]In Part V of Appendix S1 we also present a comparative statics analysis of $s_{c|i}^*$ with respective to other variables and parameters appearing in Equation (11).

sufficiently large (less negative) such that the YP indemnity is never triggered when all of $\widetilde{y}_i - \mu_i < 0$, $\varepsilon_i < 0$ and $\widetilde{y}_c - \mu_c > 0$ apply. Equation (A3) in Appendix S1, Part III, provides us with such a condition, namely $-\underline{\varepsilon}_i \leq \mu_i(1-\phi_i)$, where $-\underline{\varepsilon}_i$ can be viewed as the worst possible idiosyncratic yield loss and $\mu_i(1-\phi_i)$ is the YP deductible. [7]

Proposition 4. Ceteris paribus, $s^*_{c|i}$ increases with an increase in β_i whenever $-\underline{\varepsilon}_i \leq \mu_i(1-\phi_i)$.

The condition in Proposition 4 is likely to hold because the YP deductible is included to remove moral hazard, which is reflected in idiosyncratic yield loss. Moreover, deep losses in crop yields are generally caused by systemic weather events, and crop insurance pays less frequently in good weather years where idiosyncratic yield risk dominates.

Proposition 4 has important implications. Because R_i^2 also increases with an increase in β_i, then an increase in β_i leads to increases in both $s^*_{c|i}$ and R_i^2 whenever $-\underline{\varepsilon}_i \leq \mu_i(1-\phi_i)$ applies. Thus, under the mild condition that the YP deductible is greater than the worst possible idiosyncratic yield loss, an increase in unit yield's sensitivity to county yield has two opposing effects on farmers' choices of AYP: farmers enjoy better risk protection from AYP; they also receive more YP payments as the increased sensitivity amplifies the effect of county yield risk on total unit yield risk. This finding contrasts with predictions given in previous studies, where both individual loss and area loss are exogenously given and only an artificial correlation level is allowed to vary. When individual loss level is fixed, an increase in yield correlation always favors AYP as area yield improves at tracking individual yield.

The following remark, a corollary to Proposition 4, sheds lights on conditions under which Proposition 4 is more likely to hold.

Remark 1. Ceteris paribus, $s^*_{c|i}$ is more likely to increase with an increase in β_i for (i) a higher μ_i, (ii) a smaller ϕ_i, and (iii) a greater value of $\underline{\varepsilon}_i$.

Claims (i) and (ii) indicate that, ceteris paribus, farmers operating high-yield land and choosing lower YP coverage levels are more likely to find their $s^*_{c|i}$ values increase with an increase in β_i. However, farmers operating productive land, as in Iowa and Illinois, generally choose high coverage levels. They also generally encounter smaller worst possible idiosyncratic yield loss as they plant on more shock-resilient lands.

Claim (iii) provides clues about the relationship between $s^*_{c|i}$ and R_i^2 across units. Because a mean-preserving contraction of $G(\varepsilon_i)$ is generally associated with an increase in $\underline{\varepsilon}_i$, Claim (iii) implies that units with less dispersed idiosyncratic yield distributions are more likely to see an increase in β_i have a positive effect on $s^*_{c|i}$. Thus, units with less dispersed idiosyncratic yield distributions and larger β_i values tend to have larger $s^*_{c|i}$ values. Because county yield risk is the same for all units in a county, Proposition 1 then implies that within a county, units with larger R_i^2 values tend to have less dispersed idiosyncratic yield distributions and larger β_i values, and thus larger $s^*_{c|i}$ values. This result indicates that farmers who enjoy good risk protection from AYP will be more likely to find current AYP subsidy rates financially unrewarding. It is then unsurprising to see low AYP take-up rates.

3 | DATA

Unit corn yield data have been obtained from the 2008 unit-level RMA records. Locations of these unit-level data are known to the county level only. The data are sequences of 4–10-year yield historical yields used to establish APH yields. Our sample consists of 213,429 unirrigated units with

[7]Note that $-\underline{\varepsilon}_i \leq \mu_i(1-\phi_i)$ is not a constraint built into LAM and does not apply to all units we investigate in this paper.

10 actual yield records from 1998 through 2007 in 580 counties where the irrigation rate does not exceed 20%.

County average corn yield data are from NASS.[8] We consider only counties in 12 major corn production states in the Midwest and Great Plains: IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, and WI. To obtain sufficient observations to estimate county yield trend, we only keep counties with 50 consecutive years of observations from 1958 through 2007. To ensure that each county's unit set is representative, we also drop counties with <30 units. See Part VI in Appendix S1 for details on the data screening process.

We use data from the National Oceanic and Atmospheric Administration (NOAA) to construct two sets of county-level weather variables. The first set contains growing degree days (GDD) and stress degree days (SDD). These variables are widely used to measure heat conditions (Du et al., 2015; Schlenker & Roberts, 2006, 2009). For each county, the GDD variable, labeled as G_c, measures the 10-year (1998–2007) average growing season (May to August) accumulation of beneficial degrees in the [10°C, 30°C] range (Neild & Newman, 1987). The SDD variable, labeled as S_c, measures the 10-year average growing season accumulation of degrees exceeding 32.22°C (Schlenker & Roberts, 2009). The second climate variable set measures the relative moisture in a county. We use the Palmer's Z (PZ) index to measure the departure of monthly weather from average moisture conditions. PZ values within the range [−2, 2.5] are viewed as normal, whereas values below −2 indicate severe drought and values above 2.5 indicate severe wetness. We construct a drought variable, D_c, to measure the number of months where severe drought occurred in county c over 1998–2007, and a wetness variable, W_c, to measure the number of months where severe wetness occurred in county c over the same period. Details on constructions of weather variables are provided in Appendix S1, Part VII.

Land quality data are from the National Resource Conservation Service. County land quality, labeled as L_c, is defined as the percent of all land that is in land capability classes (LCC) I or II in that county. There are eight LCCs in total, where classes I and II are most favorable for cultivation, whereas classes III or higher have gradually more severe limitations for cultivation. Land quality has little variation across years, and we use the 2010 measure to construct L_c.

In Figure 2 we map the geographic distributions of weather and land quality variables while descriptive statistics can be found in Table A3 in Appendix S1, Part VII. Panels a and b show that GDD and SDD generally increase as one moves south. SDD also increases as one moves west. Panel c shows that counties in the Western and Eastern Corn Belts generally experienced more severe drought, whereas Panel d shows that counties in the Northern Corn Belt generally experienced more severe wetness. Counties with higher fractions of good land, as shown by Panel e, are mainly located in Iowa, Illinois, Indiana, and Western Ohio.

4 | EMPIRICAL RESULTS

In this section we empirically estimate systemic risk and calibrate $s^*_{c|i}$. Propositions and conjectures derived in the conceptual framework section are also examined.

4.1 | Measuring systemic risk

We first adapt Equation (1) to obtain empirical systemic risk estimates with

$$\widetilde{y}_{i,t} - \mu_{i,t} = \alpha_i + \beta_i \left(\widetilde{y}_{c,t} - \mu_{c,t} \right) + \varepsilon_{i,t}, \tag{12}$$

[8]We also conduct an analysis where the NASS county yield is replaced by the acre-weighted RMA county average. These results are reported in Part IX in Appendix S1 and are very similar to results reported in the main context, to follow.

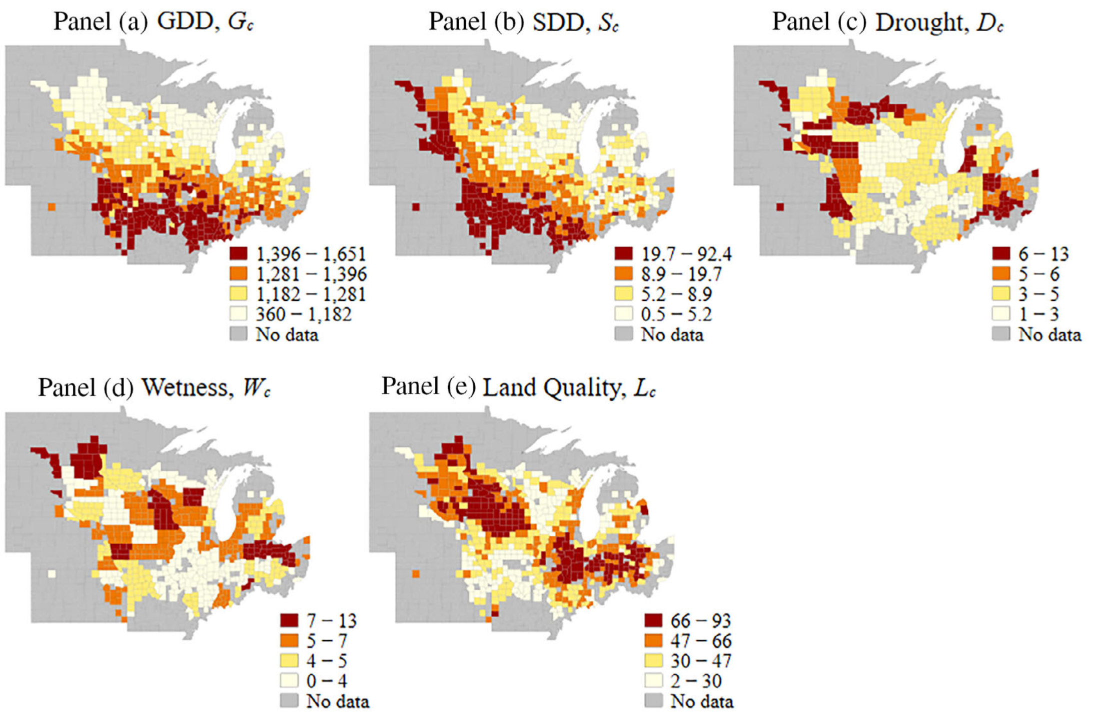

FIGURE 2 Geographic distributions of natural resource endowments *Notes*: 1. This figure plots geographic distributions of county GDD, county SDD, frequencies of severe drought and severe wetness, and the percent of county land that is in either land capability class I or class II. Numbers in legends are quartile ranges. 2. Weather variable frequencies are monthly observations over 1998–2007 out of the 120-month interval.

where α_i is the unit-specific constant term. Unit-level systemic risk, R_i^2, is then measured by the R^2 statistic when Equation (12) is estimated by ordinary least squares (OLS), that is, $R_i^2 = \beta_i^2 \mathrm{Var}(\tilde{y}_{c,t} - \mu_{c,t}) / \mathrm{Var}(\tilde{y}_{i,t} - \mu_{i,t})$. We follow Deng et al. (2007) by applying a log-linear model to detrend yield data as well as to establish unit APH yields and county yield expectations. We also follow RMA by adjusting up APH yields as APH yields lag true expected yields due to improved crop genetics and cultural practices (Plastina & Edwards, 2014). Part VIII in Appendix S1 provides more details on the detrending and APH adjustment methods.

We estimate Equation (12) and decompose the resulting systemic risk measure according to Equation (4). Table 1 presents the descriptive statistics for unit-level systemic risk and its three components. Mean R_i^2, at 0.46, suggests that systemic risk generally explains slightly less than half of total unit yield variation. Thus, on average, the risk reduction potential of AYP is limited, which might be an important reason for the low area insurance take-up rate. But the magnitude of systemic risk varies considerably across units, ranging from near 0 to near 1. The mean β_i estimate is 1.04 with range -4.78 to 9.19.[9] Only about 2.6% of β_i estimates are negative. The means of σ_{ε_i} and σ_c are 18.3 and 18.2, respectively.

Figure 3 plots the geographic distributions of county average systemic risk and county averages of systemic risk components. Panel a shows that systemic risk is highest at the southern and western

[9]The 1.04 mean deviates slightly from Miranda's (1991) assertion that acre-weighted average β_i within a given county should equal to 1. This might be because our county yield data are from NASS whereas unit yield data are from RMA. The NASS county yield generally does not equal the mean of the acre-weighted RMA unit yield (Zulauf et al., 2017). In addition, by dropping units in our data screening process, we have further loosened the connection between county yield and unit yield.

TABLE 1 Descriptive statistics for estimates of systemic risk and systemic risk components

Variable	N	Mean	St. dev	Min	Max
R_i^2	213,429	0.46	0.25	0.00	1.00
β_i	213,429	1.04	0.59	−4.78	9.19
σ_{ε_i}	213,429	18.3	9	0.85	95.02
σ_c	580	18.2	6.32	6.64	43.5

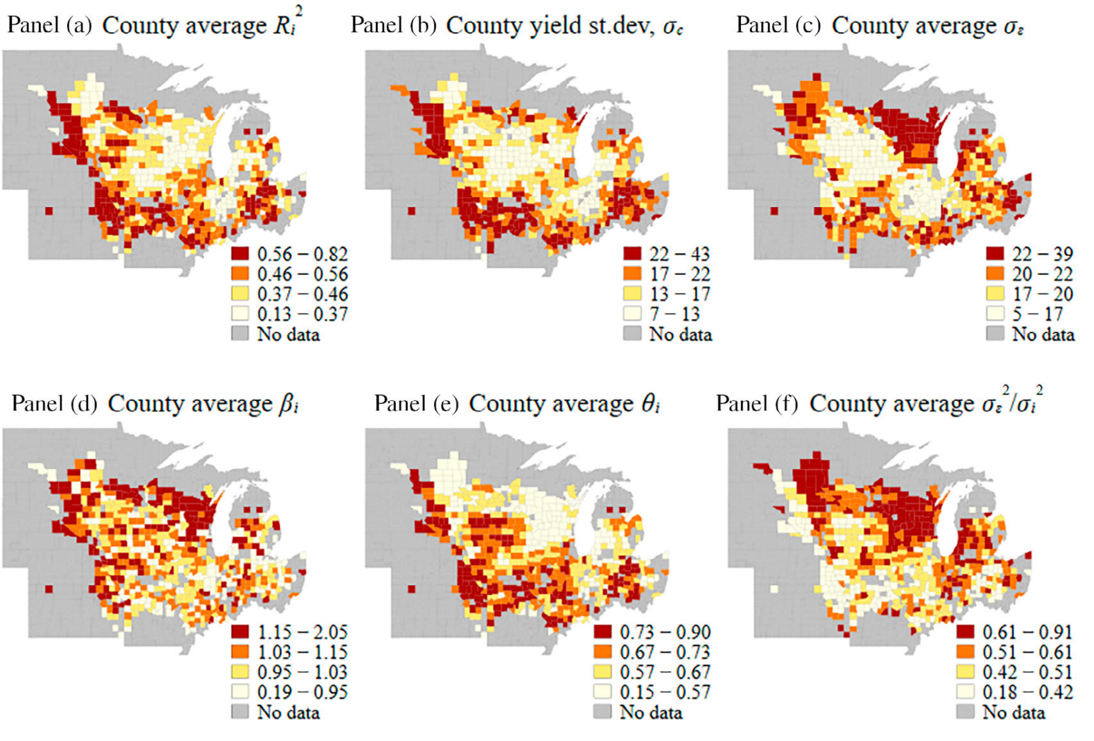

FIGURE 3 Geographic distributions of county average systemic risk and county averages of systemic risk components
Note: Panels a to f respectively plot county averages of unit-level systemic risk, county yield standard deviation, unit-level idiosyncratic yield standard deviation, unit yield's sensitivity to county yield, the correlation coefficient between unit yield and county yield, and the share of idiosyncratic yield variation in total unit yield variation. Numbers in legends are quartile ranges.

fringes of the Corn Belt, but is comparatively low in much of Iowa and counties to its northeast. Intuition, however, might suggest that AYP would work best in the latter areas, which have homogenous natural resource endowments and strong yield correlations. This incongruity arises because, as is shown in Panel b, these areas also have small county yield variances. When discussing Proposition 2, Claim (ii), we commented that AYP is ineffective in removing yield risk when county yield variance accounts for only a small part of total unit yield variance. Panels e and f of Figure 3 show that although Iowa has a relatively strong correlation between unit yield and county yield, it has a moderate share of idiosyncratic yield variation in total unit yield variation. On the contrary, counties in the southern and western fringes of the Corn Belt are characterized by both strong yield correlations and small shares of idiosyncratic yield variation. This mismatch between major corn production areas and high systemic risk areas may also contribute to area insurance's low overall take-up rate.

Panel c of Figure 3 shows that counties at the Corn Belt periphery have relatively large idiosyncratic yield variances, especially counties in Wisconsin and the Eastern Dakotas. On the contrary, counties in Iowa and Illinois have low idiosyncratic yield variances. Panel d presents evidence that Corn Belt fringe counties have relatively large unit yield sensitivities to county yield, but the pattern is not as evident because some counties in the central part also have large yield sensitivities, whereas counties at the southern fringe have small yield sensitivities.

4.2 | The effects of farmers' reactions to yield risks on systemic risk

Chambers and Quiggin (2002) criticizes LAM for characterizing unit yield as a stochastic variable not subject to farmers' control. It is true that LAM does not explicitly model farmers' behaviors. However, as pointed out by Ramaswami and Roe (2004) on its page 422, "if the LAM is derived from the aggregation of individual technologies, then its parameters can be seen to be functions of individual choice variables. The criticism of Chambers and Quiggin will then no longer apply." An implication of the argument in Ramaswami and Roe (2004) is that different reactions to yield risks will lead to different estimates of LAM parameters and thus different estimates of systemic risk. We find evidence for this conjecture from a sample of units in counties where irrigation rates are no no less than 20%.

Figure 4 plots the respective average systemic risks of irrigated and unirrigated units with respect to county irrigation rate. The average systemic risk of unirrigated units, denoted as $\overline{R}^2_{uir}$, is above 0.5 in counties where irrigation rates are less than 30% whereas the average systemic risk of irrigated units, denoted as $\overline{R}^2_{ir}$, is below 0.2 in these counties. As county irrigation rate increases, $\overline{R}^2_{uir}$ decreases and $\overline{R}^2_{ir}$ increases. These results suggest that in less irrigated counties, yields of irrigated units are detached from yields of the more prevalent unirrigated units, leading to low systemic risk. In heavily irrigated counties, yields of non-irrigated units are detached from those of the more prevalent irrigated units. AYP is unlikely to work well for irrigated units in rainfed dominant counties and unirrigated units in irrigation-intensive counties.

4.3 | The effects of natural resource endowments on systemic risk

To study how natural resource endowments determine systemic risk, we regress each of the three systemic risk components on county weather and land quality variables. The following unit-level log-linear model is estimated by OLS,

$$\ln(X_i) = \delta_0 + \delta_1 G_c + \delta_2 S_c + \delta_3 D_c + \delta_4 W_c + \delta_5 L_c + \delta_6 APH_i + \nu_i, \tag{13}$$

where $X_i \in \left\{\beta_i^2, \sigma^2_{\varepsilon_i}, \sigma^2_c\right\}$ is a $n \times 1$ vector, G_c, S_c, D_c, W_c, L_c are $n \times 1$ natural resource endowment variables as defined before, ν_i is a $n \times 1$ error term, and $n = 213{,}429$. The variable APH_i represents each unit's 2008 APH yield. We include this variable to control for land heterogeneity within a county. If land heterogeneity is correlated with natural resource endowment variables, then omitting it will lead to biased estimates. Because we do not have unit-level land quality data, we use each unit's 2008 APH yield as a proxy variable. Although weather conditions and unit land quality jointly determine APH yield, the variation remaining in APH is presumably primarily related to unit land qualities after controlling for weather variables. Another concern is that, because county yield variance and natural resource endowment variables are at county level, the unit-level regression of $\ln\left(\sigma_c^2\right)$ on natural resource endowment variables has many duplicated observations. For this reason, we also run a county-level regression of $\ln\left(\sigma_c^2\right)$ on natural resource endowment variables, that is, $\ln\left(\sigma_c^2\right)$ and all natural resource endowment variables are 580×1 vectors, whereas each observation represents a county.

Regression results for Equation (13) appear in Table 2. Column (1) shows that GDD has a significant negative effect on β_i, whereas SDD has a significantly positive effect. Thus, more excessive heat increases unit yield's sensitivity to county yield, whereas more beneficial heat decreases the

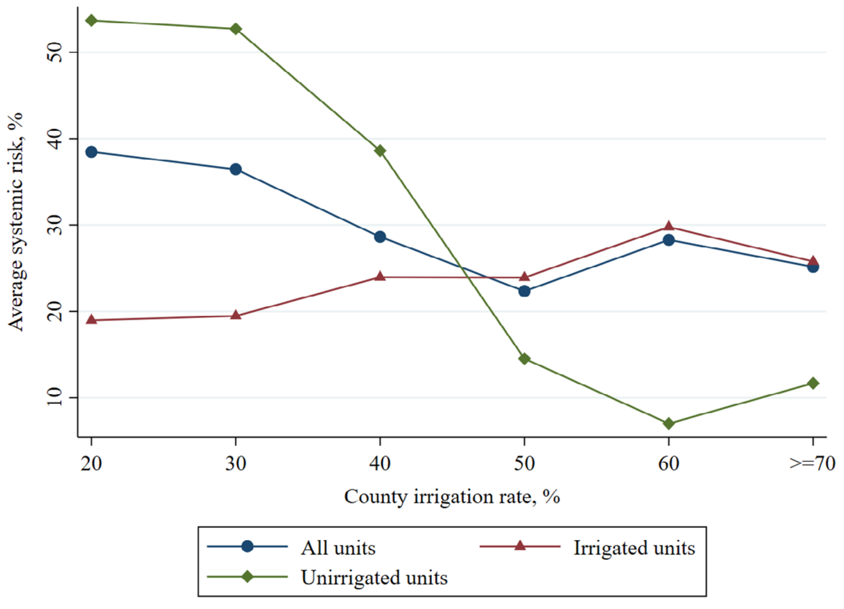

FIGURE 4 Average systemic risks of irrigated and unirrigated units with respect to county irrigation rate *Note*: Irrigation rate is at the county level and equals the share of irrigated units among all units in a county.

sensitivity. Drought occurrence significantly increases unit yield's sensitivity to county yield, whereas wetness has the converse effect. Better unit land tends to decrease unit yield's sensitivity. Overall, results in Column (1) show that β_i increases as climate conditions and land quality deteriorate. The marginally negative effect of wetness constitutes a counterexample to the previous statement, an outcome that may be because the adverse effects of severe wetness are localized and depend on whether the land unit is flood prone.[10]

Column (2) shows that GDD has a significantly positive effect on $\sigma^2_{\varepsilon_i}$, but SDD has a significantly negative effect. Thus, yield risk is less influenced by idiosyncratic factors in years with excessive heat. Drought occurrence and wetness occurrence have no significant effects on $\sigma^2_{\varepsilon_i}$. An increase in land quality significantly decreases $\sigma^2_{\varepsilon_i}$. Because better land also reduces σ^2_c, as shown by Columns (3) and (4), we may expect better land to play a buffering role in reducing the effects of extreme climate on crop yields.[11] Column (3) and column (4) also show that more heat accumulations and drought incidence tend to increase σ^2_c. Wetness incidence tends to reduce σ^2_c. County yield variability thus decreases as overall moisture conditions improve.

Column (5) reports the aggregate effects of natural resource endowments on systemic risk as obtained by the OLS regression of $-2\ln(\tau_i)$ on natural resource endowment variables. One can verify that, consistent with Equation (4), the coefficient of a natural resource endowment variable on $-2\ln(\tau_i)$ equals the sum of the coefficients of that variable on $2\ln(\beta_i)$ and $2\ln(\sigma_c)$ less the coefficient on $2\ln(\sigma_{\varepsilon_i})$. Overall, systemic risk increases with SDD and drought but decreases with wetness. Systemic risk also increases with unit land quality, suggesting that the positive effect of land quality in reducing idiosyncratic yield variance dominates its negative effects in reducing unit yield's sensitivity to county yield and county yield variance (please refer to Equation 4). However, our

[10]Specifically, and as with irrigation, flooding separates units into two groups that correlate differently with county yield. In counties where flooding affects a large area, affected units should follow county yield closely, but in counties where flooding only affects a small area, unaffected units should follow county yield closely. Overall, flooding likely reduces yield correlations. We also report regression results for Equation (13) but replace the wetness and drought variables with the county average precipitation variable, see Table A5 in Appendix S1, Part X.

[11]See Du et al. (2018) for the interaction effects between land quality and climate conditions.

TABLE 2 Regression results of systemic risk variables on natural resource endowments variables

	(1) $2\ln(\beta_i)$	(2) $2\ln(\sigma_{\varepsilon_i})$	(3) $2\ln(\sigma_c)$	(4) $2\ln(\sigma_c)$	(5) $-2\ln(\tau_i)$
$G_c/100$	-0.039^{b}	0.063^{a}	0.101^{a}	0.061^{a}	-0.001
	(0.017)	(0.012)	(0.026)	(0.022)	(0.034)
$S_c/10$	0.053^{a}	-0.144^{a}	0.110^{a}	0.140^{a}	0.307^{a}
	(0.019)	(0.019)	(0.035)	(0.028)	(0.044)
D_c	0.039^{a}	-0.007	0.093^{a}	0.101^{a}	0.139^{a}
	(0.009)	(0.007)	(0.014)	(0.014)	(0.017)
W_c	-0.016^{c}	-0.007	-0.040^{a}	-0.057^{a}	-0.050^{a}
	(0.008)	(0.007)	(0.014)	(0.012)	(0.016)
$L_c(10\%)$	0.001	-0.049^{a}	-0.024^{c}	-0.028^{b}	0.026
	(0.010)	(0.006)	(0.014)	(0.012)	(0.018)
APH_i	-0.003^{a}	-0.012^{a}	-0.007^{a}		0.002^{b}
	(0.001)	(0.001)	(0.001)		(0.001)
APH_c_CV				1.007^{a}	
				(0.348)	
Constant	0.514^{b}	7.085^{a}	4.948^{a}	4.540^{a}	-1.623^{a}
	(0.230)	(0.209)	(0.329)	(0.311)	(0.399)
Observations	213,429	213,429	213,429	580	213,429
R^2	0.012	0.111	0.441	0.351	0.076

Notes: 1. Column (3) reports OLS estimation results of $2\ln(\sigma_c)$ on natural resource endowment variables at the unit level of analysis where one observation represents one unit. Column (4) reports OLS estimation results of $2\ln(\sigma_c)$ on natural resource endowment variables at the county level where one observation represents one county. 2. The variable APH_c_CV denotes the coefficient of variation of units' 2008 APH values in county c, which captures the dispersion of land quality in a county and thus reflects land heterogeneity within a county. 3. Standard errors in parentheses are clustered at the county level; [a], [b], and [c] denote significance at 0.01, 0.05, and 0.1 levels, respectively.

investigations of systemic risk are subject to the time period for the data available. Because no catastrophic weather events for national corn production occurred during our sample years, our estimates of systemic risk and of the relationship between systemic risk and natural resource endowments are better understood as normal year outcomes.[12]

In addition to signs and significances, we also investigate the importance of each natural resource endowment variable in determining systemic risk. Following Huettner and Sunder (2012), we use the Shapley value to measure the "bargaining" power of each natural resource endowment variable in claiming explanation for the variation component of systemic risk. Their idea is to remove each explanatory variable from all possible combinations of other explanatory variables and so observe the variable's average contribution to the R^2. Column (1) of Table 3 shows that β_i is the most important determinant of systemic risk as it accounts for about 66% of systemic risk variation. County yield variance and idiosyncratic yield variance explain about 14% and 20% of systemic risk variation, respectively.

Results in Columns (2) through (4) of Table 3 show that natural resource endowment variables, drought occurrence, SDD, and unit land quality are the most important factors in explaining variations of systemic risk components. However, as shown in Column (5), the overall effect of unit land quality on systemic risk is small, but the overall effects of SDD and drought occurrence on systemic risk remain large. This is because, as shown in Table 2, the effect of unit land quality on $\sigma^2_{\varepsilon_i}$ is offset

[12]See Figure 2 at https://www.agry.purdue.edu/ext/corn/news/timeless/YieldTrends.html. Our data sit between the drought years in the 1980s and the 2012 drought year where the flood years in the early 1990s were more geographically confined and had more moderate impacts on higher ground even where they decimated crops on lower ground.

TABLE 3 Shapley values of natural resource endowment variables in explaining systemic risk variables, %

	(1) $-2\ln(\tau_i)$	(2) $2\ln(\beta_i)$	(3) $2\ln(\sigma_{\varepsilon_i})$	(4) $2\ln(\sigma_c)$	(5) $-2\ln(\tau_i)$
$2\ln(\beta_i)$	65.9				
$2\ln(\sigma_{\varepsilon_i})$	19.8				
$2\ln(\sigma_c)$	14.3				
G_c		4.7	1.5	13.3	9.2
S_c		17.6	5.9	27.6	39.5
D_c		35.9	1.8	23.9	38.2
W_c		4.2	0.5	3.7	7.1
L_c		2.8	17.7	7.2	1.8
APH_i		34.7	72.6	24.3	4.3

by its effects on β_i and σ_c^2 upon aggregation. On the contrary, the effects of SDD and drought occurrence on the three systemic risk components are concordant, and so the overall effects are larger.

4.4 | Calibrating TRASR

We turn now to calibrating $s_{c|i}^*$ and then investigating the relationship between $s_{c|i}^*$ and R_i^2. To calibrate $s_{c|i}^*$ from Equation (11), we need to know both $F(\widetilde{y}_c)$ and $G(\varepsilon_i)$.[13] Studies investigating crop yield distributions mainly adopt two distinct methodologies for estimating distributions, parametric and nonparametric. Parametric methods often assume that crop yield follows a specific distribution, such as the normal, gamma, or beta distribution (Gallagher, 1987; Harri et al., 2011; Sherrick et al., 2004). Nonparametric methods offer flexibility in capturing local yield idiosyncrasies (Goodwin & Ker, 1998; Ker & Goodwin, 2000). Because our study contains many counties and units where appropriate corn yield distribution specifications might differ by location, flexibility considerations lead us to choose nonparametric kernel density estimation. Details regarding how kernel estimations are performed at both county level and unit level are reported in Part XI of Appendix S1.

Table 4 presents descriptive statistics for coverage-level conditional $s_{c|i}^*$. We set $\rho = 1.2$ because 1.2 is the protection factor level that maximizes $\mathrm{E}(\widetilde{n}_c)$. Because ϕ_i increases in 0.05 increments from 0.5 to 0.85 and ϕ_c increases in 0.05 increments from 0.70 to 0.9, we have $8 \times 5 = 40$ possible coverage level combinations. We focus on $s_{c|i}^*$ evaluations where $\phi_i \geq 75\%$ because 75% is the minimum coverage level chosen by most farmers in the Corn Belt (Schnitkey & Sherrick, 2014). Moreover, because some units have negative β_i estimates and thus negative $s_{c|i}^*$ values, and some units have extremely large $s_{c|i}^*$ values, we focus on the sample with positive β_i estimates and on median statistics.

Table 4 shows that the median $s_{c|i}^*$ value increases with an increase in ϕ_i and decreases with an increase in ϕ_c. When $\phi_i \geq 80\%$ and when $\phi_c \leq 80\%$ then median $s_{c|i}^*$ values generally exceed 100%, whereas when $\phi_c \geq 85\%$ then all $s_{c|i}^*$ median values are smaller than 100%. Thus, to coax more farmers into choosing AYP, low coverage level AYP subsidy rates must exceed YP subsidy rates, but high coverage level AYP subsidy rates may not exceed YP subsidy rates.

We then compare $s_{c|i}^*$ with $s_{c|i}$, which denotes the current ratio of AYP subsidy rate over YP subsidy rate, to investigate whether the current AYP subsidy rates discourage most farmers from choosing AYP over YP. If $s_{c|i}^*$ exceeds $s_{c|i}$, then a risk-averse or risk-neutral farmer will never choose AYP over YP because YP provides better risk protection and higher expected subsidy transfers. Table A7 in Appendix S1, Part XII, lists premium subsidy rates for individual and area insurance plans before and

[13]In light of Equation (8), a reasonable alternative approach to calculating TRASR values is by using premium data. In Part XIII of Appendix S1 we present such an analysis as a robustness check on methods used in the main text, to follow.

TABLE 4 Descriptive statistics for $s^*_{c|i}$ multiplied by 100 (measured in percent)

ϕ_i	ϕ_c	N	Mean	St. dev	Min	Median	Max
75%	70%	207,230	207	344	0	124	13,992
	75%	207,230	133	160	0	90	3843
	80%	207,230	92	97	0	66	2231
	85%	207,230	66	65	0	49	1463
	90%	207,230	48	46	0	37	1076
80%	70%	207,230	263	409	0	166	16,023
	75%	207,230	169	185	0	121	4074
	80%	207,230	117	111	0	89	2365
	85%	207,230	83	73	0	66	1515
	90%	207,230	61	51	0	49	1115
85%	70%	207,230	336	486	0	221	18,513
	75%	207,230	215	214	0	161	4313
	80%	207,230	148	126	0	118	2504
	85%	207,230	106	82	0	88	1569
	90%	207,230	77	57	0	66	1154

Notes: 1. Only the sample of units with $\beta_i > 0$ are considered here. 2. Units with extremely large $s^*_{c|i}$ values are most likely to be those with large idiosyncratic risk and in counties where county yield distributions have long and thin left tails.

after the 2008 Farm Bill. We choose the enterprise unit (EU) contract subsidy rate to derive $s_{c|i}$ because in recent years EU contracts have covered the largest share of insured corn acres (Bulut, 2020; Coble, 2017). Moreover, farmers may treat EU contracts as weak substitutes for AYP contracts because the former aggregate over several units in an area and so pool risks from a set of individual units.[14] Table A7 shows that $s_{c|i} < 1$ across all coverage levels except 85% in the post-2009 period, but $s_{c|i} > 1$ for all coverage levels in the pre-2009 period, indicating that the subsidy rate change in the 2008 Farm Bill favors EU contracts over AYP contracts.

Panel A of Table 5 reports the percent of units with $s^*_{c|i} > s_{c|i}$. When $\phi_c \leq 80\%$, $s^*_{c|i}$ exceeds $s_{c|i}$ for the majority of units. Thus, the current subsidy schedule does not encourage low coverage levels with AYP. In addition, federal legislation suggests that such low coverage levels are undesirable policy outcomes because they leave farmers exposed to basis risk. When $\phi_c > 80\%$, 24% to 40% of units continue to have $s^*_{c|i}$ values above their $s_{c|i}$ values, suggesting that the current AYP subsidy schedule also deters a significant fraction of farmers from choosing high coverage level AYP contracts over YP contracts. Moreover, the smaller percent of units with $s^*_{c|i} > s_{c|i}$ at high AYP coverage levels suggests that were AYP chosen then most likely the chosen level would exceed 80%. This conjecture matches with farmers' choices. Using the RMA Summary of Business (SOB) data, we find that among all corn AYP contracts sold over 1997–2019, about 86% are at $\phi_c \geq 80\%$ and 64% are at $\phi_c = 90\%$.

4.5 | TRASR, systemic risk, and area insurance demand

We turn now to investigating the relationship between $s^*_{c|i}$ and systemic risk variables together with how this relationship affects AYP demand. As Equation (11) suggests that any such relationship is nonlinear, we use Spearman's rank correlation test to check for correlations.

[14]However, our data were obtained at a time when EU share was low (pre-2009 policy change). Because yield aggregation under EU reduces idiosyncratic risk and Proposition 3 suggests that $s^*_{c|i}$ decreases with a decrease in idiosyncratic risk, our $s^*_{c|i}$ estimates may be larger than would be the case were data under the current EU share used.

TABLE 5 The percent of sample units with $s^*_{c|i} > s_{c|i}$ and the percent of sample units with $s^*_{c|i} > \bar{s}_{c|i}$

	ϕ_c				
ϕ_i	70%	75%	80%	85%	90%
	Panel A: Percent of units with $s^*_{c|i} > s_{c|i}$, post-2009 subsidy rates				
75%	**68.0**	**56.8**	46.6	33.2	24.0
80%	**75.2**	**64.8**	**54.6**	39.4	28.5
85%	**78.8**	**68.2**	**57.3**	39.9	27.3
	Panel B: Percent of units with $s^*_{c|i} > s_{c|i}$, pre-2009 subsidy rates				
75%	**52.7** (−15.3)	38.9 (−17.9)	28.8 (−17.8)	17.0 (−16.2)	10.5 (−13.5)
80%	**59.7** (−15.5)	45.1 (−19.6)	33.7 (−20.9)	19.6 (−19.9)	11.6 (−16.9)
85%	**63.0** (−15.8)	47.4 (−20.8)	34.6 (−22.7)	18.7 (−21.3)	10.0 (−17.2)
	Panel C: Percent of units with $s^*_{c|i} > \bar{s}_{c|i}$				
75%	48.2 (−4.6)	34.2 (−4.7)	21.4 (−7.5)	11.5 (−5.5)	5.5 (−5.0)
80%	**55.5** (−4.2)	40.5 (−4.7)	25.5 (−8.3)	13.3 (−6.2)	6.0 (−5.6)
85%	**57.7** (−5.3)	41.5 (−5.9)	24.6 (−9.9)	11.6 (−7.0)	4.5 (−5.5)

Notes: 1. Values in bold are >50%. 2. Values in parentheses in Panel B are pairwise differences between the percent of sample units with $s^*_{c|i} > s_{c|i}$ in the post-2009 period and the percent of sample units with $s^*_{c|i} > s_{c|i}$ in the pre-2009 period. 3. Values in parentheses in Panel C are pairwise differences between the percent of sample units with $s^*_{c|i} > s_{c|i}$ in the pre-2009 period and the percent of sample units with $s^*_{c|i} > \bar{s}_{c|i}$ in the post-2009 period.

Table 6 reports test results. Consistent with Proposition 3, Column (1) shows that $s^*_{c|i}$ is positively correlated with $\sigma^2_{\varepsilon_i}$. Greater idiosyncratic yield risk increases $s^*_{c|i}$ because it increases the expected YP payment but has no effect on the expected AYP payment. Column (2) shows that $s^*_{c|i}$ is marginally correlated with σ^2_c, which supports Conjecture 1 that the average effect of an increase in county yield risk on $s^*_{c|i}$ is small. Column (3) shows that $s^*_{c|i}$ is strongly positively correlated with β_i, revealing that an increase in unit yield's sensitivity to county yield amplifies the effect of county yield risk on unit yield risk.

Finally, Column (4) shows that $s^*_{c|i}$ has a relatively strong positive correlation with R^2_i at all coverage level combinations. The correlation coefficient ranges from 0.43 to 0.51 and monotonically increases with an increase in ϕ_c. These findings confirm our conjecture that units with higher systemic risk tend to have higher TRASR values. Thus, AYP is unable to simultaneously provide sufficient risk protection and meet farmer's transfer seeking demand, which further explains the low area insurance take-up.

We then check for the actual geographic pattern of AYP uptake. Figure 5 plots the geographic distribution of the share of acres insured under AYP in all acres insured under either AYP or YP for 2020. Most counties did not have any AYP policy records in the 2020 SOB data. Most remaining counties have very small shares of AYP insured acres, with a median value of 6.3%, whereas the share of yield-based contracts in total sold crop insurance contracts is already very low, with a median value of 3.3%. Overall, when $\phi_i = 75\%$ and $\phi_c = 90\%$, the respective means of county average systemic risk and county median $s^*_{c|i}$ values are 0.47 and 45% for counties whose AYP shares are above the 75th percentile, and 0.43 and 52% for counties whose AYP shares are below the 25th percentile. Differences in these numbers support our conjecture that AYP demand should be higher in areas with higher systemic risk and lower TRASR values. Given the small sample size, however, these differences are statistically insignificant.

5 | INCREASING AYP SUBSIDY RATES AS A POLICY OPTION TO GENERATE GREATER AYP DEMAND

As current AYP subsidy rates likely deter farmers from choosing AYP over YP, especially for farmers with high systemic risk, in this subsection we study whether raising AYP subsidy rates can increase AYP demand.

TABLE 6 Spearman's rank correlation coefficients between systemic risk variables and $s^*_{c|i}$

ϕ_i	ϕ_c	(1) $\sigma^2_{\varepsilon_i}$	(2) σ^2_c	(3) β_i	(4) R^2_i
75%	70%	0.3196*	0.0936*	0.8519*	0.4593*
	75%	0.3247*	0.0853*	0.8906*	0.4806*
	80%	0.3293*	0.0786*	0.9129*	0.4912*
	85%	0.3327*	0.0798*	0.9231*	0.4987*
	90%	0.3369*	0.0973*	0.9221*	0.5064*
80%	70%	0.3025*	0.0833*	0.8269*	0.4472*
	75%	0.3106*	0.0742*	0.8770*	0.4740*
	80%	0.3187*	0.0668*	0.9099*	0.4892*
	85%	0.3250*	0.0681*	0.9283*	0.5004*
	90%	0.3319*	0.0880*	0.9323*	0.5111*
85%	70%	0.2786*	0.0653*	0.7884*	0.4257*
	75%	0.2893*	0.0549*	0.8505*	0.4587*
	80%	0.3012*	0.0460*	0.8970*	0.4799*
	85%	0.3115*	0.0471*	0.9276*	0.4967*
	90%	0.3224*	0.0702*	0.9403*	0.5124*

Note: *Significance at 0.05 level.

We consider two subsidy schemes. We first study whether returning to pre-2009 relative subsidy rates could generate adequate transfers to farmers. As shown in Figure 1, there was a notable demand for area insurance before the 2008 Farm Bill adjusted down the relative subsidy rates of area insurance contracts over EU contracts, making the pre-2009 relative subsidy rate a reference point for any subsidy schemes that aim to increase area insurance demand. We then investigate whether offering free AYP contracts could increase AYP demand. The area insurance literature claims that area insurance plans are superior to individual plans in reducing information and transaction costs. If so, then completely replacing individual insurance plans with fully subsidized area insurance plans may help reduce the overall costs of FCIP.

Panel B of Table 5 reports the units with $s^*_{c|i} > s_{c|i}$ as a percent of all units in the pre-2009 period. Compared with the post-2009 period, the pairwise percent of units with $s^*_{c|i} > s_{c|i}$ is 14–23 percentage points lower in the pre-2009 period. We also find that for units with systemic risk estimates above the 75th percentile, the magnitude of decline increases to more than 30 percentage points. Thus, the relative subsidy rate change arising from the 2008 Farm Bill significantly increased the share of units for which the net returns from buying AYP are lower than the net returns from buying YP. Units enjoying relatively good risk protection from AYP are most affected. Returning to the pre-2009 relative subsidy rate may help resuscitate AYP demand.

Panel C reports the units with $s^*_{c|i} > \bar{s}_{c|i}$ as a percent of all units, where $\bar{s}_{c|i}$ denotes the 100% AYP subsidy rate over the post-2009 YP subsidy rate. Results show that units with $s^*_{c|i} > \bar{s}_{c|i}$ amount to < 6% of all units when $\phi_c = 90\%$. Thus, fully subsidizing AYP contracts at the highest coverage level meets almost all farmers' minimum subsidy transfer requirements for choosing AYP over YP, and so may generate a sizable demand for AYP. However, among all units, the percent of units with $s^*_{c|i} > \bar{s}_{c|i}$ is only 4–10 percentage points lower than the percent of units for which $s^*_{c|i} > s_{c|i}$ in the pre-2009 period, suggesting that the AYP demand under full AYP subsidy rates is unlikely to significantly surpass its pre-2009 counterpart.

It is worth noting that the above results are not based on a strict counterfactual analysis and thus should be interpreted cautiously. Other factors might have also contributed to the decrease in AYP

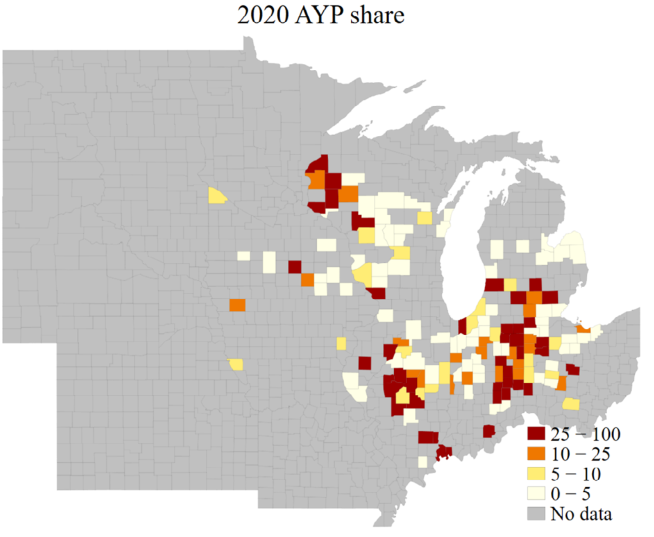

FIGURE 5 Geographic distribution of AYP share in 2020 *Notes*: 1. Data Source: Summary of Business, 2020, RMA. 2. AYP share is defined as the share of AYP insured acres in total acres insured under either AYP or YP in a county. Numbers in legends are in %. 3. Three counties had AYP shares >80%. In these counties, fewer than 10 yield insurance contracts were sold in 2020 and farms that bought AYP contracts were more representative of the area than farms that bought YP contracts.

demand. For example, Figure 1 shows that the area insurance insured acre share peaked in 2006 and declined thereafter. The subsidy rate change in 2009 substantially accelerated this downward trend. One explanation for the pre-2009 shift downward is that some area insurance buyers who had suffered losses but had not been paid ceased buying area insurance; that is, area insurance buyers realized basis risk and then abandoned area insurance. If so, then raising AYP subsidy rates is unlikely to re-engage this group. Similarly, new AYP buyers will be exposed to basis risk and may switch back from AYP to YP after they experience adverse outcomes. So AYP demand may first increase but then decrease after a rise in subsidy rate. In addition, AYP does not provide several benefits that YP provides, such as prevented planting and replanting payments (Barnett et al., 2005). These constraints may further limit farmers' willingness to choose AYP.[15]

Besides these effectiveness concerns, raising AYP subsidy rates to increase AYP demand presents several other concerns. First, the federal government has long sought to reduce the FCIP cost, while raising AYP subsidy rates will increase AYP subsidy costs. This would be of less concern were AYP more cost efficient than YP in reducing the overall FCIP cost. However, to our best knowledge, no studies have systematically investigated the actual cost efficiency of area insurance plans over individual plans, as applied in practice. In contrast, some current program features provide good reasons to be skeptical about this efficiency claim. For example, RMA requires area insurance buyers to report their acreage and production data as individual insurance buyers do. The data collection costs of area insurance plans are thus comparable with those of individual insurance plans. Second, expanding area insurance programs will likely diminish the risk protection efficiency of crop insurance programs and undermine FCIP's role in deterring ad hoc disaster aid. Innes (2003) and Bulut (2017) have shown that individual insurance can effectively deter disaster aid expectations. However, although ad hoc disaster aid and area insurance payments are both generally triggered by catastrophic events, heterogeneity in basis risk may cause some area insurance contract buyers to suffer

[15]The advents of the Supplemental Coverage Option (SCO) in 2015 and the Enhanced Coverage Option (ECO) in 2021 may further reduce farmers' willingness to choose AYP over YP because AYP buyers are not eligible to buy SCO or ECO. AYP subsidy rates need to further increase to equalize expected net returns from purchasing AYP contracts and from purchasing YP-SCO, YP-ECO, or YP-SCO-ECO contracts.

more than others and so call for ad hoc disaster aid.[16] Finally, free area insurance contracts may bias farmers' optimal decisions (see Proposition 3 on p. 326 of Innes, 2003) and lead to a lemon-like problem in the individual insurance market. Proposition A1 in Appendix S1 shows that when the relationship between unit yield and county yield follows LAM, then TRASR decreases with an increase in the expected unit yield. The analysis validates the proposition for historical data. Free AYP contracts thus are likely to drive high-yield (and usually low-risk) farms out of YP. To the extent that premium rates on high-risk land for a given county are set lower than the actuarially fair rate (Maisashvili et al., 2019; Price et al., 2019; Ramirez & Shonkwiler, 2017), the remaining YP contracts in the book of business are more likely to give rise to net losses.

6 | SYSTEMIC YIELD RISK VERSUS SYSTEMIC REVENUE RISK

Our study focuses on systemic yield risk and thus on yield insurance instead of systemic revenue risk and revenue insurance. Revenue insurance is the most popular crop insurance contract form among U.S. row crop farmers (Schnitkey et al., 2020). Its payment can be triggered by a decline in either price or yield, thus protecting farmers against both yield and price risks. As crop price risk needs to be accounted for, systemic revenue risk is a more complicated issue where systemic yield risk is just one piece. Another major piece is how prices relate to the systemic and idiosyncratic components of yield variability. Introducing price variation will require a very different set of tools, perhaps including copula methods, in order to appropriately model correlation structures (Goodwin & Hungerford, 2015). Systemic revenue risk will likely exceed price-scaled systemic yield risk, as price variation is the same for both individual revenue and area revenue. However, price and yield should to some extent move in opposing directions due to market forces. This market force effect will strengthen whenever individual yield correlates strongly with aggregate yield. We refer to aggregate yield as national yield or global yield because the effect of county yield on price variation is negligible. Thus, although farmers face the same (or quite similar) price risks, their systemic revenue risks likely differ from their systemic yield risks due to different correlation levels with the aggregation yield.

Systemic revenue risk is also likely to differ across revenue contract forms. Revenue insurance contracts with Harvest Price Exclusion (HPE) pay indemnities whenever the product of the realized yield and the realized price falls below the product of the guaranteed yield and the projected price, and thus incorporates the natural hedge. Revenue contracts without HPE, which is by far the most popular insurance contract form, allow farmers to use harvest price in determining indemnity payment whenever the harvest price exceeds the projected price. Thus, HPE is likely to fundamentally alter the systemic component of revenue risk. The magnitude, geographic distribution, and decomposition of systemic revenue risk needs study both in its own right and in comparison with yield risk. We leave these questions for further studies.

7 | CONCLUDING REMARKS

Systemic risk partly justifies government intervention in crop insurance markets and the introduction of area insurance plans, but the existing relevant literature was not intended to build up our understanding of systemic risk from its fundamental sources. Emphasizing natural resources endowments, in this paper we have modeled, measured, and decomposed systemic risk in corn yield across the Greater Midwest. These we have done both in concept and by implementing on unit-level RMA yield data. We find that systemic risk explains a little less than half of unit yield risk on average,

[16]It is noteworthy that recent ad hoc payments were more often triggered by non-yield shocks, such as the Market Facilitation Program and the Coronavirus Food Assistance Program, see Zulauf et al. (2020) for more information.

revealing a moderate level of co-movement between unit yield and area yield. This finding suggests limited risk management effectiveness of AYP. We also investigate whether AYP has provided sufficient premium subsidies to compete with YP. We develop a new concept, the threshold relative area subsidy rate, or TRASR, the relative subsidy rate of AYP over YP at which AYP's expected net return equals that of YP. Our calibrated TRASR values indicate that current AYP subsidy rates discourage farmers from choosing AYP over YP, especially at low AYP coverage levels. We also find that TRASR is positively correlated with systemic risk at the unit-level of analysis. Thus, in the presence of subsidized YP contracts, AYP contracts are typically unable to simultaneously meet farmers' risk protection and transfer-seeking demands.

We also briefly evaluate the policy option of increasing AYP subsidy rate to generate greater AYP demand. We find that even free AYP contracts are unlikely to support an AYP demand that significantly exceeds the pre-2009 level. It is generally acknowledged that basis risk deters farmers from choosing AYP contracts and discourages AYP buyers from renewing that contract form. Our study of systemic risk helps quantify the extent of such deterrence. Further inquiries are needed into the sensitivity of AYP demand to subsidy rates as well as into implications for budgetary costs and risk protection efficiencies of FCIP.

Climate change may alter future systemic risk patterns and area insurance demand. Our analysis finds that systemic risk significantly increases with drought occurrence and more excessive heat events. These events are projected to be more frequent with the changing climate. Notwithstanding, our result also shows that systemic risk decreases with more excessive precipitation events, which are also projected to occur with higher frequency. This impact may, however, be ameliorated or even negated because century-old U.S. midwestern drainage systems are midway through major upgrades that commenced around 1990 (Castellano et al., 2019). Looking forward, area-specific systemic risk patterns and area insurance demand can be investigated by linking downscaled climate and weather projection data to statistical yield models that account for intracounty, weather-conditioned yield distributions. Additional opportunities will arise whenever quality estimates of annual yield information at point locations become available because such data can be connected to soil maps. Findings in Jin et al. (2017), Li et al. (2019), Jiang et al. (2020), and elsewhere provide evidence that remote sensing and related inference methods may be close to making this connection.

It is also worth noting that switching from individual insurance to area insurance may change farmers' production behavior. Previous studies generally agree that area insurance helps remove moral hazard issues and thus should not alter farmers' production decisions. One exception is Chambers and Quiggin (2002), who argue that farmers would adjust their production behavior to align their own risks with area risk and thus to take advantage of the income-smoothing properties of AYP contracts. Although we do not model farmers' behavior, our decomposition of systemic risk and our study of how irrigation affects systemic risk suggest that farmers who adopt the prevalent production practice in a county bear higher systemic risk and should enjoy better risk protection from AYP than those who adopt less common production practices. One implication of this inference is that AYP may discourage farmers from choosing a technology new to an area and yet in time encourage laggards to adopt so that their yield realizations become better aligned with those of other producers in the area. Moreover, farmers' tendency to align their own production choices with prevalent production practices in the presence of AYP is likely to increase systemic yield risk and promote lock-in of Pareto-dominated production practices induced by networking effects.[17] Insurance policy design would benefit from a deeper understanding of the interactions among systemic risk, AYP, and related production choices.

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[17]See Cowan and Gunby (1996), Holmes and Lee (2012), and Arora et al. (2021) for discussions on network lock-in in agriculture.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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