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Alternative Crop Insurance Indexes

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Three index-based crop insurance contracts are evaluated for representative south Georgia corn farms. The insurance contracts considered are based on indexes of historical county yields, yields predicted from a cooling degree-day production model, and yields predicted from a crop-simulation model. For some of the representative farms, the predicted yield index contracts provide yield risk protection comparable to the contract based on historical county yields, especially at lower levels of risk aversion. The impact of constraints on index insurance choice variables is considered and important interactions among constrained, conditionally optimized, choice variables are analyzed.

Key Words: area yield insurance, cooling degree days, DSSAT, group risk plan

JEL Classifications: G13, G22, Q12

In 2006, the U.S. Federal Crop Insurance Program (FCIP) had an insurance liability of just under $50 billion on 242 million acres of cropland. Approximately 75% of that liability was for *farm-level* yield and revenue insurance contracts that establish guarantees based on the insured unit's actual production history (APH) yield (e.g., APH Yield Insurance, Crop Revenue Coverage, Revenue Assurance).

In recent years, alternative insurance contracts known as the Group Risk Plan (GRP) and Group Risk Income Protection (GRIP) have become more popular with farmers. In 2006, these contracts accounted for almost 14% of FCIP liability, up from only 3% in 2002.[1] GRP establishes guarantees and makes payments based on *county-level* yields rather than *farm-level* yields (Skees, Black, and Barnett). GRIP is a revenue insurance version of GRP, with guarantees and payments based on the product of *county-level* yields and futures market prices. Recently, these contracts have received significantly more attention as some have suggested replacing existing federal agricultural income support programs (e.g., the marketing loan program and the *countercyclical* payment program) with a federally provided GRIP policy (Babcock and Hart).

GRP and GRIP are specific examples of a general class of insurance contracts known as "index insurance." For these contracts, guarantees and indemnities are based not on *farm-level* yields or revenues but rather on an index that is considered to be highly correlated with *farm-level* outcomes (Skees and Barnett). For

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[1] The remaining 11% of FCIP liability is spread across various other insurance products, most of which are for specialty crops.

GRP and GRIP, the underlying index is *county-level* yield and revenue, respectively. Access to GRP and GRIP policies is, therefore, limited by the availability of National Agricultural Statistical Service (NASS) data on *county-level* yields. Thus, for some marginal production areas, it would not be possible to replace existing federal agricultural income support programs with a federally provided GRIP policy because NASS *county-level* yield data are not available. But other index insurance contracts may be possible.

This article compares index insurance contracts based on 1) historical area (county) yields (like the GRP contract), 2) predicted yields from a *county-level* cooling degree-day production model, and 3) predicted yields from a crop growth-simulation model. The analysis is conducted for representative corn farms in four southern Georgia counties. From a national perspective, corn production in these counties is quite marginal. However, unlike some marginal production areas, NASS county yield data are available for these counties. This allows us to compare area yield insurance with alternative index insurance designs, such as might be required in marginal production areas where NASS yield data are not available. If the alternative index contracts perform well relative to an area yield insurance contract, this suggests that it may be possible to use alternative index insurance contracts in areas where NASS *county-level* yield data are not available. This has implications both for expanding the availability of FCIP index insurance contracts and for the recent proposal to replace existing federal income support programs with a federally provided GRIP policy.

A second contribution of the work presented here relates to the *coverage* and *scale* choice variables used in the current GRP area yield index insurance contract (Skees, Black, and Barnett). Previous conceptual analyses have shown how binding constraints on *coverage* should affect the optimal value of *scale* or, alternatively, how binding constraints on *scale* should affect the optimal value of *coverage* (Mahul; Miranda; Vercammen). We generalize these conceptual findings to other index insurance contracts and also demonstrate empirically the interdependent adjustments required when binding constraints are imposed on *coverage* and *scale*. This contribution has important policy implications because some crop insurance industry organizations have recently proposed more binding constraints on these GRP and GRIP choice variables (Parkerson).

The next section provides background on index insurance. This is followed by a description of the data and methods used to compare the various index insurance contracts. Later sections discuss empirical results and present concluding comments.

Index Insurance

Index insurance contracts pay indemnities based not on the actual yield (or revenue) losses experienced by the insurance purchaser but rather based on realized values of an index that is correlated with *farm-level* losses. For the GRP insurance contract, the underlying index is the county average yield. Index insurance contracts based on various weather measures have also been proposed (Deng et al.; Martin, Barnett, and Coble; Richards, Manfredo, and Sanders; Turvey; Vedenov and Barnett). The GRP indemnity function can be generalized such that for an index x that is denominated in units of production per acre, indemnity per acre $\tilde{n}^x$ is calculated as

$$\tilde{n}^x(\tilde{y}^x|coverage,scale) = \max\left(\frac{(y^x - \tilde{y}^x)}{y^x}, 0\right) \times fcast^x \times scale, \tag{1}$$

where $fcast^x$ is the expectation of the underlying stochastic index (county yield in the case of GRP), $\tilde{y}^x$ is the realization of the index, and $y^x = fcast^x \times coverage$.[2] *Coverage* and *scale* are choice variables selected by the policyholder. For GRP, these variables are bounded

[2] For simplicity, indemnities are denominated in units of production rather than currency units.

so that $70\% \leq coverage \leq 90\%$, and $90\% \leq scale \leq 150\%$.

Note that the actual yield experienced on the policyholder's farm is not an argument in the calculation of $\tilde{n}^x$. Instead, if $\tilde{y}^x < y^x$, the index insurance policyholder will receive an indemnity, irrespective of the actual yield experienced on the policyholder's farm. Thus, the risk protection provided by the index insurance contract is directly related to the correlation between the underlying index and actual *farm-level* losses.

A primary advantage of index insurance is that it is less susceptible to the asymmetric information problems that plague conventional APH-based insurance (Chambers; Coble et al.; Just, Calvin, and Quiggin; Quiggin, Karagiannis, and Stanton; Smith and Goodwin). There is little potential for adverse selection because there is no need for *farm-level* risk classification. Because the policyholder can not significantly affect the realized value of the index, moral hazard is not a problem. Index insurance contracts also have lower transaction costs because there is no need to establish and verify expected *farm-level* yields for each insured unit nor is there any need to conduct on-farm loss adjustment. The primary disadvantage of index insurance is that the policyholder is exposed to basis risk—meaning that it is possible for the policyholder to experience a loss and yet receive no indemnity.

Optimal Coverage and Scale

Miranda formalized a theoretical framework for evaluating the effectiveness of area yield crop insurance that can be generalized for any index insurance contract. If *farm-level* yields $\tilde{y}_i$ are projected orthogonally onto an index $\tilde{y}^x$, then

$$(2) \qquad \tilde{y}_i - \mu_i = \beta_i(\tilde{y}^x - \mu^x) + \tilde{\varepsilon}_i,$$

where $\mu_i = E(\tilde{y}_i)$, $\mu^x = E(\tilde{y}^x)$, β_i is a coefficient that measures the sensitivity of *farm-level* yield deviations from the expected value to deviations of the index from its expected value, and ϵ_i reflects idiosyncratic deviations in *farm-level* yields that are not associated with deviations in the index. This implies

$$(3) \qquad \beta_i = \frac{\mathrm{cov}(\tilde{y}_i, \tilde{y}^x)}{\mathrm{var}(\tilde{y}^x)},$$

which is similar to the notion of β in the capital asset pricing model (CAPM).

Miranda noted that a risk-averse policyholder's optimal choice of *scale* would approach β_i. Mahul and Wang et al. formalized this by showing that if no constraints were imposed on *coverage* and *scale* and the premium rate was actuarially fair, the optimal *scale* would be equal to β_i and the optimal *coverage* would be that which sets the critical yield y^x equal to the maximum possible realization of the stochastic index, i.e., $coverage = y_{\max}/\mu^x$. Mahul also showed that if *scale* is constrained to be greater than β_i, the optimal *coverage* would set y^x less than the maximum possible realization of the index, i.e., $coverage < y_{\max}/\mu^x$, even if the insurance premium is actuarially fair. In other words, when policyholders are constrained to accept a higher-than-optimal *scale*, they should compensate by choosing a level of *coverage* that is less than the unconstrained optimum.

Similarly, Barnett et al. and Deng, Barnett and Vedenov suggest that if *coverage* is constrained by an upper bound, policyholders compensate by choosing a level of *scale* that is higher than the unconstrained optimum. The intuition behind this is that because of the binding constraint on *coverage*, the index insurance contract will not trigger an indemnity as frequently as policyholders would wish. By increasing *scale*, policyholders increase the amount of indemnity that is paid whenever the constrained index insurance contract does trigger a payment.

Alternative Indexes

In addition to index insurance based on area yields, a number of previous studies have examined the potential for creating index insurance based on a particular weather variable measured over a specified period of time (Deng et al.; Martin, Barnett, and Coble;

Richards, Manfredo, and Sanders; Turvey; Vedenov and Barnett). In principal, it should also be possible to create more sophisticated indexes that are functions of multiple weather variables, weather variables measured over multiple time periods, or weather variables interacted with other production variables. More sophisticated weather indexes may exhibit less basis risk than those based on a single weather variable.

The analysis presented here considers two weather-based, predicted-yield indexes. The first is based on Cao's examination of the relationship between detrended county corn yields for several counties in southern Georgia and cumulative monthly measures of rainfall and temperature for weather stations located in those counties. Cooling degree days (CDD) were used to measure cumulative monthly temperature. For a month consisting of 31 days, CDD is calculated as

$$(4)\ CDD = \sum_{k=1}^{31} \max(\textit{average temperature}_k - 65),$$

where k indicates the day of the month, and the average temperature is measured in degrees Fahrenheit. Cao found that CDD for various months was significant in explaining county yield variation, whereas cumulative monthly rainfall was not.

The second *weather-based* predicted yield index uses the CERES-Maize model, a crop growth-simulation model, under the software program package Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al.). The crop simulation models under DSSAT are dynamic and physiologically based, and simulate growth, development, and yield on a daily basis as a function of weather and soil conditions and different crop management scenarios. The models also include a genetic component to handle differences between individual varieties or cultivars. For instance, the maize (corn) model includes six parameters that define the number of photothermal days to flowering and maturity, sensitivity to photoperiod, the maximum number of seed kernels per plant, individual seed filling rate, and the phyllochron interval for each cultivar (Bannayan, Hoogenboom, and Crout; Román-Paoli, Welch, and Vanderlip). It has advanced from a simple stand-alone model (Duchon; Jones and Kiniry) into a generic grain cereal model (Ritchie et al.). Moreover, the CERES–Maize model under DSSAT has been evaluated extensively across a wide range of environments, including Georgia.

To generate a predicted yield index via DSSAT, weather realizations were imported into the model while all other choice variables were held constant. It was hypothesized that index insurance based on DSSAT predicted yields would have lower basis risk than index insurance based on a single weather variable because DSSAT incorporates several weather variables and attempts to model interactions between those weather variables and other variables that also affect realized yields.

Figure 1 presents shortfalls relative to the expected value for each of the indexes (*area-yield*, CDD, and DSSAT) over the period 1971–2004. Also shown are the pairwise correlations between shortfalls for the area yield index and each of the alternative indexes.

Data and Methods

Farm-level corn yield data were obtained from the U.S. Department of Agriculture (USDA) Risk Management Agency (RMA). These data are the 4- to 10-year yield histories from 1991 to 2000 that were used to establish APH yields for 2001 Multiple Peril Crop Insurance (MPCI) purchasers. The data were aggregated to the level of an enterprise unit meaning that for a given year, the yield reflects all production in the county that is associated with a specific taxpayer identification number. To be included in the analysis, each farm had to have yield data for at least the last four consecutive years of the period (i.e., 1997–2000).

Historical *county-level* yield data were collected from NASS. These data were collected from 1971 to 2004. The daily weather data used to construct the CDD and DSSAT indexes were obtained from the U.S. National Climatic Data Center (NCDC).

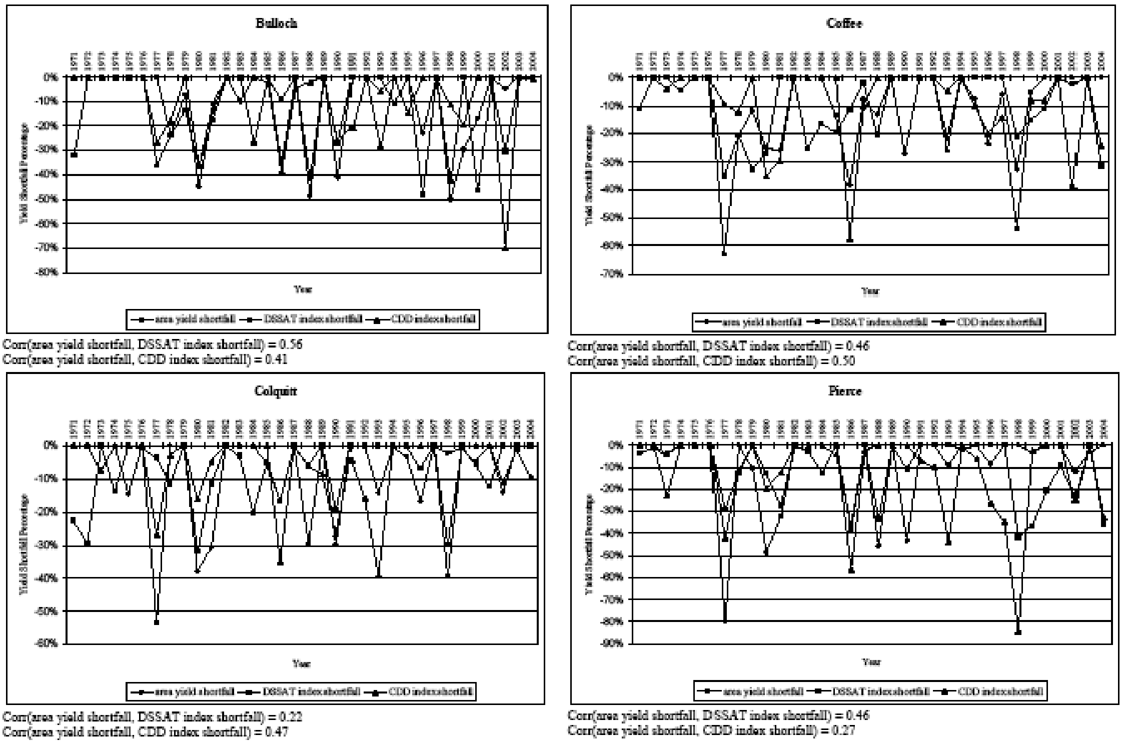

Figure 1. Yield Shortfall Percentage among the Three Indexes over the Period 1971–2004

The four counties included in the study each have less than 30% of the planted acreage under irrigation (Table 1). These counties also have weather stations located within the county and daily weather data (with relatively few missing observations) available for the time period 1971–2004.

Regression analyses revealed statistically significant time trends in all county yields. To account for the temporal component, a detrending procedure was implemented by estimating a linear trend model:

$$(5) \qquad \tilde{y}_{jt} = \alpha_{j0} + \alpha_{j1} t + \varepsilon_{jt},$$

where j is the county, t is the year with t = 1971, 1972, . . . , 2004, and $\tilde{y}_{jt}$ is the yield in county j and year t. Detrended county yields were then calculated as

$$(6) \qquad y_{jt}^{det} = \frac{\tilde{y}_{jt}}{\hat{y}_{jt}} \hat{y}_{j2004},$$

where $\hat{y}_{jt}$ is the predicted county yield estimated from Equation (5). The detrended county yields were then used to construct a GRP-like area yield index insurance contract.

Using the available weather data for each county, CDD predicted yield indexes were created based on Cao's findings. The predicted yield indexes are linear functions of cumulative monthly CDD measures as shown in Table 2.

Table 1. Counties Included in the Study

County	Number of Farms for Which Actual Yield Data Were Available	2002 Percentage of Harvested Cropland That Was Irrigated
Bulloch	25	23.3
Coffee	12	22.0
Colquitt	10	29.0
Pierce	18	21.6

Source: Irrigation data is from the 2002 Census of Agriculture.

Table 2. Regression Equations used to Generate CDD Predicted Yield Indexes

County	Regression Equations	$Pr > F$	R^2
Bulloch	$\hat{y} = 234.410 - 0.2855(April) - 0.1450(July) - 0.1696(September)$	0.0004	0.41
	(0.0106) (0.0262) (0.0142)		
Coffee	$\hat{y} = 297.304 - 0.0746(June) - 0.2728(July) - 0.1317(September)$	<0.0001	0.51
	(0.3255) (0.0094) (0.0713)		
Colquitt	$\hat{y} = 231.458 - 0.1282(June) - 0.0839(July) - 0.1644(September)$	0.0085	0.30
	(0.1452) (0.3633) (0.0608)		
Pierce	$\hat{y} = 320.565 - 0.1473(June) - 0.2035(July) - 0.2062(September)$	0.0016	0.44
	(0.1422) (0.1617) (0.0276)		

Note: Regression equations are from Cao (2004). The variable names are cumulative CDD measured in that month. Numbers in parentheses below each formula are standard errors.

DSSAT predicted yield indexes were also created for each county. The corn cultivar 'PIO 31G98' was used in the DSSAT model, along with choice variables that included three planting dates, three soil types, irrigated and rain-fed conditions, and two technology levels.[3] Thus, in each county, 36 scenarios associated with all possible combinations of the choice variables were used to generate DSSAT predicted yields. Under each scenario, the DSSAT predicted yield was modeled using historical data on daily minimum and maximum temperatures, rainfall, and solar radiation throughout the growing season. To generate a single predicted yield for each county, a simple average yield (across planting dates and technology levels) was created for each of the six possible *soil-type* and irrigated versus rain-fed combinations. The irrigation percentages in each county (see Table 1) were then used as weights to generate *soil-type*–specific weighted average yields for each county. A county weighted average yield was then calculated using the percentage of the county's crop land in each of the three soil types as weights. A DSSAT index insurance contract was constructed based on DSSAT county weighted average yields simulated over the period 1971 to 2004.

Farm-Level Yield Simulation

The 4 to 10 years of available farm yield data provide only limited information about the underlying yield distribution for each representative farm. Low-frequency, high-magnitude yield losses may be underrepresented (or overrepresented) in the small sample of available farm yield data. To adequately assess the performance of various insurance instruments, it is necessary to estimate representative farm yield distributions. To do this, for each individual farm i, *farm-level* shocks are calculated relative to the simple average of the 4 to 10 years of *farm-level* yields. Specifically, the shocks ε_{is} are calculated as

$$(7) \qquad \varepsilon_{is} = \frac{\widetilde{y}_{is}}{y_i},$$

where s indicates each year between 1991 and 2000 for which the farm yield data are available and $\bar{y}_i$ is the simple average yield for farm i. Then, a large number of pseudo *farm-level* yields can be calculated as all possible combinations of the available detrended county-yield data and the 4 to 10 *farm-level* shocks. Specifically,

$$(8) \qquad \boldsymbol{y}_i^{pseudo} = \boldsymbol{y}_j^{\det} \times \varepsilon_i^{'},$$

where $\mathbf{y}_j^{\det}$ is a $t \times 1$ column vector of detrended yields for county j with $t = 1971$,

[3] 'PIO 31G98' is very common corn cultivar in Georgia. It is characterized as a high-yield, short- to mid-season hybrid. The choice variables were selected based on recommendations from crop scientists in the region. Details about the choices of the planting dates, soil types, irrigation systems, and technology levels will be provided upon request.

1972, ..., 2004; $\boldsymbol{\epsilon}_i'$ is a $1 \times s$ row vector of shocks for farm i located in county j; and $\mathbf{y}_i^{pseudo}$ is a $t \times s$ matrix of pseudo *farm-level* yields for farm i. Designate z as a counter variable for the pseudo *farm-level* yields with $z = 1, 2, \ldots, Z$ and $Z = t \times s$. Then, each farm i has between $136 \leq Z \leq 340$ pseudo *farm-level* yields.

Given the very limited number of farms for which yield data were available in each county (see Table 1), the pseudo *farm-level* yields within a given county were combined for purposes of estimating a yield distribution for a representative farm in that county. Thus, all of the pseudo *farm-level* yields within a given county were stacked into a single vector $\mathbf{y}_f{}^{pseudo}$ where the subscript f designates a representative farm for county j. For each representative farm f, the stacked vector contains $R = \sum_i Z \,\forall i \in j$ pseudo *farm-level* yields.[4]

A kernel-smoothing approach was used to estimate distributions for the three indexes and representative farm yields in each county. Formally, $\tilde{y}_{fr}$ is used to designate each of the R elements of the stacked vector $\mathbf{y}_f{}^{pseudo}$. Each element of the vector $\mathbf{y}_j{}^x$, the index x for county j, is repeated for the corresponding element of $\mathbf{y}_f{}^{pseudo}$, so that the size of the index is also R with $\tilde{y}_{jr}^x$ being used to designate the elements of the extended index vector. Then the joint kernel-density function of yield for representative farm f and the particular index x is calculated as

$$(9a)\quad h\left(\tilde{y}_f, \tilde{y}_j^x\right) = \frac{1}{R\Delta_f \Delta_j^x} \sum_{r=1}^{R} K\left(\frac{\tilde{y}_f - \tilde{y}_{fr}}{\Delta_f}, \frac{\tilde{y}_j^x - \tilde{y}_{jr}^x}{\Delta_j^x}\right),$$

the marginal density function of yield for representative farm f is calculated as

$$(9b)\quad \begin{aligned} h(\tilde{y}_f) &= \int h(\tilde{y}_f, \tilde{y}_j^x) d\tilde{y}_j^x \\ &= \int \frac{1}{R\Delta_f \Delta_j^x} \sum_{r=1}^{R} K\left(\frac{\tilde{y}_f - \tilde{y}_{fr}}{\Delta_f}, \frac{\tilde{y}_j^x - \tilde{y}_{jr}^x}{\Delta_j^x}\right) d\tilde{y}_j^x, \end{aligned}$$

and the marginal density function of a particular index x for county j is calculated as

$$(9c)\quad \begin{aligned} h\left(\tilde{y}_j^x\right) &= \int h(\tilde{y}_f, \tilde{y}_j^x) d\tilde{y}_f \\ &= \int \frac{1}{R\Delta_f \Delta_j^x} \sum_{r=1}^{R} K\left(\frac{\tilde{y}_f - \tilde{y}_{fr}}{\Delta_f}, \frac{\tilde{y}_j^x - \tilde{y}_{jr}^x}{\Delta_j^x}\right) d\tilde{y}_f. \end{aligned}$$

$K(\bullet)$ is a joint kernel function and Δ_f, $\Delta_j{}^x$ are bandwidths for the representative *farm-level* yield and the yield index, respectively (Härdle). Because the joint density is for bivariates, and following Bowman and Foster, two bandwidths are used (each multiplied by 0.5) to better capture the curvature of the simulated *farm-level* yield and each of the three indexes. The lower and upper bounds used in the joint kernel density function for each coordinate's direction are the realized lowest and highest values for the simulated *farm-level* yield and the index.

The estimated joint *farm-level* yield and index distributions were used to assess the performance of each index insurance contract. Descriptive statistics calculated from the estimated joint distributions are presented in Table 3.

Premium Rating

For each county j, indemnities for all three index insurance contracts are calculated as in Equation (1) with $fcast^x$ being the expectation of $h\,(\tilde{y}_j{}^x)$. *Coverage* and *scale* are constrained as in the actual GRP contract ($70\% \leq$ *coverage* $\leq 90\%$ and $90\% \leq$ *scale* $\leq 150\%$).

The actuarially fair premium $\pi_{j\_fair}^x$ is the expectation of the indemnity function

$$(10a)\quad \begin{aligned} \pi_{j\_fair}^x &= E\left[\tilde{n}_j^x\left(\tilde{y}_j^x | \text{coverage, scale}\right)\right] \\ &= \int \max\left(\frac{(y_j^x - \tilde{y}_j^x)}{y_j^x}, 0\right) \\ &\quad \times fcast^x \times scale \times h\left(\tilde{y}_j^x\right) d\tilde{y}_j^x, \end{aligned}$$

where $h\,(\tilde{y}_j{}^x)$ is the marginal kernel density for a particular yield index in county

[4] To eliminate unrealistically high yields for the representative farm in each county, any pseudo *farm-level* yield greater than three standard deviations from the expected county yield was censored.

Table 3. Descriptive Statistics for the Representative Farm Yield and the Three Indexes Calculated from the Estimated Joint Kernel Densities

Yield	Mean (bu/acre)	Standard Deviation	Coefficient of Variation	Minimum (bu/acre)	Maximum (bu/acre)
Bulloch County					
Farm-Level Yield	73.15	42.40	0.58	2.23	159.39
Area Yield Index	84.50	24.06	0.28	42.94	124.05
DSSAT Index	54.56	15.36	0.28	28.70	79.40
CDD Index	74.87	17.49	0.23	22.57	99.63
Coffee County					
Farm-Level Yield	102.27	45.72	0.45	2.93	199.76
Area Yield Index	108.27	26.88	0.25	41.60	186.80
DSSAT Index	79.14	19.50	0.25	51.39	130.10
CDD Index	75.71	19.33	0.26	32.45	111.99
Colquitt County					
Farm-Level Yield	101.56	43.11	0.42	1.21	183.35
Area Yield Index	108.57	22.76	0.21	51.64	159.56
DSSAT Index	77.09	13.52	0.18	52.24	105.72
CDD Index	71.85	13.55	0.19	44.12	99.24
Pierce County					
Farm-Level Yield	106.67	49.97	0.47	0.49	208.50
Area Yield Index	111.36	30.64	0.28	22.73	172.49
DSSAT Index	61.56	16.68	0.27	36.11	96.58
CDD Index	73.77	23.12	0.31	11.65	109.98

j.[5] The integral under the kernel density was calculated using numerical methods. The actuarially fair-premium rate ρ_j^x is calculated as

$$(10b)\qquad \rho^x_{j\_fair} = \frac{\pi^x_j}{yfcast^x \times scale}.$$

For GRP, reserve loads are applied by dividing the actuarially fair-premium rate by 0.9. Premium subsidies vary with the level of *coverage*. The premium subsidy for 70% and 75% *coverage* is 64%, for 80% and 85% *coverage* is 59%, and for 90% *coverage* is 55%. For this analysis, we assume that the other indexes use the same reserve loading and premium subsidy structure.[6] Thus, the actual premium for each index is

$$(11a)\qquad \pi^x_{j\_actual} = \frac{E\left[\tilde{n}^x_j\left(\tilde{y}^x_j|coverage,\ scale\right)\right]}{0.9} \times (1 - subsidy\ \%) = \frac{\pi^x_{j\_fair}}{0.9}(1 - subsidy\ \%),$$

and the actual premium rate is

$$(11b)\qquad \rho^x_{j\_actual} = \frac{\pi^x_{j\_actual}}{yfcast^x \times scale}.$$

Decision Criterion

Assume that each representative farm f holds a portfolio consisting of only two assets: corn production and a specific index insurance contract. For any realization of *farm-level* yield $\tilde{y}_f$ and insurance contract x, the yield net of insurance premiums and indemnities is

$$(12)\qquad \widetilde{ynet}^x_f = \tilde{y}_f - \pi^x_j + \tilde{n}^x_j.$$

[5] This burn method of establishing premiums is analogous to that used for the existing GRP product. Because the insurance product would not trade in secondary markets, there is no need to use continuous time pricing models.

[6] The optimized coverage in this study is not discrete with 5% increments as it is for the actual GRP contract. Thus, premium subsidy is set at 64% for 70% $\leq$ *coverage* $<$ 80%, 59% for 80% $\leq$ *coverage* $<$ 90%, and 55% for *coverage* at 90%.

The subscripts for actuarially fair or actual premium are dropped to maintain conciseness.[7]

When premium rates are not actuarially fair because of the reserve load and premium subsidies, insurance purchasing will not only affect the variance of the net yield but also the expected net yield. Thus, the contracts cannot be compared based simply on the reduction in the variance of net yield as in previous studies (Barnett et al.; Miranda; Smith, Chouinard, and Baquet). For this reason, certainty-equivalent revenues (CER) are used to make comparisons across insurance contracts.

Revenue $R_f{}^x$ for representative farm f and index insurance contract x is calculated as

$$(13) \quad R_f^x = p \times \tilde{y}net_f^x,$$

where p is a constant price per bushel of corn.[8] For each combination of index insurance contract x and representative farm f, the CER was calculated based on a constant relative risk aversion (CRRA) utility function

$$(14) \quad U\left(R_f^x\right) = \frac{(R_f^x)^{1-\gamma}}{1-\gamma},$$

where γ is the measure of relative risk aversion. Myers estimated that for a representative U.S. crop farmer $1 \leq \gamma \leq 3$. We consider three levels of γ: 1.5, 2.0, and 2.5 where higher values indicate higher levels of relative risk aversion. CER is then calculated as

$$(15) \quad CER_f^x = \left[\int U\left(R_f^x\right) h(\tilde{y}_f)\, d\tilde{y}_f\right]^{-1},$$

where $h(\tilde{y}_f)$ is the marginal kernel yield density (Equation 9b) for representative farm f.

[7] The actuarially fair premium is used to analyze empirically the relationship between constrained optimal coverage and scale. The actual premium is used to evaluate certainty-equivalent revenue outcomes for the various index contracts.

[8] The price used for corn was the 2004 Chicago Board of Trade June daily average price on the July contract.

Results

Optimal Coverage and Scale

For each of the index insurance contracts, *coverage* and *scale* were optimized within the existing GRP constraints to maximize the difference between the CER with index insurance and the CER with no insurance. The optimal *scale* and *coverage* were found simultaneously using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Greene; Miranda and Fackler).[9]

The premium subsidy may distort crop producers' preferences on insurance *coverage*. When the subsidy is factored into premium rating, crop producers may choose *coverage* not only based on the risk reduction that can be achieved but also based on capturing more premium subsidies. For this reason, actuarially fair premiums are used to evaluate empirically the relationship between *coverage* and *scale*.

For the representative farm in each county, Tables 4a–c present optimal *coverage* and *scale* for the three index insurance contracts when these choice variables are constrained as in the existing GRP contract. Results are shown for the three different risk-aversion levels γ.

For each of the Tables 4a–c, there are 12 representative farm/index insurance combinations. Recall that when *coverage* is unconstrained and premiums are actuarially fair, the optimal *scale* is equal to the value of the beta coefficient regardless of the level of risk aversion. However, for each of the 12 representative farm/index insurance combinations, the beta coefficient is less than 0.90, which is the lower bound for *scale* under the existing GRP contract. To see how that constraint on

[9] The BFGS algorithm is used instead of a simple genetic algorithm (such as a gradient method) because the convergence rate of BFGS is superlinear, which is faster than the liner convergence rate of a gradient method. The search directions for BFGS are often more accurate than the gradient method, thus allowing for fewer iterations to converge to a local optimum. Also, the gradient method can stall before finding a solution.

Table 4a. Constrained Optimal *Coverage*, Unconstrained Optimal *Coverage*, Constrained Optimal *Scale*, and Beta Coefficient for the Three Index Insurance Contracts When Premiums Are Actuarially Fair (CRRA = 1.5)

Index Insurance	Constrained Optimal *Coverage* (70–90%)	Unconstrained Optimal *Coverage* if *Scale* = Beta Coefficient	Constrained Optimal *Scale* (90–150%)	Beta Coefficient
Bulloch County				
Area Yield Index	70%	147%	90%	0.54
DSSAT Index	70%	146%	90%	0.53
CDD Index	70%	133%	90%	0.42
Coffee County				
Area Yield Index	70%	173%	90%	0.69
DSSAT Index	75%	164%	90%	0.39
CDD Index	70%	148%	90%	0.62
Colquitt County				
Area Yield Index	90%	147%	90%	0.75
DSSAT Index	75%	137%	90%	0.25
CDD Index	90%	138%	103%	0.68
Pierce County				
Area Yield Index	70%	155%	90%	0.86
DSSAT Index	85%	157%	90%	0.62
CDD Index	70%	149%	90%	0.43

Table 4b. Constrained Optimal *Coverage*, Unconstrained Optimal *Coverage*, Constrained Optimal *Scale*, and Beta Coefficient for the Three Index Insurance Contracts When Premiums Are Actuarially Fair (CRRA = 2)

Index Insurance	Constrained Optimal *Coverage* (70–90%)	Unconstrained Optimal *Coverage* if *Scale* = Beta Coefficient	Constrained Optimal *Scale* (90–150%)	Beta Coefficient
Bulloch County				
Area Yield Index	70%	147%	90%	0.54
DSSAT Index	70%	146%	90%	0.53
CDD Index	70%	133%	90%	0.42
Coffee County				
Area Yield Index	70%	173%	90%	0.69
DSSAT Index	84%	164%	90%	0.39
CDD Index	70%	148%	90%	0.62
Colquitt County				
Area Yield Index	90%	147%	100%	0.75
DSSAT Index	75%	137%	90%	0.25
CDD Index	90%	138%	118%	0.68
Pierce County				
Area Yield Index	70%	155%	90%	0.86
DSSAT Index	90%	157%	90%	0.62
CDD Index	72%	149%	90%	0.43

Table 4c. Constrained Optimal *Coverage*, Unconstrained Optimal *Coverage*, Constrained Optimal *Scale*, and Beta Coefficient for the Three Index Insurance Contracts When Premiums Are Actuarially Fair (CRRA = 2.5)

Index Insurance	Constrained Optimal *Coverage* (70%–90%)	Unconstrained Optimal *Coverage* if *Scale* = Beta Coefficient	Constrained Optimal *Scale* (90%–150%)	Beta Coefficient
Bulloch County				
Area Yield Index	70%	147%	90%	0.54
DSSAT Index	70%	146%	90%	0.53
CDD Index	70%	133%	90%	0.42
Coffee County				
Area Yield Index	84%	173%	90%	0.69
DSSAT Index	90%	164%	115%	0.39
CDD Index	90%	148%	90%	0.62
Colquitt County				
Area Yield Index	90%	147%	115%	0.75
DSSAT Index	75%	137%	90%	0.25
CDD Index	90%	138%	135%	0.68
Pierce County				
Area Yield Index	70%	155%	90%	0.86
DSSAT Index	90%	157%	103%	0.62
CDD Index	77%	149%	90%	0.43

scale affects the optimal *coverage*, the three tables also show the unconstrained optimal *coverage* when *scale* is unconstrained so that it can be set equal to the value of the beta coefficient.

Likewise recall that when *scale* is unconstrained and premium rates are actuarially fair, the optimal *coverage* for a risk averse policyholder is that which sets y^x equal to the maximum possible value of the index regardless of the level of risk aversion. This implies an optimal *coverage* that will always be greater than or equal to 100%. However, the existing GRP program requires that 70% ≤ *coverage* ≤ 90%.

When both *coverage* and *scale* are constrained, the level of constant relative risk aversion γ can affect the constrained optimal *coverage* and *scale*. For 3 of the 12 representative farm/index insurance combinations shown in Tables 4a–c, constrained optimal *coverage* increases with the level of risk aversion but constrained optimal *scale* is unchanged. Two combinations have constrained optimal *scale* increasing with risk aversion though constrained optimal *coverage* is unchanged. Two combinations have both constrained optimal *coverage* and *scale* increasing with risk aversion. For five of the combinations, both constrained optimal *coverage* and *scale* are unchanged over the range of constant relative risk aversion coefficients considered.

To see the interaction between constrained, conditionally optimized values of *coverage* and *scale* consider the results for $\gamma = 2$ (Table 4b). Six of the representative farm/index insurance combinations have both optimal *scale* and optimal *coverage* constrained by the lower bounds of 90% and 70%, respectively. Were it not for the lower bound on *coverage*, the optimal *coverage*, conditioned on the constrained *scale*, would be reduced even further.

Consider a case where the optimal *coverage*, conditioned on the constrained *scale*, is unconstrained. For example, in Coffee County the beta coefficient for the DSSAT index is 0.39.

The optimal *scale* is constrained by the lower bound of 90%. The optimized *coverage*, conditioned on the constrained scale, is 84%. If *scale* were not constrained to be higher than desired, *coverage* would have been optimized at 164%. Similar results occur for the DSSAT index in Colquitt County and the CDD index in Pierce County. In general, when *scale* is constrained by the lower bound, the optimal *coverage* is reduced to compensate for the higher than desired *scale*.

Next consider a case where the beta coefficient is less than the lower bound on *scale* of 90%, and the optimal *coverage*, conditioned on the constrained *scale*, is constrained by the upper bound on *coverage* of 90%. For example, in Colquitt County, *scale* on the area yield index would be constrained by the lower bound of 90% because the beta coefficient is equal to 0.75. The policyholder would choose to reduce *coverage* to offset the higher *scale*. In this case, however, the optimized *coverage*, conditional on the constrained *scale*, would still be higher than the 90% upper bound. When both *scale* and *coverage* are constrained, the policyholder must make interdependent adjustments to these two choice variables. To compensate for the upper bound on *coverage*, the optimal *scale* (conditioned on the constrained *coverage*) actually increases to 100%, even though the beta coefficient is equal to only 0.75. A similar outcome occurs for the CDD index in Colquitt County.

These results demonstrate the important interdependencies between constrained and conditionally optimized index insurance choice variables. Further, these results demonstrate that existing constraints on GRP and GRIP *coverage* and *scale* likely prevent policyholders from obtaining optimal index insurance protection. Further constraints on these choice variables, as has been proposed by some in the insurance industry, would make index insurance contracts even less attractive to potential purchasers.

Changes in Producer Well-Being

Table 5 shows, for each representative farm, the CER without insurance and the change in CER with index insurance (using actual premiums with subsidies) when the choice variables are optimized within the current GRP constraints. Positive (negative) changes imply that producers are better (worse) off as a result of purchasing the specific insurance contract. Percentage changes in CER, as a result of insurance purchasing, are shown in brackets.

With the exception of the CDD index in Bulloch County, the index insurance contracts increase CER for the representative corn farms regardless of the level of risk aversion. The area yield index performs best for all the representative farms, especially at higher levels of risk aversion. With the exception of Colquitt County, the DSSAT index insurance contract performs better than the simple CDD index insurance contract. In Pierce County, when risk aversion is low, the DSSAT index contract generates increases in CER that are comparable to that of the area yield index contract. However, as risk aversion increases, the optimal *coverage* on the Pierce County DSSAT index contract increases whereas that on the area yield index contract does not. This greatly increases the cost of the DSSAT index contract so the increase in CER is much lower for higher levels of risk aversion.

These results suggest that, at least for some crops and regions, when county yield data are not available, it may be possible to base index insurance on predicted yields from crop simulation or *weather-based* production models. Further research is required to determine how robust this finding would be across other crops and regions.

Conclusion

This study evaluated the performance of three index insurance contracts for corn production in southern Georgia. The study had two primary objectives. The first was to compare area yield insurance with alternative index insurance designs, such as might be required in marginal production areas where NASS yield data are not available. The second was to generalize previous conceptual findings to other index insurance contracts and demonstrate empirically the mutually interdependent adjustments required when binding constraints are imposed on *coverage* and *scale*.

Table 5. Changes in Certainty-Equivalent Revenues (CER) Using Actual Premium Rates for the Three Index Insurance Contracts at Three CRRA Levels

County	CER Without Contract	Change in CER with Insurance		
		Area Yield Index	DSSAT Index	CDD Index
CRRA = 1.5				
Bulloch	177.85	11.46 (6.44%)	8.18 (4.60%)	−0.15 (−0.09%)
Coffee	264.57	15.93 (6.02%)	13.83 (5.23%)	13.25 (5.01%)
Colquitt	306.40	15.49 (5.06%)	5.20 (1.70%)	12.14 (3.96%)
Pierce	290.05	24.54 (8.46%)	19.74 (6.81%)	18.49 (6.37%)
CRRA = 2				
Bulloch	142.38	7.19 (5.05%)	4.69 (3.30%)	−0.87 (−0.61%)
Coffee	230.22	12.03 (5.22%)	11.26 (4.89%)	4.46 (1.94%)
Colquitt	282.17	16.80 (5.95%)	3.49 (1.24%)	8.17 (2.89%)
Pierce	249.82	23.59 (9.44%)	11.72 (4.69%)	10.91 (4.37%)
CRRA = 2.5				
Bulloch	115.74	4.28 (3.70%)	3.16 (2.73%)	−1.41 (−1.22%)
Coffee	197.89	7.81 (3.94%)	7.61 (3.84%)	1.51 (0.76%)
Colquitt	263.38	18.12 (6.88%)	2.46 (0.94%)	6.65 (2.53%)
Pierce	209.40	20.76 (9.91%)	6.53 (3.12%)	3.99 (1.91%)

Both of these objectives are relevant in the current public policy context. The first has implications both for expanding the availability of FCIP index insurance contracts and possibly for the recent proposal to replace existing federal income support programs with a federally provided GRIP policy. The second is important because some crop insurance industry organizations have recently proposed that more binding constraints be placed on GRP and GRIP choice variables.

With regard to the first objective, all of the index insurance contracts increased CER for the representative farms except for the CDD index for the Bulloch County representative farm. The area yield index insurance contract was always preferred to either of the alternatives. However, in each county either the CDD or DSSAT index insurance contracts also provided comparable increases in CER, especially at lower levels of risk aversion. This implies that, at least for some crops and regions, when county yield data are not available, it may be possible to base index insurance on predicted yields from *weather-based* production models or more sophisticated crop simulation models.

With regard to the second objective, the study showed how constraints on index insurance *coverage* and *scale* affect the optimal choices of these two variables. To maximize CER, the policyholder must simultaneously optimize these two variables within the constraints. If *scale* is constrained by a lower bound, the optimal value of *coverage* will be lower than if *scale* were not constrained. If *coverage* is constrained by the upper bound, the optimal value for *scale* will be higher than if *coverage* were not constrained. Because GRP currently has a 90% upper bound on *coverage*, this explains why many purchasers would choose a value of *scale* that exceeds their beta coefficient and, in some cases, exceeds 100%. Increasing the *scale* increases the amount of indemnity paid whenever an indemnity is triggered. This compensates, in part, for the fact that indemnities are triggered less often than desired because of the upper bound on *coverage*. When both choice variables are constrained, the conditional optimums for each choice variable must be determined through interdependent adjustments. Providing policyholders with sufficient flexibility to optimize these two choice variables is critical for index insurance contracts. Further constraints on these choice variables, as has been proposed for GRP and GRIP, would make these index insurance contracts less attractive to potential purchasers.

A limitation of this study is that representative farm yields had to be simulated based on short-term (4 to 10 years) *farm-level* yields and longer-term *county-level* yields. It is unclear how robust the findings would be across alternative data sources or alternative procedures for simulating representative farm yields. Further, the analysis was conducted for only one crop in selected counties in southern Georgia. Analyses based on additional crops and other regions are required to test the consistency and robustness of these findings.

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