Is Area Yield Insurance Competitive with Farm Yield Insurance?

Barry J. Barnett, J. Roy Black, Yingyao Hu, and Jerry R. Skees

This article compares risk reduction from MPCI and GRP crop insurance contracts. The analysis extends and improves on the existing area-yield insurance literature in four important respects. First, the geographical scope greatly exceeds that of previous work. Second, unlike previous efforts, the area is not assumed to consist only of those farms included in the analysis. Third, the analysis is based on the actual GRP indemnity function rather than the area-yield indemnity function commonly used in the literature. Fourth, the analysis avoids the questionable assumption that GRP scale can be optimized at the individual farm level. Even with a number of conservative assumptions favoring MPCI relative to GRP, results indicate that at least for some crops and regions GRP is a viable alternative to MPCI.

Key words: area yield insurance, Multiple Peril Crop Insurance, risk reduction

Introduction

The Federal Crop Insurance Program (FCIP), administered by the U.S. Department of Agriculture's Risk Management Agency (RMA), facilitates provision of a variety of yield and revenue insurance contracts to crop farmers. For some of the currently available FCIP contracts, indemnity payments are triggered by losses measured at the farm level. For others, indemnity payments are triggered by losses measured at an area (county) level. The contracts can be further classified according to the characteristics of the underlying measure of loss (table 1). Some contracts are based on yield losses while others are based on revenue index losses. In addition, some of the available revenue index insurance products have an additional harvest price feature that causes the dollars of insurance protection to increase if price increases during the growing season.[1] Each contract is only available for selected crops and in selected regions. For example, a corn producer in New England may only have one type of FCIP contract available, while a corn producer in the Midwest may have as many as six. All FCIP contracts are

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[1] We use the term "revenue index" because indemnities are triggered by the product of farm-level yield losses and a price index based on futures market prices. A true farm-level revenue insurance contract would trigger indemnities based on farm-level revenue losses. The FCIP currently offers several redundant revenue index insurance contracts. The RMA has announced its intention to collapse these contracts into a single revenue index insurance contract that will be available either with or without the harvest price feature. For this reason, we describe the available revenue index insurance contracts according to characteristics rather than name.

Table 1. Types of FCIP Crop Insurance Contracts

Farm-Level Contracts	Area-Level Contracts
■ Farm-level yield insurance (MPCI)	■ Area-level yield insurance (GRP)
■ Farm-level revenue index insurance	■ Area-level revenue index insurance
■ Farm-level revenue index insurance with harvest price feature	■ Area-level revenue index insurance with harvest price feature

sold through private insurance companies. RMA provides significant premium subsidies to producers and a portion of the reinsurance needed by insurance companies.

There is a substantial economic literature on the conditions under which insurance markets exist and, if they exist, their degree of completeness. Rothschild and Stiglitz (1976), in an important early contribution, explored the consequence of heterogeneity in the risk characteristics of potential insureds and asymmetry in knowledge between potential insureds and insurance companies. They examined how a menu of insurance contracts could be used to induce insureds to self-select into pools with similar risk characteristics (e.g., high-risk versus low-risk pools). This self-selection partially ameliorates the heterogeneity problem and reduces the amount of costly information required for risk classification.

This study focuses on two very different FCIP yield insurance contracts that differ in their exposure to asymmetric information problems and in the extent to which risk classification is required. Specifically, we compare the primary FCIP farm yield insurance contract, known as Multiple Peril Crop Insurance (MPCI), to the area yield insurance contract, known as the Group Risk Plan (GRP).

The remainder of the article is organized as follows. We begin with a brief review of MPCI and GRP. We also present a slightly different area yield contract that has been widely discussed in the literature but, as of yet, has not been implemented in the United States. Next, the issue of basis risk is discussed. Basis risk is inherent in area yield insurance contracts. We argue, however, that a different, and often unrecognized, form of basis risk also exists with farm-level yield insurance contracts such as MPCI. The next section provides a synthesis of the literature on area yield contracts and relates that literature to the GRP area yield contract which has been implemented in the United States. Finally, results are presented from an empirical analysis comparing the risk transfer effectiveness of MPCI and GRP. This analysis is conducted for alternative MPCI coverage levels and GRP contract provisions. The focus is on investigating the potential viability of GRP in the marketplace, not on which contract is "better."

MPCI and GRP

MPCI provides protection against yield losses, from a variety of natural causes, at the farm, or even sub-farm, level.[2] Area yield insurance, on the other hand, is essentially a put option on the expected county yield. The holder of an area yield insurance policy receives an indemnity whenever the realized county yield falls below some specified

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[2] If a farm consists of parcels in different sections or with different Farm Service Agency serial numbers, MPCI purchasers can choose to insure the parcels as separate insurance units.

critical yield (i.e., strike), *regardless of the realized yield on his or her farm*.[3] As with any option, basis risk is an important factor affecting the efficacy of area yield insurance. The higher (lower) the positive correlation between the farm and county yield, the lower (higher) the basis risk.

For simplicity, assume that indemnities are paid in units of production (e.g., bushels) per acre.[4] For insurance unit i, the MPCI indemnity function is designated by:

$$(1) \qquad \tilde{n}_i = \max(y_{ic} - \tilde{y}_i, 0),$$

where $\tilde{n}$ is the indemnity per acre, $\tilde{y}_i$ is the realization of the stochastic yield, and y_{ic} is the critical yield calculated as

$$(2) \qquad y_{ic} = \mu_i \times coverage,$$

with $50\% \le coverage \le 85\%$ in 5% increments. For MPCI, predicted yield (μ_i) is calculated as a moving 4- to 10-year average of historical yields for the insurance unit.

The indemnity function in Miranda's (1991) model of area yield insurance is similar to equation (1), except yield is now defined at the area level rather than a farm or sub-farm level as in MPCI. Specifically,

$$(3) \qquad \tilde{n} = \max(y_c - \tilde{y}, 0) \times scale, \quad \text{and}$$

$$y_c = \mu \times coverage,$$

where $\tilde{y}$ is the realization of the stochastic area yield, μ is the predicted area yield, and *scale* is a choice variable that allows a policyholder to increase or decrease the amount of protection per acre.[5]

To better understand the role of the scale variable, assume for a moment that this variable was removed from equation (3) (i.e., scale is constrained to equal one for all policyholders). Any nonzero indemnity would be calculated as the simple difference between the critical area yield and the realized area yield. However, policyholders differ with regard to how expected indemnities on area yield insurance track expected farm-level losses. By their choice of scale, policyholders can attempt to better match area yield insurance indemnities to expected farm-level losses.

A slightly different indemnity function is used for the actual GRP contract:

$$(4) \qquad \tilde{n} = \max\left(\frac{y_c - \tilde{y}}{coverage}, 0 \right) \times scale,$$

where $70\% \le coverage \le 90\%$ in 5% increments, $90\% \le scale \le 150\%$, and

$$protection\ per\ acre = \mu \times scale.$$

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[3] Area yield insurance should not be confused with the FCIP's MPCI contract in existence prior to 1984. That contract based farm-level expected yields on the soil and climate conditions in the area where the farm was located (rather than on the farm's actual historical yields). Loss adjustment, however, was conducted at the farm level.

[4] Alternatively, one can assume that each unit of production is worth exactly one unit of currency (e.g., one dollar).

[5] The literature on area yield insurance contains a confusing mix of terminology. The term "trigger yield" is sometimes used in place of what is here called "critical yield." The terms "scale" and "coverage" are here used in a manner consistent with actual GRP terminology. With the exception of Skees, Black, and Barnett (1997), the remainder of the literature has consistently used the term "coverage" to mean what is here called "scale." Smith, Chouinard, and Baquet (1994) use the Greek alpha (α) to designate what is here called "coverage."

The indemnity function exhibits a declining deductible such that, in the extreme, if $\bar{y} = 0$, then $\bar{n}$ equals 100% of protection regardless of the choice of coverage. For GRP, the area is defined by county boundaries and μ is calculated using a linear spline (Skees, Black, and Barnett, 1997).

Most of the academic literature on area yield insurance has followed Miranda (1991) in assuming an indemnity function as in equation (3) (e.g., Smith, Chouinard, and Baquet, 1991; Mahul, 1999; Vercammen, 2000). However, GRP, the only area yield insurance contract currently available in the United States, is based on the indemnity function in equation (4).

MPCI has been plagued with problems related to the use of individual farm yields in measuring yield loss. Large underwriting losses in the 1980s have been attributed, in part, to the heterogeneity of yield risk exposure across farmers. Farmers, who presumably have better information about their farm yield distributions than does the insurer, can through both hidden information (adverse selection) and hidden action (moral hazard) use such information to their advantage (Skees and Reed, 1986; Chambers, 1989; Quiggin, Karagiannis, and Stanton, 1994; Smith and Goodwin, 1996; Coble et al., 1997; Just, Calvin, and Quiggin,1999). To compensate for resulting underwriting losses, MPCI premium rates are increased. For some farmers, the premium cost, even with federal subsidies, is higher than expected indemnities. There are also high administrative costs associated with establishing expected yields, calculating insured losses, and monitoring at the farm level (Skees and Barnett, 1999; Barnaby and Skees, 1990; Wang et al., 1998). To achieve targeted rates of participation, the government heavily subsidizes premiums.

GRP offers a number of potential advantages relative to MPCI. There is no reason to believe that farmers have any better information on county yield distributions than does the insurer. Assuming GRP is offered only where minimum acreage requirements are met, it is unlikely that any individual insured farmer can engage in actions which will impact the aggregate county yield (Skees, Black, and Barnett, 1997). Thus, there should be no opportunities for farmers to benefit, at the expense of the FCIP, from hidden information or hidden action. Since there is no need to establish farm-level expected yields or conduct loss adjustment at the farm level, administrative costs are significantly lower than those for MPCI (Barnaby and Skees, 1990; Miranda, 1991; Skees, Black, and Barnett, 1997; and Skees and Barnett, 1999).

For many farmers, GRP will also have a significantly lower wedge than MPCI. The term "wedge" is used to describe the positive difference between premium cost and expected indemnity for a given insured (Wang, Hanson, and Black, 2003). A wedge generally contains two components: transactions costs and misclassification. Transactions costs create a positive wedge for all insureds. Heterogeneous risk exposure that results in misclassification can have either a positive or negative effect on the wedge. Consequently, some insureds may face a premium cost that exceeds the expected indemnity, while others may face exactly the opposite situation. GRP has lower transactions costs than MPCI. In addition, there is little potential for misclassification since there is no need to classify farm-level risk exposure. Thus, GRP will have a significantly lower wedge than MPCI for many farmers.

Finally, since it offers a very different type of insurance protection, GRP provides opportunities for potential insureds to self-select across insurance contracts, which should facilitate better classification for other FCIP contracts, such as MPCI.

Basis Risk

Basis risk is inherent with GRP (Skees, Black, and Barnett, 1997; Skees and Barnett, 1999; Wang et al., 1998). It is possible for a farm to experience a yield shortfall and yet receive no indemnity. This would occur if a peril reduced the yield on a farm but was not sufficiently systemic to reduce yield measured at the county level. Of course, the inverse is also true. It is possible for a farm to experience no yield shortfall and yet receive a GRP indemnity. As a result, some have questioned whether GRP should even be considered insurance. Typical in this regard is an amusing statement by Robert Parkerson, president of National Crop Insurance Services, a service organization for U.S. crop insurance companies. As Mr. Parkerson recollects, "A state insurance commissioner sent me a personal note saying he was sure that GRP was meant to go to the Lottery and Gaming Commission for review, not to him" (quoted in Taylor, 2001).

Yet when comparing GRP to MPCI, it is important to note that MPCI is also subject to basis risk. This basis risk derives from sampling and measurement errors in the calculation of μ_i and $\tilde{y}_i$. A moving average, based on only 4 to 10 years of actual yield history, is used to estimate μ_i. The appendix describes how so few observations can lead to large sampling errors in the calculation of mean yield. Measurement errors can also occur if insureds, either inadvertently or deliberately, provide inaccurate or incomplete yield records. Anecdotal evidence indicates this is a common problem.

Further, for many crops and regions, MPCI implicitly assumes relative risk (measured as the coefficient of variation) varies inversely with μ_i (i.e., standard deviation is assumed constant). For a given crop and practice (e.g., irrigated versus non-irrigated), the ratio of μ_i to the mean county yield is the primary mechanism used to assign policyholders to a particular risk classification with an associated premium rate. Thus, errors in calculating μ_i affect not only y_{ic}, but also the premium rate charged to the policyholder.

Even with professional loss adjusters, it is impossible to avoid errors in estimating $\tilde{y}_i$. Sampling error can occur, if sampling methods are used to estimate $\tilde{y}_i$. Measurement errors can also occur. As with calculating μ_i, these measurement errors can be either inadvertent or deliberate.

Due to errors in estimating μ_i and $\tilde{y}_i$, it is quite possible for MPCI policyholders to receive indemnities when farm-level yield losses have not occurred, or to not receive indemnities when losses have occurred. Hence, basis risk is not limited only to area yield contracts like GRP. In fact, GRP makes use of much longer data series than does MPCI when establishing the expected yield. Also, for most farms, the standard deviation of county yields is much lower than that of farm yields. Thus, that portion of basis risk which is due to sampling and measurement errors should be much less for GRP than for MPCI.

Literature Review

Harold Halcrow introduced the concept of area yield insurance in his 1948 Ph.D. dissertation at the University of Chicago and in a subsequent article in the *Journal of Farm Economics*. More than 40 years later, the Congressionally appointed Commission for the Improvement of the Federal Crop Insurance Program (1989) issued a report calling for a pilot program to test the feasibility of an area yield insurance contract.

Barnaby and Skees (1990) later described how an area yield contract might work and the potential advantages over existing crop insurance contracts. Miranda (1991) formalized these insights using a framework that partitioned risk into systemic and idiosyncratic (residual) components. If $\tilde{y}_i$ is projected orthogonally onto $\tilde{y}$, then

(5)
$$\tilde{y}_i - \mu_i = \beta_i(\tilde{y} - \mu) + \tilde{\varepsilon}_i,$$

where

$$\beta_i = \frac{\mathrm{Cov}(\tilde{y}_i, \tilde{y})}{\mathrm{Var}(\tilde{y})}$$

and

(6)
$$E\tilde{\varepsilon}_i = 0, \quad \mathrm{Var}(\tilde{\varepsilon}_i) = \sigma_{\varepsilon_i}^2, \quad \mathrm{Cov}(\tilde{y}, \tilde{\varepsilon}_i) = 0;$$

$$E\tilde{y}_i = \mu_i, \quad \mathrm{Var}(\tilde{y}_i) = \sigma_{\tilde{y}_i}^2;$$

$$E\tilde{y} = \mu, \quad \mathrm{Var}(\tilde{y}) = \sigma_{\tilde{y}}^2.$$

This framework, commonly used in optimal hedge ratio (Stoll and Whaley, 1993) and capital asset pricing model (CAPM) (Doherty, 2000; Leunberger, 1997) contexts, decomposes the farm yield deviation from expectation into a systemic component, measured by β_i times the area yield deviation from expectation, and an idiosyncratic component, $\tilde{\varepsilon}_i$. The coefficient β_i measures how sensitive the farm yield deviations from expectation are to area yield deviations from expectation.

Assume initially that insurance contracts are actuarially fair. Then, following Miranda (1991),

$$\pi_{ij} = E\tilde{n}_{ij} \ \forall i, j,$$

where π_{ij} is the per acre insurance premium for farm i and insurance contract j, and $\tilde{n}_{ij}$ is the per acre insurance indemnity. Abstracting away from price risk and assuming that farmers are mean variance utility maximizers, the performance of each insurance contract can be evaluated by its impact on the variance of net yield, $\tilde{y}_{ij}^{net}$, where

$$\tilde{y}_{ij}^{net} = \tilde{y}_i + \tilde{n}_{ij} - \pi_{ij}.$$

The variance of net yield is measured as

$$\mathrm{Var}(y_{ij}^{net}) = \sigma_{\tilde{y}_i}^2 + \sigma_{\tilde{n}_{ij}}^2 + 2\,\mathrm{Cov}(\tilde{y}_i, \tilde{n}_{ij}),$$

where $\sigma_{\tilde{y}_i}^2$ is as defined in equation (6), and $\sigma_{\tilde{n}_{ij}}^2 = \mathrm{Var}(\tilde{n}_{ij})$ is the variance of the indemnity for farm i and insurance contract j. Purchasing insurance contract j reduces the farmer's yield risk by

$$\Delta_{ij} = \mathrm{Var}(\tilde{y}_i) - \mathrm{Var}(\tilde{y}_{ij}^{net}) = -\sigma_{\tilde{n}_{ij}}^2 - 2\,\mathrm{Cov}(\tilde{y}_i, \tilde{n}_{ij}).$$

Converting this into percentage terms, the variance reduction due to the insurance contract is

$$\theta_{ij} = \frac{\Delta_{ij}}{\sigma_{\tilde{y}_i}^2},$$

which is consistent with measures commonly used for evaluating the effectiveness of hedging strategies involving futures and options contracts.

Miranda (1991) compared two stylized versions of area yield insurance to a farm yield insurance contract. The farm yield insurance contract was based on the MPCI indemnity function in equation (1) and, unlike MPCI, was assumed to be actuarially fair. Miranda obtained data for 1974–88 for 102 soybean farmers in western Kentucky, and these 102 farmers were assumed to constitute all the soybean production in the area so that, for any given year, the average soybean yield for the area was the acre-weighted average yield of the 102 farmers. Using the indemnity function in equation (3), Miranda defined two area yield insurance contracts, which he referred to as "full coverage" and "optimal coverage." For the full coverage contract, coverage was set at 88.5% and scale at 100%. For the optimal coverage contract, coverage was set at 95% and farmers were assumed to optimally select a value for scale so as to maximize percent variance reduction, θ_{ij}.[6]

On average, the optimal coverage area yield insurance contract was preferred to the farm yield insurance contract, which, in turn, was preferred to the full coverage area yield insurance contract. The less restrictive optimal coverage area yield insurance contract was always preferred to the more restrictive full coverage contract. The lower the farm's correlation with the area yield, the more likely the farm was to prefer the farm-level insurance contract to either of the area yield insurance contracts.

As argued by Smith, Chouinard, and Baquet (1994), ideal area yield insurance would allow the purchaser to optimally select both coverage and scale. Recognizing that political considerations might not allow for unrestricted choice of coverage and scale, they propose an "almost ideal" area yield insurance contract where scale is set equal to 100% but coverage is bounded only by the condition that it must be greater than zero. Their empirical analysis was conducted using 1981–90 farm yield data for 123 dryland wheat farms in Chouteau County, Montana. Like Miranda (1991), they assume these wheat farms constitute all of the wheat production in the defined insurance area. Almost ideal area yield insurance is compared to: (*a*) an ideal area yield insurance contract where both coverage and scale are allowed to take on any nonnegative values, (*b*) an area yield insurance contract with coverage and scale constrained as in GRP, (*c*) farm yield insurance with coverage set at 75%, and (*d*) farm yield insurance with coverage set at 90%. It is important to note that Smith, Chouinard, and Baquet's area yield insurance contracts are based on Miranda's indemnity function [equation (3)] rather than the actual GRP indemnity function [equation (4)]. As with Miranda's analysis, all of the insurance contracts are assumed to be actuarially fair with premiums paid in units of production per acre.

On average across all farms, the ideal area yield insurance contract reduced net yield variability by over 65%. The 90% coverage farm yield insurance reduced net yield variability per acre by over 64%, and the almost ideal area yield insurance contract reduced net yield variability per acre by 63%. Smith, Chouinard, and Baquet note that for this data set, the simpler almost ideal area yield insurance provided almost as much risk reduction as the ideal area yield contract. The two contracts most closely related to actual FCIP contracts—the area yield insurance with coverage and scale constrained as in GRP and the 75% coverage farm yield insurance—generated lower percentage

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[6] Despite the moniker, the constraint on coverage prevents this from being a true optimal (or ideal) area yield insurance contract.

reductions in net yield variability per acre at 52.5 and 46.6, respectively. Interestingly, the constrained area yield insurance contract reduced net yield variability more than the 75% coverage farm yield insurance contract.

Miranda (1991) indicated that a producer's optimal scale would approach β_i. Mahul (1999) formalized this insight by demonstrating that for an area yield contract with an indemnity function as specified in equation (3), if β_i is positive, then the optimal choice for a policyholder would be to set scale = β_i. Again, this is consistent with the optimal hedge and CAPM literatures. Note that the optimal choice of scale does not depend on the policyholder's degree of risk aversion or on the cost of the insurance premium.

Vercammen (2000) extended Mahul's (1999) analysis by deriving the optimal form of an area yield insurance contract with indemnity function as in equation (3) when coverage is politically constrained to be below the level desired by policyholders. For the constrained contract, Vercammen showed it is still optimal to choose scale = β_i. However, the optimal constrained contract would have a discontinuous indemnity function whereby the policyholder would receive a lump-sum indemnity if the realized area yield were below y_c. Vercammen recognized that a discontinuous indemnity function would likely not be politically feasible, and suggested the GRP indemnity function, with its declining deductible feature, was a reasonable second-best alternative.

Bourgeon and Chambers (2003) examined area yield insurance when the insurance premium contains a load to cover fixed costs and thus is not actuarially fair to the policyholder. In this case, the optimal contract would contain a premium load which is conditioned on β_i, such that individuals with higher betas would pay proportionally higher premium loads. But if information on β_i is asymmetrically distributed, farmers would always choose the area yield insurance contract designed for individuals with the lowest betas. This would prevent the insurer from being able to raise the additional premium needed to cover fixed costs.

Mahul and Wright (2003) extended Mahul's (1999) optimal insurance analysis to the case of area revenue insurance. They assume that farm yield is positively correlated with the yield index and farm price is positively correlated with the price index. In contrast to Mahul's earlier finding on area yield insurance, optimal area revenue insurance was found to be conditioned on producer risk preferences.

The GRP area yield insurance contract was introduced in 1994. Baquet and Skees (1994) describe the basic characteristics of the contract. Skees, Black, and Barnett (1997) provide significantly more detail on contract design and implementation, including a discussion of how the coverage and scale choice variables were politically constrained.[7]

Empirical Analysis

This analysis compares the performance of MPCI and GRP contracts using farm-level yield data on 66,686 corn farms from 10 states in the Corn Belt and 3,152 sugar beet farms from two states in the upper Midwest. Recall that our research objective is not to

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[7] Coverage was constrained politically to be between 70% and 90%. Farmers were also required to insure all of their acres of a given crop in a given county. This politically dictated requirement is conceptually analogous to forcing a 100% hedge ratio on all farmers who forward price through hedging. After much debate, the scale choice variable in equation (4) was adopted to allow policyholders some flexibility in setting effective hedge ratios.

determine which contract (MPCI or GRP) is "best" or to explain current purchasing patterns. Rather, our objective is to evaluate the potential viability of GRP in the face of implicit critiques that the basis risk is unacceptable. Like Miranda (1991) and Smith, Chouinard, and Baquet (1994), we evaluate the performance of insurance contracts by how much they reduce the variance of net yield.

Also, as in earlier studies, it is implicitly assumed that the premium paid is equal to the expected indemnity for all FCIP contracts. This is a reasonable assumption for area yield contracts like GRP since farm-level risk classification is not required. But for MPCI, farm-level risk classification is required and, as indicated earlier, a substantial literature suggests that, in practice, MPCI risk classification is highly imperfect. Thus, there exists a probability distribution of wedges across potential MPCI purchasers, implying farmers do not simply maximize the reduction in net yield variance. Rather, they make tradeoffs between risk and expected return. However, modeling this tradeoff is problematic since one must capture the joint probability distribution of wedges and farmer risk preferences. Therefore, our assumption of actuarial soundness greatly simplifies the task of comparing performance across the two contracts. To the extent this assumption is unrealistic for MPCI, our results will be biased in favor of MPCI.

Unlike previous studies, we do not attempt to optimize GRP scale for individual farms. When only eight to 10 years of yield data are available for each farm, estimating a farm-level β_i as in equation (5) is a significant challenge because the use of ordinary least squares regression with such small samples would be problematic. Accordingly, we take the very conservative approach of constraining coverage and scale to be the same for all corn farms in a given state and for all sugar beet farms associated with a given cooperative processor. Farm-level values for θ_{ij} are aggregated across larger geographic regions (states for corn, processing cooperative regions for sugar beets) as follows:

$$\overline{\theta}_{ij} = \sum_i \frac{w_i \theta_{ij}}{\sum_i w_i} \quad \forall i \in l = state, \ cooperative,$$

where $\overline{\theta}_{ij}$ is the weighted average percentage of variance reduction in region l due to insurance contract j, and w_i is the acres planted to the insured crop on farm i.

The farm-level corn yield data utilized in this analysis are yield histories used to calculate MPCI estimates of μ_i. The principal data source contained yield histories used to calculate μ_i for the 1995 crop year. Therefore, this source contained actual farm yields for 10 or fewer consecutive years over the period 1985–94. To be included in the analysis, farms were required to have at least six years of actual yield data over this period. In a few cases, the principal data source was supplemented by sources containing yield histories used to calculate μ_i for crop years prior to 1995. Thus some farms have as many as 12 years of actual yield data extending back to 1983. These farms account for less than 5% of the total corn farm observations. Farm-level corn yields were obtained for Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Nebraska, Ohio, and Texas. In 2001, these states accounted for almost 79% of U.S. corn production. County-level corn yield data were obtained from the USDA's National Agricultural Statistics Service (NASS) online database.

Farm-level sugar beet yield data were acquired from three sugar beet processing cooperatives in the Red River Valley of eastern North Dakota and southwestern

Minnesota.[8] American Crystal has six plants that process beets from a 14-county area in the mid- and northern valley. Farm-level yield data from farms associated with American Crystal were available for the years 1980–96. Min-Dak has one processing plant that serves a five-county area in the southern valley. Min-Dak data were available for the years 1988–97. Southern Minn has one processing plant serving a six-county area in southwestern Minnesota. Southern Minn data were available for the years 1989–97. These cooperatives are the only sugar processors in the region, and together account for over 30% of the beet sugar produced in the United States.

Using the cooperatives' farm-level yield data, county-level yields were constructed as an acre-weighted average of farm-level yields in the county. Mahul (1999) demonstrated that this procedure (also utilized by Miranda, 1991; and Smith, Chouinard, and Baquet, 1994) will cause the average optimal scale to tend toward a value of one. However, these farm-level sugar beet data actually represent all of the production in the county since these cooperatives are the only sugar processors in the region. In fact, NASS constructs sugar beet county yield estimates using the yield data provided by these processing cooperatives. Thus, as used here, this procedure should not introduce bias in the estimation of the optimal scale.

To ensure only commercial farms were included in the analysis, corn farms with less than 50 planted acres and sugar beet farms with less than 20 planted acres were dropped from the farm yield data sets. Also removed from the data sets were farms with mean yields (calculated across all years of available data) that were extreme outliers. Specifically, only those farms with mean farm yields between 65% and 135% of the mean county yield (calculated over the same period) were retained.

MPCI indemnities are modeled as in equation (1). As indicated in equation (2), y_{ic} is a function of μ_i which, for the actual MPCI contract, is calculated as a 4- to 10-year moving average of actual realized yields. Thus, to accurately simulate MPCI indemnities over a 10-year period, one would need 14 to 20 years of actual yield data—4 to 10 years to initiate μ_i and 10 more years to simulate indemnities out-of-sample. However, given the limited years of available farm yield data, we calculated μ_i in-sample as the average of the available farm yield data. In other words, it is implicitly assumed that the 10-year moving average used to calculate μ_i for MPCI perfectly predicts the central tendency of future realized farm yields. Since sampling error in the calculation of μ_i is an important source of MPCI basis risk, our approach will generate estimates of risk reduction due to MPCI purchasing which are unrealistically favorable. In short, due to limited farm-level yield data, we are forced to adopt a modeling approach that "stacks the deck" in favor of MPCI.

GRP indemnities are modeled as in equation (4). As with the actual GRP program, a linear spline is used to predict expected county yields from historic data (Skees, Black, and Barnett, 1997). Recall that the sugar beet county yield data are constructed as acre-weighted averages of farm-level yields in the county. Hence, the time series of county yields covers the same period as the farm-level yields. For corn, county yield data were available beginning in 1972. Thus, μ is calculated completely in-sample for sugar beets and partly in-sample for corn. In reality, GRP expected county yields are out-of-sample

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[8] To be specific, the corn farm yield data are at what RMA calls the "enterprise unit" level of aggregation. This includes all of the crop assigned to a given taxpayer identification number within a given county. The sugar beet farm yield data are for a given marketing contract with a processing cooperative within a given county.

predictions. This accommodation creates a slight upward bias in risk reduction from GRP, but this bias should be small relative to the similar in-sample bias in the calculation of μ_i.

Mahul (1999) showed that for an area yield contract with an indemnity function as specified in equation (3), if β_i is positive, then the optimal choice for a policyholder would be to set scale = β_i. As noted earlier, farm-level regression estimates of β_i are problematic due to the limited years of available farm-level data. Thus, we empirically estimate optimal scale for GRP as:

$$(7) \qquad \tilde{y}_{il} = \alpha_l + \beta_l \tilde{n}_{Cl} + \tilde{\varepsilon}_{il}$$

$$\forall i \in C = county \in l = state, cooperative,$$

where $\tilde{n}_{Cl}$ is the GRP indemnity calculated as in equation (4) for county C in the multi-county region l. For all farms in each multi-county area, optimal scale is set equal to β_l. For corn, the multi-county area is the state. For sugar beets, the multi-county area is the region served by a given processing cooperative. Similarly, coverage is constrained to be the same for all farms within a multi-county area. These constraints will again bias our results against GRP.

Three MPCI scenarios and three GRP scenarios are modeled. MPCI is modeled at 65%, 75%, and 85% coverage levels. Because of moral hazard concerns, MPCI is not currently offered at coverage levels higher than 85%. The first GRP scenario has coverage set at 90% and scale at 100%. In the second scenario, we solve for optimal coverage and scale subject to the constraints imposed by the actual GRP program. Specifically, coverage is allowed to vary between 70% and 90% in 5% increments, and scale is allowed to vary between 90% and 150%. For each possible coverage level, scale is set at its optimal level by solving for β_l as in equation (7). The optimal coverage level (and the associated optimal scale) is chosen by searching across the possible coverage levels for the one that generates the largest reduction in net yield risk.

There is no theoretical rationale for imposing constraints on the choice of either scale or coverage. Consequently, in the third GRP scenario, scale is unconstrained. Further, the upper bound on coverage is relaxed. As demonstrated by Mahul (1999) and Wang et al. (1998), if area yield contracts are actuarially fair, a risk-averse policyholder would choose a coverage level that equates y_c with the maximum possible area yield. While buyers might desire extremely high coverage levels, it is highly unlikely any seller would be willing to offer such high coverage levels due to extreme ambiguity about the upper tail of the county yield distribution. Thus, for the third scenario, coverage levels of up to 130% are allowed. This upper bound ensures y_c remains within one standard deviation of expected county yields.

No attempt is made at farmer risk classification and wedge size estimation for the MPCI contract—once again biasing the analysis in favor of MPCI since many farmers, including those not purchasing MPCI, have wedges significantly larger than 1.0.

Results

For corn, results for each of the MPCI and GRP scenarios described earlier are presented in table 2. For each scenario, the table presents the weighted average percentage of variance reduction $\bar{\theta}_{ij}$ where the region (l) is defined as the state. During the sample period, most MPCI policies were sold at the 65% coverage level. Even the most constrained GRP

Table 2. Corn Percentage Variance Reduction Under GRP and MPCI Scenarios by State

State	No. of Farms	GRP Scenarios			MPCI Scenarios		
		[1] Cover. = 90%, Scale = 100%	[2] Optimal Coverage and Scale: 70% ≤ Cover. ≤ 90%, 90% ≤ Scale ≤ 150%	[3] Optimal Coverage and Scale: 70% ≤ Cover. ≤130%, Scale Unconstrained	[1] 65% Cover.	[2] 75% Cover.	[3] 85% Cover.
Ill.	11,364	49.0	54.6	65.3	31.0	45.5	60.0
Minn.	11,189	56.0	58.8	62.7	44.9	57.1	68.9
Ky.	178	44.1	50.9	61.4	34.8	47.0	59.0
Iowa	31,506	43.5	48.7	60.8	30.6	44.3	58.6
Kans.	1,205	35.2	43.4	56.0	33.0	44.4	56.4
Ohio	1,163	31.6	38.9	51.5	21.1	34.9	51.3
Ind.	2,939	38.4	43.4	50.7	24.8	39.8	56.1
Nebr.	6,257	15.5	19.6	43.5	25.2	36.1	49.7
Tex.	665	35.7	40.2	42.4	40.1	50.0	60.3
Mich.	220	5.4	6.1	10.6	23.4	35.5	50.5

Table 3. Corn GRP Optimal Coverage and Scale by State

State	No. of Farms	GRP Scenarios			
		[2] Optimal Coverage and Scale: 70% ≤ Coverage ≤ 90%, 90% ≤ Scale ≤ 150%		[3] Optimal Coverage and Scale: 70% ≤ Coverage ≤ 130%, Scale Unconstrained	
		Coverage (%)	Scale (%)	Coverage (%)	Scale (%)
Ill.	11,364	90	144	116	117
Minn.	11,189	90	134	116	112
Ky.	178	90	142	118	125
Iowa	31,506	90	147	115	115
Kans.	1,205	90	150	126	125
Ohio	1,163	90	150	113	117
Ind.	2,939	90	150	114	109
Nebr.	6,257	90	150	115	128
Tex.	665	90	149	101	127
Mich.	220	90	106	111	86

scenario, where all farms are required to have 90% coverage and 100% scale, generates more risk reduction than 65% MPCI in every state except for Nebraska, Texas, and Michigan.

GRP scenario 2 reflects the case where coverage and scale are optimized for each state, subject to existing contract constraints. Note that coverage and scale are not optimized for each farm in the data set. Rather, they are optimized across all farms located in a given state. The state-level optimal levels of coverage and scale are then applied to each farm in the state. Thus, while GRP coverage and scale can vary across states, we are still requiring each farm within a given state to have exactly the same levels of GRP coverage and scale. Table 3 presents the optimized values for coverage and scale. GRP

Table 4. Correlation Between Farm and County Corn Yield by State

State	Correlation Between Farm and County Corn Yield	State	Correlation Between Farm and County Corn Yield
Illinois	0.82	Ohio	0.71
Minnesota	0.80	Indiana	0.74
Kentucky	0.78	Nebraska	0.68
Iowa	0.78	Texas	0.49
Kansas	0.76	Michigan	0.36

scenario 2 generates more risk reduction than 65% MPCI for every state except Nebraska and Michigan. In fact, GRP generates more risk reduction than 75% coverage MPCI in Illinois, Minnesota, Kentucky, Iowa, Ohio, and Indiana.

MPCI with 85% coverage (table 2, MPCI scenario 3) generates more risk reduction than any of the GRP scenarios that are subject to existing constraints on coverage and scale. Under GRP scenario 3 (table 2), the GRP scale is unconstrained and coverage is allowed to increase up to 130% (but again requiring every farm in the state to have the same coverage and scale). In this scenario, risk reduction generated by GRP exceeds that of 65% MPCI in every state except Michigan. It also exceeds the risk reduction generated by 75% MPCI in every state except Texas and Michigan and the risk reduction generated by 85% MPCI in Illinois, Kentucky, Iowa, and Ohio. The last two columns of table 3 report the optimal coverage and scale values when scale is unconstrained and coverage is constrained between 70% and 130%.

These results are broadly consistent with the notion that area yield insurance works best in relatively homogeneous production regions (Skees, Black, and Barnett, 1997). Table 4 presents correlations between farm and county corn yields for the data used in the analysis. The states where GRP did not perform well relative to MPCI (Nebraska, Texas, and Michigan) have relatively lower correlations between farm and county yields. Interestingly, in these three states GRP performance relative to MPCI was much better for farms with mean yields μ_i higher than the average of the μ_i's for the state. This was particularly noticeable in Texas and Michigan. While this finding requires further research, it seems to imply that in these states, farms with above-average mean yields are more highly correlated with county average yields, and thus better suited to GRP.

Table 5 presents sugar beets results for the weighted average percentage of variance reduction $\bar{\theta}_{lj}$ where the region (l) is now defined as the processing cooperative. For farms associated with the Southern Minn cooperative, all three GRP scenarios generate more risk reduction than 65% and 75% MPCI. When scale is unconstrained, GRP performs better than 85% MPCI. For farms associated with American Crystal, all three GRP scenarios generate as much or more risk reduction than 65% MPCI. Only when scale is unconstrained does GRP generate more risk reduction than 75% MPCI. No GRP scenarios generate as much risk reduction as 85% MPCI. Finally, for farms associated with the Min-Dak cooperative, none of the GRP scenarios generate as much risk reduction as even 65% MPCI. Optimal coverage and scale values for sugar beets are presented in table 6.

Differences in GRP performance between the sugar beet cooperatives are likely due, in part, to different drainage structures in the geographic regions served by the

Table 5. Sugar Beet Percentage Variance Reduction Under GRP and MPCI Scenarios by Processing Cooperative

| Cooperative | No. of Farms | GRP Scenarios | | | MPCI Scenarios | | |
		[1] Cover. = 90%, Scale = 100%	[2] Optimal Coverage and Scale: 70% ≤ Cover. ≤ 90%, 90% ≤ Scale ≤ 150%	[3] Optimal Coverage and Scale: 70% ≤ Cover. ≤130%, Scale Unconstrained	[1] 65% Cover.	[2] 75% Cover.	[3] 85% Cover.
Southern Minn	296	48.0	53.3	69.3	29.3	42.7	56.0
Min-Dak	519	11.5	13.1	16.4	31.1	42.6	57.4
American Crystal	2,337	17.6	23.5	32.4	17.6	29.4	47.1

Table 6. Sugar Beet GRP Optimal Coverage and Scale by Processing Cooperative

| Cooperative | No. of Farms | GRP Scenarios | | | |
| | | [2] Optimal Coverage and Scale: 70% ≤ Coverage ≤ 90%, 90% ≤ Scale ≤ 150% | | [3] Optimal Coverage and Scale: 70% ≤ Coverage ≤ 130%, Scale Unconstrained | |
		Coverage (%)	Scale (%)	Coverage (%)	Scale (%)
Southern Minn	296	90	135	125	106
Min-Dak	519	90	130	105	87
American Crystal	2,337	90	150	115	88

cooperatives. For example, Min-Dak serves a region containing soils with widely varying drainage capacity. When excess precipitation occurs, as in 1993, substantial yield reductions result on farms with poor drainage while the impact is much less for farms with better draining soils. Southern Minn, on the other hand, serves a region with largely homogeneous and well-drained soils. Hence, there is substantial positive correlation across farms in this region when systemic precipitation events occur.

These results suggest that for corn and sugar beets grown in some regions, GRP provides opportunities for reductions in net yield variance which are certainly comparable to those provided by MPCI. Thus, contrary to widespread perceptions, the basis risk inherent in GRP does not necessarily destroy its market viability.

The results of this study are particularly striking given that in many instances modeling assumptions biased the analysis in favor of MPCI. Perhaps the most important example of this is the assumption that MPCI is actuarially sound at the individual farm level. However, it is also important to note MPCI contracts provide coverage for quality losses, losses due to prevented planting and, in some cases, replanting costs. Also, under certain circumstances, MPCI coverage can be purchased separately for sub-farm level "optional units." The ability to purchase coverage at the optional unit level increases the expected aggregate indemnity for the whole farm relative to insuring the whole farm as one insurance unit. This analysis does not account for these MPCI benefits that are not available with GRP contracts.

Conclusions

This analysis, comparing GRP to MPCI, extends and improves upon the existing literature in four important respects. The first is the scope of the region considered. Miranda (1991) studied 102 soybean farmers in western Kentucky, and Smith, Chouinard, and Baquet (1994) studied 123 wheat farmers in Chouteau County, Montana. This analysis examines 66,686 corn farms in 10 Corn Belt states and 3,152 sugar beet farms from two states in the upper Midwest.

Second, previous area yield insurance studies have assumed that the insurance area consists only of farms included in the analysis—implying the weighted average β_i across all of the farms will be equal to one (Miranda, 1991). Since, as Mahul (1999) demonstrates, the optimal choice for scale is the farm's β_i, this artificial construction of the insurance area biases the average optimal choice of scale toward a value of 100%. This study avoids that bias by using actual NASS county yield data for corn to construct and analyze area yield insurance contracts. For sugar beets, county yields are constructed as an acre-weighted average of farm-level yields. However, unlike earlier studies, the farm yield data used in the analysis reflect the entire population of sugar beet farmers in the county. Therefore, this procedure should not introduce bias in the estimation of optimal values for scale.

Third, while previous studies have investigated the efficacy of an area yield insurance contract with an indemnity function as in equation (3), this is the first study to conduct such an analysis using the actual GRP indemnity function found in equation (4).

Fourth, unlike Miranda (1991) and Smith, Chouinard, and Baquet (1994), we do not attempt to optimize GRP scale for individual farms. Given the limited years of available farm-level yield data, the standard error around farm-level regression estimates of β_i would be quite high. Thus we take the very conservative approach of constraining the coverage and scale to be the same for all farms in an area.

The primary objective of this analysis was to assess whether or not basis risk rendered GRP unviable in the market place. The results indicate that at least for some crops and regions this is not the case, since GRP provides risk reduction at least as good as that provided by standard choices of MPCI coverage. This finding is particularly noteworthy because in many instances modeling assumptions were made which biased results in favor of MPCI. However, this analysis cannot account for quality loss, prevented planting, replant, and optional unit benefits that are included in MPCI contracts but not GRP contracts.

Finally, it is important to note that private-sector insurance companies are now exploring the possibility of selling GRP contracts with a basis risk rider. This rider would provide additional protection against the possibility of an idiosyncratic event causing a farm to suffer a significant yield loss when the county yield does not trigger a GRP indemnity.

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Appendix:
Errors in Multiple Peril Crop Insurance
Estimates of Expected Yield

The "square root of n rule" states that a sample mean estimates the true central tendency of the distribution with standard error calculated as

$$Standard\ Error\ of\ Estimate\ =\ \frac{\sigma}{\sqrt{n}},$$

where σ is the standard deviation of the true underlying distribution and n is the size of the sample from which the mean was calculated. The higher (lower) the standard deviation of the underlying distribution, the higher (lower) is the error around the sample estimate of the true mean. The higher (lower) the sample size, the lower (higher) is the error around the sample estimate of the true mean.

To demonstrate the potential for error in MPCI estimates of expected yield, consider a corn farm with an expected yield of 150 bushels per acre. For simplicity, assume the yield is distributed normally. If the standard deviation is 55 bushels per acre and the MPCI estimate of expected yield is calculated using only four years of data, the standard error around the estimate of the expected yield is 27.5 bushels per acre. This implies there is a 33% chance that the MPCI estimate of expected yield will be less than 122.5 bushels per acre or more than 177.7 bushels per acre.

Suppose the MPCI estimate of the expected yield is 180 bushels per acre. If the policyholder selects 85% coverage, the critical yield will be 153 bushels per acre, which is actually higher than the true mean of 150 bushels per acre. The farmer has been charged a premium rate based on 85% coverage but, due to the error in the MPCI estimate of expected yield, has been given coverage in excess of 100%.

Similarly, if the MPCI estimate of the expected yield is 120 bushels per acre and the policyholder selects 85% coverage, the critical yield will be 102 bushels per acre. While the policyholder has been charged a premium rate for 85% coverage, the effective coverage level is only 68% (102 bushels per acre ÷ 150 bushels per acre). If the expected yield had been estimated accurately, a yield loss of 22.5 bushels per acre would have triggered an indemnity. Due to the estimation error, the policyholder must have a yield loss in excess of 48 bushels per acre to receive an indemnity.