WEATHER INFORMATION AND THE POTENTIAL FOR INTER-TEMPORAL ADVERSE SELECTION IN CROP INSURANCE

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This study investigates the potential usefulness of early-season weather information in forecasting corn yields for the Midwest. To the extent that farmers are able to forecast yields prior to sales closing dates for crop insurance, farmers may use such information in deciding which years to purchase crop insurance and which years not to purchase insurance. Such intertemporal adverse selection would result in increased losses for the crop insurance program. Three yield forecasting models were developed using early-season weather information: (1) simple weather forecasts; (2) yield-weather regression models; and (3) yield-weather discriminant functions. This study presents procedures that would allow farmers to predict low corn yields before the purchasing deadline of corn insurance on 95 percent of planted acreage in the Midwest.

Public policy surrounding the Federal Crop Insurance Program has been the subject of much debate in recent years. Policymakers generally focus on two factors when discussing crop insurance: (1) low participation; and (2) high Federal cost. Adverse selection may contribute to both of these problems. In simple terms, adverse selection can occur when farmers know more about their yield risk than the government or the insurance company. Due to lack of information, the crop insurance program may place farmers with heterogeneous risk into a homogeneous risk-pooling group. Farmers will purchase crop insurance when they believe the expected return is greater than the price of the contract. Conversely, they are less likely to purchase insurance when they perceive the expected return to be less than the price of the contract. Over time, this adverse selection behavior can lead to higher premium rates as well as a smaller and more adversely selected market (Skees and Reed; Miranda; Coble et al.; Goodwin).

Previous research investigated "*spatial* adverse selection," a phenomenon caused by using a geographic area as a risk-pooling group for crop insurance (Driscoll; Skees). For example, to those farmers with no historical yield data, premium calculation of the Multiple Peril Crop Insurance (MPCI) is based on risk-pooling over a county, while the indemnity is paid on an individual farm. As a result, farmers with a higher-than-county-average loss risk purchase insurance, while those with lower-than-county-average loss risk do not participate (Just, Calvin, and Quiggin).

This study contributes to the research on adverse selection by identifying a different type of adverse selection: "*intertemporal* adverse selection." Intertemporal adverse selection refers to the behavior of an insurance buyer selecting only high-risk periods to purchase insurance with no adjustments being made by the seller to reflect this behavioral pattern.

The premise of this study is that farmers can glean information from early-season weather data in order to make the crop insurance purchase decision from year to year. Since sales closing dates for the current crop insurance program are April 15th for corn in the Midwest, some farmers may wait until just before this deadline to make their decisions. Under these circumstances, current weather information may enable farmers to select purchasing years and increase their expected returns from crop insurance. This study focuses on the potential for intertemporal adverse selection in corn insurance.

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The objectives include: (1) to determine how accurately a climate division's yield can be forecast prior to the insurance purchase deadline using early-season weather information; and (2) to illustrate the potential value of using such information in crop insurance purchasing decisions.

Overview

The basic process of the study includes three steps: (1) establishing weather models to forecast corn yields in the Midwest;[1] (2) comparing the distributions of corn yields in all years to the yield distributions from a subset of years forecasted by the weather models as low-yield years; and (3) identifying climate divisions[2] in the Midwest where weather information can forecast yield shortfalls indicating that intertemporal adverse selection may be a problem for MPCI under the current program design. In addition to corn yield forecasts and cumulative distribution comparisons, an extreme assumption is made that all farmers fully use the information developed in the forecasting models. This allows one to illustrate the payoff for crop insurance under such conditions. It also provides an opportunity to summarize the vast amount of model results using a descriptive rather than a formal statistical procedure.

Since this study focuses on farmers' crop insurance purchasing decisions, the first step is to identify a standard indicator to decide which year(s) to purchase crop insurance using various quantitative models. Of factors that determine corn yields, weather is the major uncontrollable variable leading to random yield variation. This study assumes that farmers can forecast weather-induced variation in yields before the insurance purchase deadline (April 15th for corn). The logical and available predictor is the early-season weather information, i.e., the weather data prior to April 15th.

For illustrative purposes, potential farmers are assumed to be able to connect weather information with yields in three ways: (1) using 90-day weather forecasts directly as indicators of low-yield crop years; (2) forecasting yield *levels* by using all weather information; and (3) forecasting yield *shortfalls* (yields less than the most likely [median] yield) by using all weather information. Three forecasting models are developed to mimic this assumed behavior: (1) a simple weather forecast model; (2) a yield-weather regression model; and (3) a yield-weather discriminant model.[3]

Each model has its own yield shortfall criterion. A "low-yield" crop year is defined as a year in which a model forecasts a yield shortfall. A set of low-yield years from the study period (1956 to 1989) is selected according to each model. Finally, the extreme behavioral assumption is made that farmers in each climate division select the most effective forecasting model to determine low-yield years and they only purchase corn insurance in those years (selected years).

The second step of this study compares yield distributions from two types of behavior: (1) using early-season weather information to select low-yield years and buying insurance in only those years (selected-year); and (2) not using weather information and buying insurance in all years over the entire sampling period (all-year). The selected-year yield distribution is a subset of the all-year distribution. When a selected-year distribution has a lower mean and differs significantly from the all-year distribution, the cumulative net return from the selected years will be higher than that from all years. This is the potential value of early-season weather information in crop insurance.

The third step is to identify the climate divisions in the Midwest with the most potential for intertemporal adverse selection in crop insurance. In this study, all model estimations and distribution comparisons are undertaken at

[1] The Midwest includes nine states: Illinois, Indiana, Ohio, Kentucky, Iowa, Missouri, Minnesota, Wisconsin, and Mississippi (see Figure 2).

[2] The National Weather Service divides each state into climate divisions. A climate division comprises about ten counties with similar climate. There are 75 climate divisions in the Midwest.

[3] Although individual crop insurance is available with deductibles, we assume that growers know that some farmers will have losses that trigger payments when climate division yields are below the average. Therefore, we use median yield values to split our population with the forecasting procedures.

the climate division level. When yield distribution comparisons indicate that weather information can forecast a yield shortfall in a climate division, the division is identified as an area with the potential for intertemporal adverse selection. Thus, the percent of the 75 climate divisions in the Midwest with the potential of intertemporal adverse selection can be estimated.

Literature Review

Three areas of previous research were used in this study. The first included models that used pre-seasonal weather information to forecast yields. Model forecast results were made prior to the growing season while actual seasonal weather data were unrealized. Duchon (p. 581) forecasted yield distributions in a weather-yield model using "combined information," i.e., the actual pre-seasonal weather data were combined with historical seasonal weather data to forecast conditional yield distributions for the coming season.

Previous forecasting analysis using discriminant functions was also useful. A discriminant function uses a classification rule to assign unknown observations of a dependent variable into groups according to the given values of selected independent variables (Cooper and Weekes; Dillon and Goldstein). With yields as the dependent variable, weather-yield-discriminant functions can be estimated from historical weather data. The function identifies the range of given weather variable values and forecasts whether yield data will fall in the lower-than-mean yield group or in the higher-than-mean group. Finally, research assessing changes in risk by comparing cumulative distributions was relevant. French and Headley (p. 271) developed methods to detrend distributions of crop yields using regression techniques and measuring changes in crop yield risks by comparing cumulative distributions.

Process and Theoretical Model Specification

Step 1: Establishing Weather-Yield Models and Selecting Low-Yield Crop Years

Three forecasting models were used to identify the sets of low-yield crop years: (1) seasonal weather forecasts; (2) yield-weather regressions; and (3) yield-discriminant functions. All data came from a 34-year sample (1956 to 1989). The sample data came from four sources: (1) county yield data from the National Agricultural Statistics Service (NASS) were used to develop yields for the climate divisions; (2) county crop insurance information from the Federal Crop Insurance Corporation (FCIC) were used to develop loss ratios (payouts/premiums) for the climate divisions; (3) weather record and soil moisture data from the Midwestern Climate Center; and (4) weather outlooks from the National Weâther Service. Each model used only information that was available on April 1st – providing sufficient time for a crop insurance purchase decision prior to April 15th.

Among the most accessible information at farmers' disposal are the temperature and rainfall forecast from the National Weather Service for April, May, and June. The forecasts in the *seasonal weather forecast model* were used to develop the set of low-yield crop years. When the forecasts suggested a higher-than-average probability for temperature or rainfall anomalies, that year was selected as a low-yield crop year. Three sets of low-yield crop years were selected using temperature anomalies, rainfall anomalies, and a combination of both anomalies. This approach is the most direct as it assumes that farmers use only weather forecast information in a naive way – if bad weather is forecast, farmers purchase insurance.

The *yield-weather regression model* used time series, and quadratic polynomial regressions to select a set of low-yield crop years. The general functional form was:

$$\begin{aligned} Y_j = {} & \beta_{0j} + \beta_{1j}(R456)_j + \beta_{2j}(R456)_j^2 + \beta_{3j}(T456)_j \\ & + \beta_{4j}(T456)_j^2 + \beta_{5j}(R3)_j + \beta_{6j}(R3)_j^2 + \beta_{7j}(R12)_j, \\ & + \beta_{8j}(R12)_j^2 + \beta_{9j}(T3)_j + \beta_{10j}(T3)_j^2 + \beta_{11j}(S50)_j \\ & + \beta_{12j}(S50)_j^2 + \beta_{13j}(S150)_j + \beta_{14j}(S150)_j^2 \\ & + \beta_{15j}(D)_j + \epsilon_j \end{aligned} \tag{1}$$

$$(j = 1, 2, \ldots, 75 \text{ climate divisions})$$

where Y equals detrended corn yield (bu/acre);[4] R456 equals the forecast index of rainfall anomalies for April, May, and June; T456 equals the forecast index of temperature anomalies for April, May, and June; R3 equals the actual cumulative monthly rainfall for January through March (inches); R12 equals the actual cumulative monthly rainfall for the 12 months of the previous year (inches); T3 equals the summation of actual monthly average temperature of January through March (degrees Fahrenheit); S50 equals the actual soil moisture index at 50 centimeters in depth during the 13th week of the current year; S150 equals the actual soil moisture index at 150 centimeters in depth during the 13th week of the year; D equals the dummy variable representing a transformation of monthly weather forecast to 90-day forecast;[5] β equals the parameter estimate; and ε equals the stochastic disturbance.

Among the independent variables, seasonal forecasts (R456, T456) represent weather conditions for part of the growing season, which may influence yields directly; pre-seasonal weather (R3, T3) influences yields directly via pests and soil conditions, and indirectly via correlation with seasonal weather; planting time soil moisture conditions (S50, S150) influence yield through their impacts on germination; and last year's rainfall (R12) is believed to be correlated with the current year's weather (temperature/rain), which in turn influences yields. The squared terms in equation (1) recognize that there are limits to yields as weather reaches extremes.

A sample year was classified as a low-yield crop year if the yield forecasted by the estimated regression was lower than the historical mean yield of the climate division. This criterion could well have been more restrictive since insurance is purchased at levels that are 75, 65, or 50 percent below average. However, a conservative criterion was chosen because farmers may want to minimize the chances that they will be wrong in deciding which years to purchase crop insurance. That is, even when farmers are going to buy crop insurance covering only 65 percent of their average yield, they may decide to buy it whenever the forecasted yields are below the historical mean.

The *yield-discriminant model* used linear functions to select low-yield crop years. The general functional form for yield-discriminant models was:

$$\begin{aligned}&\beta_{1j}(R456)_j + \beta_{2j}(R456)_j^2 + \beta_{3j}(T456)_j \\ &+ \beta_{4j}(T456)_j^2 + \beta_{5j}(R3)_j + \beta_{6j}(R3)_j^2 + \beta_{7j}(R12)_j \\ &+ \beta_{8j}(R12)_j^2 + \beta_{9j}(T3)_j + \beta_{10j}(T3)_j^2 \\ &+ \beta_{11j}(S50)_j + \beta_{12j}(S50)_j^2 + \beta_{13j}(S150)_j \\ &+ \beta_{14j}(S150)_j^2 + C_j = D_j\end{aligned} \tag{2}$$

where previous definitions hold and C equals the intercept; D equals the discriminant score; j equals the climate division; and β equals the parameter coefficient.

Based on the predetermined sample group (using the median of detrended yields as the criterion), the functions were estimated using the discriminant procedure within SAS Institute, Inc. The estimated functions provided the following classification rule: when the observations of pre-seasonal and seasonal weather and soil variables generated a discriminant score D, the score indicated the corn yield for that year would be in either a lower-than-median yield group or a higher-than-median yield group. The theoretical rationale of this method is that as yields are influenced by weather, pre-seasonal weather information can be used to forecast corn yields. Therefore, an unknown yield can be classified into a high- or low-yield group using pre-seasonal weather data.

The first step of the study resulted in five sets of low-yield years for each climate division. Three of the low-yield year groups were selected by seasonal weather forecasts (temperature anomalies, rainfall anomalies, and temperature

[4]Since this study compares yield distributions, only detrended yields are used in all models. Detrended corn yields follow the approach used by Barnett, Skees, and Hourigan:

$Y_t^{raw} = \alpha + \beta(t) + \varepsilon$, where t=1956, ..., 1988.

$Y_t^{detrended} = Y_t^{raw} + \beta$ (1987 to t).

[5]The weather outlook for April through June became available in 1984. This study transformed the monthly outlook for April, May, and June of 1956 to 1983 into a 90-day forecast by weighting April's outlook 50 percent, May's 30 percent, and June's 20 percent. A dummy variable was added to the regression for the period of 1956 to 1983 to reflect the error that may have been introduced by making this adjustment.

plus rainfall anomalies). One group was selected by the estimated regression function, and the last group was selected by the discriminant function. These five sets of selected low-yield years were used to identify which forecasting method farmers may use to make crop insurance purchase decisions in each climate division. Farmers were assumed to choose the most effective forecasting approach to support their crop insurance decision – one that gives the largest difference between indemnity and premiums. One method for identifying the most effective forecasting model is to compare the cumulative yield distribution of a low-yield year group to that of the all-year group. Step 2 performs these comparisons.

Step 2: Comparing Yield Distributions

Given the five sets of low-yield crop years identified for each climate division using the five different models described above, the task is now to identify one model that is most effective in improving insurance purchasing decisions. Although standard tests and goodness-of-fit measures can be used for a single model evaluation, those methods do not help us rank the five models under the circumstances of crop insurance.

In crop insurance, yield distribution is a critical component in premium calculation. The general rate-making method assumes continuous participation and uses *all* historical yields to estimate a yield distribution. But if a farmer tries to forecast yields before the purchasing deadline and buy insurance only in the forecasted low-yield years, the farmer's actual yield distribution facing the insurance program is the one from the *selected* participation years. This selected-year distribution should differ from the continuous-year distribution in terms of a lower mean if the yield forecasting is accurate. This distribution shift leads to intertemporal adverse selection in crop insurance.

According to this logic, the effectiveness of a forecasting method for insurance decision-making can be measured through distribution comparison tests. When a model's selected-year yield distribution is statistically different from the all-year distribution, the model is effective in improving insurance purchasing decisions. The significance levels of distribution comparison tests are comparable among models and allow one to select the model that performs best. The general hypothesis for distribution-comparison tests in this study is:

$$\begin{aligned} H_0 &: = F(y_{kj}) = F(Y_j) \\ H_a &: = F(y_{kj}) \geq F(Y_j) \end{aligned} \tag{3}$$

where k represents the low-yield crop years as selected by: (1) temperature anomalies forecast, (2) rainfall anomalies forecast, (3) temperature and rainfall anomalies forecast, (4) the regression model, or (5) the discriminant function; j equals 1, ..., 75 (climate divisions); F represents the population cumulative distribution function (CDF) of yields; y represents the yields for the low-yield years selected by the forecasting method k in division j; and Y represents the yields for all years in division j.

The null hypothesis implies that the population-yield distribution of the selected-year set (of low-yield crop years) chosen by method k is the same as that of the all-year set in climate division j. The alternative hypothesis is that the low-yield year set distribution differs significantly from the all-year CDF and has a lower mean. In other words, H_a implies that the selected-year distribution shows a higher probability of obtaining low yields and is located to the left of all-year CDF in the plane of yield and cumulative probability.

The Z-test for comparing means and Wilcoxon's Rank-sum test for comparing the locations of two populations (Berry and Lindgren, pp. 527-39) were used to test this hypothesis. Five pairs of yield distribution comparisons were made for each climate division. The most significant set was selected as the most effective model.

Step 3: Identifying Regions with Potential for Intertemporal Adverse Selection

In this study, a measure of potential intertemporal adverse selection is present when the use of weather information can shift the actual yield distribution facing the crop insurance in a climate division. More specifically, the region-identification process is comprised of two parts. First, the most statistically significant forecasting model in distribution comparison tests[6] among models in a climate division is chosen as the "selected model." For purposes of exposition, the selected model is assumed to be used by all farmers in that climate division.

Second, the significance levels of distribution comparison for the selected models in all climate divisions are presented in a climate division map of the Midwest. This map illustrates that the significance of using weather information can change the actual yield distribution for crop insurance in different Midwestern climate divisions. The greater the statistical significance in a division, the more likely weather information can be used to shift the yield distribution in that climate division. In short, farmers who use these models could forecast the low-yield years better in these climate divisions. The map, therefore, serves to highlight areas with the greatest potential for intertemporal adverse selection in the Midwest.

Empirical Results

The three steps described above were performed for each of the 75 climate divisions in the Midwest. There is a potential for five sets of low-yield crop years to be generated for each of these climate divisions. Such a vast amount of information cannot be reported in this article.[7] The results presented build on statistical procedures, but can best be described as descriptive and statistically informal measures of weather information value in crop insurance.

Estimation of Regression and Discriminant Functions

The general functional form presented in equation (1) provided the starting point for selecting the regression equation for each climate division, depending on its statistical significance. In 57 of the 75 climate divisions (76 percent), a regression model was developed with an F-test significance at the 0.10 level or better. For the remaining 18 climate divisions, the regression model was excluded from the set of models. In 73 percent of the climate divisions, water-supply-related variables (rainfall forecasts, cumulated rainfall, and soil moisture) were the most important yield forecasters. Farmers are generally aware of these measures.

Results from the yield-discriminant function (equation 2) were consistent with the regression analysis. For all 75 climate divisions in the Midwest, 72.5 percent of the actual lower-than-median yields were forecasted by the discriminant functions. Following Dillon and Goldstein, standardized coefficients[8] were examined to determine which variables contributed the most to forecasting yields. The rank of standardized coefficients showed rainfall variables were the major contributing independent variables for most climate divisions. Variables listed in order of importance include: (1) rainfall forecasts (R456); (2) seasonal temperature forecasts (T456); (3) pre-seasonal water-supply conditions (R12, R3, S50, S150); and (4) pre-seasonal temperature conditions (T3).

Comparison of Distributions

The Wilcoxon Rank-sum test and the Z-test for comparing the location and means of two populations (Berry and Lindgren, pp. 527-39) were used to test for the differences in the CDF with the identified selected-year set (of low-yield crop years) versus the CDF from the all-year set. Figure 1 demonstrates how different models may shift the yield distributions. This figure uses the results from Division 2 of Illinois as an example. It was randomly chosen.

In Figure 1, corn yield distributions from the all-year set and from the five selected-year set of low-yield years, identified by each model, are plotted on the yield and cumulative probability plane. The all-year CDF is located to the far right, while the distribution from regression forecasted low-yield year set is located at the

[6]Distribution comparison is judged as being significant at the 0.10, 0.05, or 0.01 levels. The lower the level, the more statistically significant the selected-yield distribution (low-yield years) is located to the left of the all-year distribution.

[7]For a detailed report of this study's results, please see Luo in the references.

[8]Standardized coefficients measure the correlations between the standardized dependent variable and explanatory variables. A standardized variable is a variable weighted by its standard deviation making it unit free (Dillon and Goldstein, p. 8).

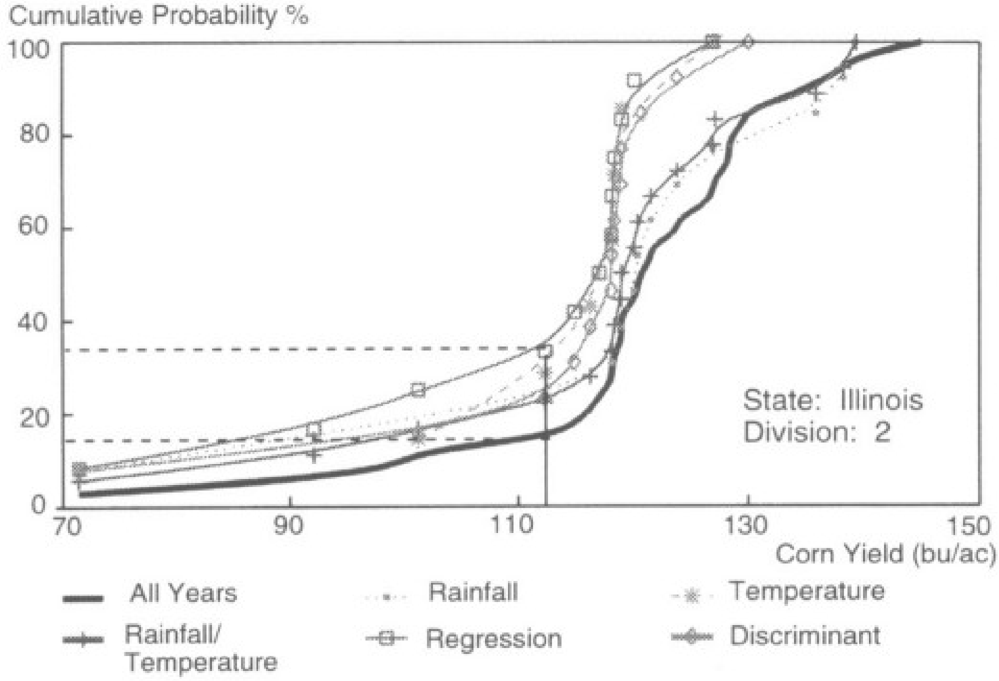


Figure 1. Yield Distribution Comparison

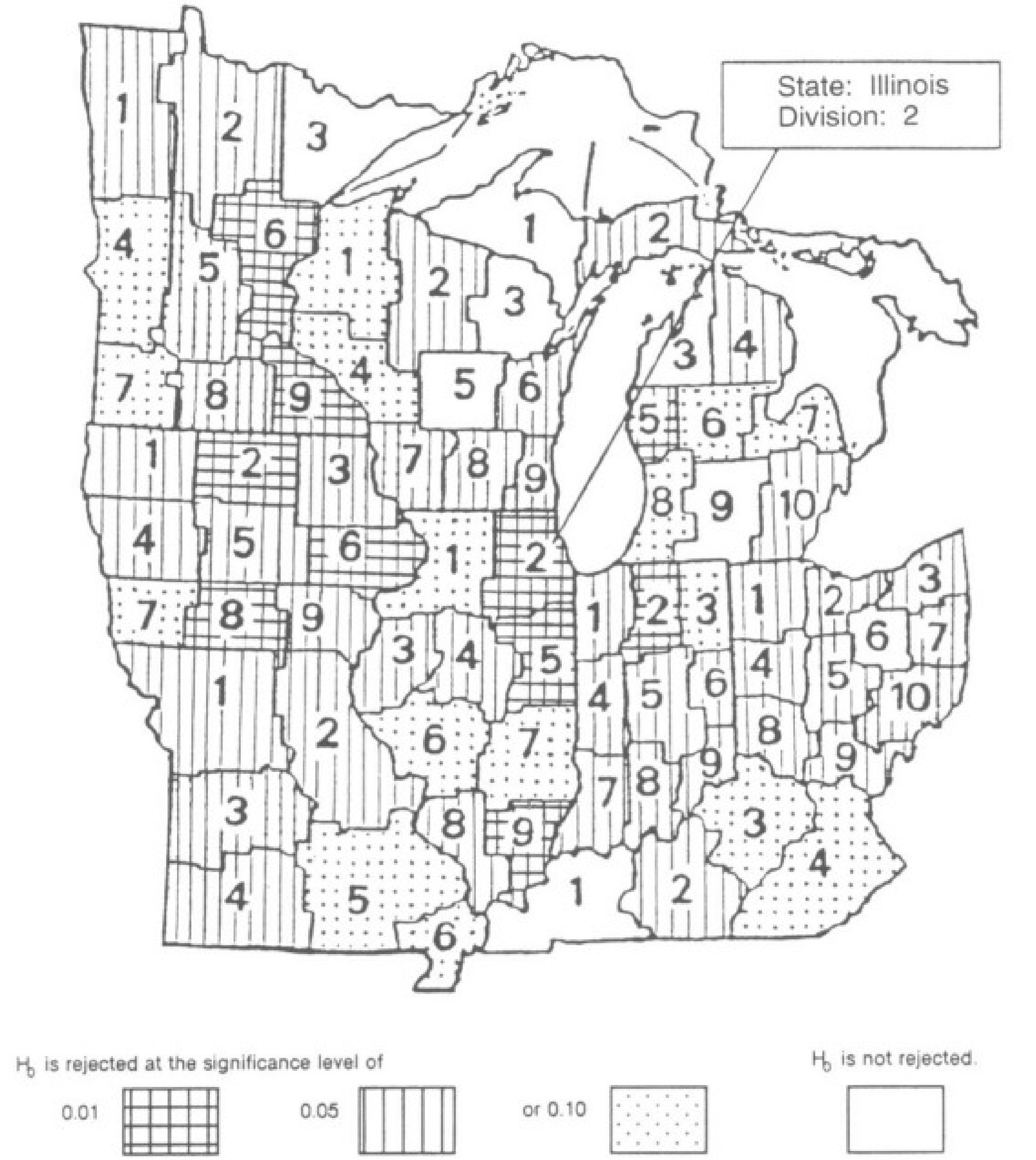
far left. As the two dotted horizontal lines show, the probability of getting 110 bu/acre or less was 15 percent if crop insurance was purchased in all years, while the probability would increase to more than 30 percent if the regression model was used to select insurance participation years.

The Wilcoxon Rank-sum tests and the Z-tests showed that among the five forecasting models for this division, only the regression method and the discriminant function method shifted the yield distribution significantly. The low-yield year distribution from the regression differed from the all-year CDF at the 0.01 significance level, while the CDF from the discriminant function differed from the all-year CDF at the 0.05 level. Thus, the regression model was selected as the most effective model for Division 2 of Illinois.

The same comparisons were made for each of the five models in each climate division. In sum, the three weather forecast models (rainfall anomalies, temperature anomalies, and combined rainfall and temperature anomalies) do not perform well in shifting yield distributions. Regression and discriminant functions can significantly change yield distributions for insurance in most divisions. In 37 of the 75 climate divisions (49.3 percent), the CDF of the low-yield year set identified by the regression analysis was statistically different from the all-year set. For the yield-discriminant function, the low-yield year CDFs were statistically different for 55 of the 75 climate divisions (73.3 percent), indicating yields can be forecasted with early-season data.

Identification of Areas with Potential Intertemporal Adverse Selection

The statistical significance levels from distribution comparison tests were used to select the most effective model to be used for the forecasting of yields in each climate division. Figure 2 is the climate division map of the Midwest which presents the significance levels of yield distribution comparisons for the selected models. The example division (Division 2 of Illinois) in Figure 1 is marked at the 0.01 significance level in Figure 2. As the map shows, in 90.7 percent of the Midwest climate divisions (representing 95.2 percent of the planted corn acres), early season weather



H_0: The yield distribution developed with pre-seasonal weather information has the same mean as the yield distribution developed without weather information;

H_a: The yield distribution developed with pre-seasonal weather information has a higher mean than the yield distribution developed without weather information.

Figure 2. The Significance Levels of H_o Rejection for Yield Distribution Comparison of All Climatic Divisions in the Midwest

information can be used to shift the yield distributions; thus, farmers can forecast low-yield years in these regions prior to the current deadline for purchasing crop insurance. The lower the significance level, the greater the likelihood that farmers can glean value from weather information. Likewise, intertemporal adverse selection is more likely in those climate divisions.

Policy Implications: Descriptive Measures of the Potential Value of Weather Information

The findings of this study have important implications for the MPCI program. If farmers incorporate weather information into their crop insurance decisions, they may increase their chance of collecting indemnity payments. In order to illustrate this point, descriptive statistics are developed for each of the five forecast models. All farmers within each climate division are assumed to use model results in order to determine which years to purchase crop insurance. In this case, farmers only purchase crop insurance in the years when the model forecasts low-yield years (the low-yield year set). The loss ratio, payouts from crop insurance (indemnities) divided by the premiums, is developed for each climate division using only the low-yield year set. These results can be compared to the actual crop insurance experiences, where all years are used to develop the loss ratio.

Table 1 presents the mean-loss ratio for all 75 climate divisions for each forecasting method. As shown in the table, if a farmer purchases insurance for the entire period sampled, the indemnity payment received equals $1.15 for each dollar of premium (on average).[9] That is, the farmer gained $0.15 compared to not purchasing insurance (row 1). The farmer could gain $0.86 if the regression results were used to select purchase years (row 5). For the entire Midwest, using weather-yield regression or discriminant function methods could generate significant gains for farmers who purchase corn insurance (row 5 or 6).

[9]All estimates of loss ratios use the historical crop insurance experience.

Figure 3 summarizes the benefit of using weather information to purchase crop insurance in another way. This figure shows that when using different forecasting methods, different percents of climate divisions in the Midwest might increase the indemnity collection for farmers. For example, as the two horizontal dotted lines show, about 50 percent of the climate divisions could increase indemnity collection by more than 50 percent if the regression method were used, while less than 10 percent of the climate divisions could increase their indemnity by more than 50 percent if the combined temperature/rainfall forecasts were used.

The measure of weather information value should be interpreted with caution. First, this measure gives a hypothetical description rather than empirical evidence. Whether farmers behave in this fashion in the MPCI program is a topic for further research. Second, the potential value of the weather information is apparent when there is a statistically significant difference between the CDFs for the all-year and the low-yield selected year samples; whereas, the summary statistics presented in Table 1 are descriptive.

Conclusions

This study evaluated the effectiveness of using early-season weather information to forecast corn yields for crop insurance purposes in the Midwest. Three methods were used to forecast low-yield years: (1) seasonal weather forecasts; (2) yield-weather regressions; and (3) yield-discriminant functions. The climate divisions in the Midwest where weather information can shift yield distributions in crop insurance were identified and indicate the ability to forecast low yields. Various weather variables were evaluated along with their relative contribution to forecasting. The rank of weather variable contributions to yield forecasting was: (1) seasonal rainfall forecasts; (2) temperature forecasts; (3) pre-seasonal water-supply conditions; and (4) temperature conditions. Corn yields can be forecasted early in the season on 95 percent of the planted corn acres in the Midwest. These conclusions imply the possibility

Table 1. A Descriptive Measure of Weather Information Value[a]

For Each Dollar of Premium a Farmer in the Midwest Received		
Methods	Indemnity ($)	Net Gain[b] ($)
1. Using all years to develop the loss ratio	1.15	+0.15
2. Using temperature forecasts to determine low-yield years	1.32	+0.32
3. Using rainfall forecasts to determine low-yield years	1.18	+0.18
4. Using temperature and rainfall forecasts to determine low-yield years	1.30	+0.30
5. Using yield-weather regressions to determine low-yield years	1.86	+0.86
6. Using yield-weather discriminant functions to determine low-yield years	1.70	+0.70

[a]The estimation of weather information value was based on the actual loss ratio data of the Midwest for the sampling period (1956 to 1989). The underlying assumption is that all farmers in the Midwest use the same method to decide whether to purchase crop insurance or not.

[b]The "Net Gain" column specifies the net gain of purchasing insurance based on a specific method versus not purchasing insurance. A value greater than zero implies that the insured received more than the amount paid and that the insurer incurs a loss.

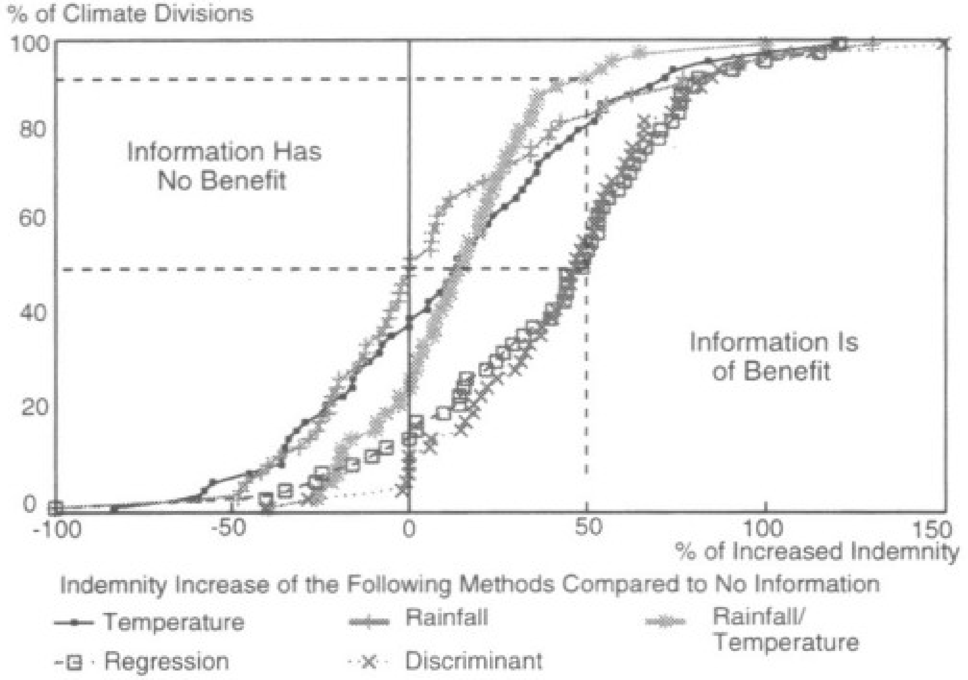


Figure 3. Benefit of Using Weather Information in the Crop Insurance Program

of intertemporal adverse selection in the MPCI program and the need for policy design adjustments.

One caveat about this study – this research used aggregate data and suggested that climate division level yield distributions for crop insurance can be shifted by using weather-yield forecasting. Since current MPCI offers an individual insurance plan, the study would be more relevant if it proved that farm-level yield distributions could be shifted using weather information. Two circumstances can lessen this weakness: (1) aggregate yield distribution shifting could be partial evidence of the possibility of farm-level yield distribution shifting; and (2) the new area-based MPCI program currently being pilot-tested (the Group Risk Plan) will make the aggregate conclusion relevant.

Future research should incorporate weather forecasts to explain participation in the MPCI program. Such research could help identify the extent to which farmers are taking advantage of early weather information in their crop insurance purchasing decisions. The sales ending date may need to be moved to an earlier deadline to prevent this type of behavior, or weather information may be used to change the coverage or the rates for MPCI as the sales closing dates approach.

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