THE IMPACT OF WEATHER CYCLES AND CROP YIELD AUTOCORRELATION ON CROP INSURANCE YIELD GUARANTEES

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The Impact of Weather Cycles and Crop Yield Autocorrelation on Crop Insurance Yield Guarantees

The Risk Management Agency (RMA) recently released the new Common Crop Insurance Policy which is known as COMBO. COMBO offers three insurance plans: Yield Protection (YP), Revenue Protection (RP), and Revenue Protection with the harvest price exclusion (RP-HPE). The yield guarantee for YP and RP is determined by a simple average of 4 to 10 years of the historical yield of the insured unit. When the crop insurance yield guarantee is based on the historical yield, properties of the sample yield distribution play an important role to determine crop insurance yield guarantee. Small sample properties (Barnett et al., 2005; Carriquiry, Babcock, and Hard, 2008; Woodard, 2009) and heteroscedasticity (Harri et al., 2011) have been shown to adversely affect crop insurance yield guarantees. Similarly, time series properties of the crop yield distribution (such as positive trend in APH yield) can also lead to under-insurance (Skees and Reed, 1986; Adhikari, Knight and Belasco, 2011). Serial correlation is another property of the yield distribution that has the potential to interact in crop insurance yield guarantee determination. The deterministic response function between weather and yields lead to the variation in the actual and contracted yield guarantee as a result of weather and, more specifically, drought cycles.

The presence of serially correlated yields has the potential to bias the variance concerning yield predictions. For example, positive serial correlation in the yield data increases the amplitude of swings in APH yields, leading to larger errors in yield guarantees relative to actual expected yields, and contributes to more serious problems of under- and over-insurance.

However, the presence of negative autocorrelation could actually have the opposite effect of dampening swings in APH yields and decreasing the magnitude of under or over insurance. More importantly, yields that do exhibit positive or negative autocorrelation relationships over time can be more accurately predicted when autocorrelation is accounted for. The existence of autocorrelation in crop yield series in the US was supported by the early work of Day (1965), which showed that distributions of corn, cotton and oat yields in Mississippi have significant autocorrelation across time. Further, Black and Thompson (1978) examined yields of wheat, corn and soybeans and weather interaction using a long time series of yield data. They reported that the parameter estimates of the drought cycle model were found significant and Durbin – Watson statistics were greater than 2 for all three crops, explaining the existence of autocorrelation in crop yields. Singh and Byerlee (1990) analyzed relative variability in wheat yields over time. They found that autocorrelation exists even in detrended crop yields. Kaylen and Koroma (1991) used crop yield data from 1913 to 1988 and concluded that the yield is highly autocorrelated and suggested to address it sufficiently in order to construct exact yield distributions.

Given the well-established link between weather and crop yields, persistent systematic cycles in weather can lead to autocorrelation in crop yield series, which causes yield guarantees to be significantly different from expected yields. For example, hot and dry weather in the crop growing season in the US Corn Belt has detrimental effects on corn yields (O'Brien, Hayenga, and Babcock 1996). Similarly, weather interactions in wheat, corn and soybean yields have also been reported by Black and Thompson (1978). They also argued that coefficient of variation is a misleading indicator of the yield risk measurement in the presence of autocorrelation. Lobel, Cahill and Field (2007) examined the relationships between crop yields and monthly temperature and precipitation for 12 major Californian crops for the period 1980–2003. Regression models based on a small number of selected climatic variables were able to explain much of the observed variability in crop yields. The existence of a weather cycle and association of crop yield with the weather variables confirmed the existence of serial correlation in the crop yield data.

Autocorrelation in crop yield has the potential to cause crop insurance premium rates to systematically deviate from the actuarially fair rate. Drought cycles and multi-year droughts undermine the effectiveness of producers' insurance coverage when not accounted for and are associated with low APH yields. In this study, we make an attempt to examine the weather cycle by constructing a drought index and testing for autocorrelation in drought index and crop yields in example counties from cotton, wheat, and corn producing states. We separate the impact of drought and non-stochastic time trend and examine autocorrelation in the residual. Further, our analysis is extended to assess the impact of yield autocorrelation in crop insurance yield guarantee.

Data and Methods

We study three crops (cotton, corn, and wheat) from three example counties (respectively, Lubbock county, Texas; Adams county, Illinois; and Dickinson county, Kansas) for the yield autocorrelation, impact of drought cycle in crop yield and crop yield autocorrelation. We make use of available yield history from the National Agricultural Statistics Service (NASS) (1972 to 2009 for cotton, 1970 to 2009 for wheat and 1940 to 2009 for corn). For the drought index, we used cooling degree days (CDD) and total monthly precipitation (TMP). Since the county level CDD have a short data series available, CDD for the example counties are replaced by the regional CDD. Weather data are available from the National Oceanic and Atmospheric

Administration (NOAA) and start in 1948. For the regression analysis, we used a similar length of weather and available crop yield data.

Drought Index

In this study, we define drought as extreme hot and dry condition in the crop growing season. The monthly weather measures; CDD and TMP are summed over the crop growing period and used to construct a drought index. The growing period for cotton is May to September, June to September for corn, and October to May for wheat. The relative heat is represented by the CDD, which is a deviation of number of degrees of the temperature above the mean. Relative dryness is represented by the deviation of TMP below the mean. The product of these two measures is the drought index used by Yu and Babcock (2010). We utilize their formulation as:

$$DI_t = \left[-\max\left(0, CDD_t^{Stand}\right)\right] \times \left[\min\left(0, TMP_t^{Stand}\right)\right] \qquad (1)$$

where t denotes the year. Both of the weather variables were standardized by subtracting each observation from the county mean and dividing by the standard deviation. The process scales the drought index so as to be comparable across time. We evaluate the cyclical movement of the weather index and test for autocorrelation by using the Durbin-Watson test and Lagrange Multiplier test developed by Breusch- Godfrey with null hypothesis; H_o: no autocorrelation.

Weather and Crop Yield Interaction

The interaction between crop yield and the drought index is an important relationship, especially if autocorrelation is found in the drought index. We use regression analysis to determine the relationship. Crop yield series frequently exhibit a time trend as an effect of technological advancement. Therefore, effects of weather and technological trend in crop yields are captured together with the regression equation used by Yu and Babcock (2010). We use their log-linear model in our analysis.

$$Ln(Y_t) = \beta_0 + \beta_1 \, DI_t + \beta_2 \, DIT_t + \beta_3 \, DISQ + \beta_4 \, DISQT + \varepsilon_t \qquad (2)$$

The subscript t denotes the year, Y denotes county yield, T is the trend variable which takes a value 1 for the first year. DI is the drought index, DIT is the product of drought index and trend, $DISQ$ is the squared drought index, and $DISQT$ is the product of the square of the drought index and trend variable. In this model, we considered a simple linear trend in the crop yield. Drought driven deviation in county yield depends on the drought index and technological trend depends on the trend variable. The quadratic terms $DISQ$ and $DISQT$ make the model more flexible for the marginal effect of drought with different level of severities. The log-linear model specification provides the percentage change in yield due to per unit changes in explanatory variables. Equation (2) separates the non-stochastic components such as intercept, technological effect, and impact of drought and stochastic error term (ε_t). We test for autocorrelation in the error term using the Durbin-Watson test and Lagrange Multiplier test. Given our estimates, we then evaluate the effect of autocorrelation on crop insurance yield guarantees.

Impact on Crop Insurance Yield Guarantee

We compute the expected yield with the assumption of no autocorrelation and with autocorrelation. We compare the differences in the expected indemnity in order assess the impact of autocorrelation. Our analysis is divided into two stages; at first we evaluate the impact of weather cycles and in the second step we assess the impact of autocorrelation after removing the effect of weather. In any case, our main concern is to evaluate the impact of yield autocorrelation in crop insurance. The time series yield data is expected to have correlation among the observations. The error term (ε_t) from equation (2) is assumed to be homoscedastic but correlated across the observations.

$$E[\varepsilon_t \varepsilon_t'] \; = \sigma^2 \, \Omega$$

$$Var(\varepsilon_t) = \sigma^2$$

We assume the p order autocorrelation in the yield time series. In this case,

$$\varepsilon_t = \; \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \; \dots\dots\dots.. + \theta_p \varepsilon_{t-p} + v_t \; , \quad E[v_t] = 0 \quad (3)$$

With the presence of an autocorrelated error term we cannot recover the yield series by using equation (2). For simplicity, we assume APH yield series with the first order autocorrelation. The APH yield series consists of intercept as expected yield and non stochastic component determined by lag of error term and white noise.

$$y_{APH} = \; \mu_{APH} + \; \rho \; \varepsilon_{t-1} + v_t \qquad (4)$$

The expected yield is $\mu_{APH} + \; \rho \; E(\; \varepsilon_{t-1})$ which is higher than μ_{APH} when there is positive trend and positive autocorrelation. Further, the variance of expected yield increases. The implication of this is that the guarantee level under this scenario is much larger than the true value resulting in under insurance for insurers.

In order to assess the impact of autocorrelation in crop insurance premium, we generate 10,000 random draws of autocorrelated error terms to construct 11 years of yield history by using the Phoon, Quek, and Huang (PQH) multivariate simulation method (Phoon, Quek, and Huang, 2002; Anderson, Harri, and Coble, 2009). We simulate the actuarially fair premium rate from the yield series for the example counties. We compare the premium rate under three different scenarios: (1) with current practices, (2) with correction for weather effects, and (3) with no autocorrelation.

Result and Discussion

Crop yield modeling is very important to establish the crop insurance yield guarantee. When yield is autocorrelated the contracted yield guarantee and the effective yield guarantee differ. This phenomenon leads to a higher indemnity expectation and increased premium rates. In order to provide a clear picture of existence of autocorrelation in the crop yield, we test the existence of autocorrelation in all of the major cotton producing counties in Texas, corn producing counties in Illinois, and wheat producing counties of Kansas. In order to conduct tests for autocorrelation we run the regression of crop yield with time and test the residuals from the regression. We use the Generalized Durbin-Watson (DW) test and Breusch- Godfrey's Lagrange multiplier (LM) test to test for first to 10^{th} order autocorrelation. However, the Breusch- Godfrey test for Texas cotton and Kansas wheat yield was carried out only up to 7^{th} order. Due to smaller yield series in these states, loss of degree of freedom seriously affects inferences. Tests were carried out for 102 counties in Texas, 102 counties in Illinois, and 105 counties in Kansas. The DW test suggests that the cotton yield series in 72 counties in Texas are significantly autocorrelated of order 1 or more. But the LM test supports only 22 counties with autocorrelated county yield history. Illinois corn yield series is expected to be highly autocorrelated because the yields in the corn-belt, especially in Illinois, are highly depend on weather conditions (Yu and Babcock, 2010). Our test does not strongly support this findings because 49 county yield series out of 102 counties in Illinois are autocorrelated according to DW test. The LM test further reduces the number of yield autocorrelated counties to 18. The possible reasons behind this result are either weather variables not having significant impact on crop yield or that weather is not cyclic in nature with finite time intervals. There is no severe drought was occurred in the U. S. corn-belt since 1988. With the county wheat yield series of Kansas, the existence of autocorrelation was rarely supported by the LM test while the DW test suggest autocorrelation in 58 counties out of 105 wheat growing counties (Table 1).

Table 1. Number of Counties with Autocorrelated County Yield Series in the States

Autocorrelation Order	Texas Cotton		Illinois Corn		Kansas Wheat	
	DW	LM	DW	LM	DW	LM
1	18	8	2	2	15	-
2	19	5	15	7	5	-
3	11	-	8	1	5	3
4	2	4	6	1	1	-
5	2	2	6	1	0	1
6	8	1	4	1	6	-
7	3	2	0	1	5	-
8	4	-	1	0	10	-
9	3	-	7	3	7	-
10	2	-	0	1	4	-
Total	72	22	49	18	58	4
Total Counties	102		102		105	

The annual drought index is constructed as a weather indicator for the cropping season for the example crops and counties. The drought index reflects relative hot and dry periods during the crop growing season. Lower crop yields are expected to be positively associated with the drought index for the respective counties. The drought index is also expected to have a cyclical nature of occurrence. We tested the drought index series of all three example counties for autocorrelation. The results presented in the Table 2 reveal that the drought indexes are autocorrelated. However, Breusch-Godfrey LM tests do not support the autocorrelation in the series. In Lubbock County, the autocorrelation is of order 3 and order 6 while in Adams county autocorrelation of order 8 was suggested by DW test. Similarly, drought index for Dickinson County, Kansas is autocorrelated with order of 4 and 6. The smaller order of autocorrelation in Lubbock and Dickinson County suggests that drought cycle of smaller intervals (i.e. 3 years in Lubbock and 4 years in Dickinson County) while higher order autocorrelation in Adams County suggest drought cycles of larger interval.

Table 2. Result of the Tests of Autocorrelation in Drought Index of Example Counties

Autocorrelation Order	Lubbock County		Adams County		Dickinson County	
	DW	LM	DW	LM	DW	LM
1	2.11	0.13	1.82	0.51	2.22	0.51
2	2.18	0.56	2.23	1.58	1.97	0.52
3	1.21*	5.79	1.97	1.60	1.72	1.08
4	1.95	5.85	1.81	1.70	2.34*	2.18
5	2.09	5.86	1.73	2.06	1.96	2.29
6	2.27*	9.83	1.80	2.35	2.39*	4.96
7	2.07	10.46	1.80	2.60	2.04	6.05
8	2.09	-	1.27*	4.61	1.48	-
9	1.61	-	1.47	4.62	1.71	-
10	1.62	-	1.68	4.62	1.68	-

*Significant at 5% level of significance.

Results in Table 1 establish that yield histories in a significant number of counties are autocorrelated in Texas cotton, Illinois corn, and Kansas wheat. The serial correlation in the yield history and serial correlation in the drought index (Table 2) provides sufficient grounds to support the existence of association of crop yield with the drought index. Therefore, equation (2) becomes relevant to estimate in order to assess this association. This equation is estimated for three different crops separately and ordinary least square estimates are presented in the Table 3. Parameter estimates for the drought index and trend variable are not significant for Lubbock County cotton. Quadratic terms such as DISQ and DISQT are also not significant. Similar results are obtained for Dickinson County wheat yield. In both of the crops the linear trend is not significant and so as the interaction term of trend with drought index. In conclusion, drought and technological advances do not significantly impact the county yield series for cotton and wheat. However, the result is different in case of corn in Adams County, Illinois. All the parameter estimates are significant. Variable DI and DISQ provide the impact of the drought index in the county yield. Significant and negative parameter estimates for DI and DISQ implies that drought significantly reduces the corn yield and the impact is at a maximum when drought the index is 2.58. The interaction of drought index and trend variables is significant suggests that technological trend is not affected by drought over the time. The insignificantly negative estimate for DISQT suggests that crop yield loss is reduced by drought over the time but the marginal effect (loss) is smaller by the severe drought than less severe drought. Corn yield in particular is found highly associated with the drought index and technological advances.

Table 3. Parameter Estimates of the Log-Linear Model of the Example Counties

Variable	Lubbock County Cotton	Adams County Corn	Dickinson County Wheat
Intercept	5.8197*	4.6150*	3.5287*
DI	-0.8119	-0.6870*	-1.3044
DIT	0.0072	0.0219*	0.0723
DISQ	0.0900	0.1330	0.8108
DISQT	0.0018	-0.0055*	-0.0453

*Significant at 5% level of significance.

Regression analysis of weather effects and trend effects in the county crop yield separates the non-stochastic technological and weather effect and stochastic error term. The error term of the equation (2) is assumed normally distributed with mean zero and variance $Var(\varepsilon_t) = \sigma^2$. Instead, if the mean of the error term is not zero and the observations are related with one another, then the autocorrelation is not caused by the cyclic nature of weather. We performed DW and LM tests for the error term. The test result for up to 10th order autocorrelation is presented in the Table 4. The DW test result supports the existence of autocorrelation of 6th order in cotton and wheat yields. The LM test does not support autocorrelation in both of the crop yield series. Surprisingly, both DW and LM tests support autocorrelation in error term in Adams County corn yield series. The reason behind the correlation between each of the observations might be because of the other factors such as differences in soil condition, crop rotation, farming practices, and other weather related variables that are not included in the drought index.

Table 4. Results of the Tests of Autocorrelation in Model Residual of Example Counties

Autocorrelation Order	Lubbock County , Cotton		Adams County, Corn		Dickinson County, Wheat	
	DW	LM	DW	LM	DW	LM
1	2.03	0.02	1.34*	8.05*	1.92	0.01
2	2.03	0.07	1.98	9.03*	1.68	0.29
3	1.49	0.57	1.57	11.56*	1.90	0.39
4	1.76	0.78	1.20*	15.16*	1.79	0.38
5	1.70	1.01	1.36*	15.80*	1.73	0.42
6	1.20*	1.76	1.34*	18.30*	1.25*	3.25
7	1.91	6.77	1.30*	18.57*	1.38	3.63
8	1.66	-	1.03*	21.36*	2.02	-
9	1.28	-	1.16*	21.66*	1.93	-
10	1.39	-	1.26*	21.82*	2.00	-

*Significant at 5% level of significance.

Effects on Crop Insurance Premium Rates

Due to autocorrelation in the APH yield series, the variability of the yield guarantees are estimated in a biased fashion and can have larger or smaller than actual variability depending on positive or the negative autocorrelation. This difference in variability impacts crop insurance premium rates. At first, we simulated the crop insurance premium rate with the existing APH practices used by the Risk Management Agency (RMA). We then remove the effect of weather and simulate the premium rate and finally we assume no autocorrelation in error term and simulate the rate. Table 5 provides the premium rate under each scenario with 50, 65, 75, and 85 percent coverage levels. Our simulated results suggest that there are very subtle differences in the premium rate with and without autocorrelation in the APH yield. Autocorrelation is not very strong in these example counties and crops and premium rates are not substantially different. In case of cotton, the premium rate for the 50% coverage level is 14.07% under the simple average APH and is reduced to 13.37% if there is no autocorrelation. When we do not remove the autocorrelation but correct for the weather effect, the premium rate is 13.87%. Effects of weather and autocorrelation remain fairly similar across coverage levels. In the case of corn, the crop insurance rate is very small and the effect of weather and autocorrelation in the premium rate are also very small. For the 50% coverage level, there is virtually no effect of weather and autocorrelation. But with 65% and larger coverage levels, there are effects of weather and autocorrelation in crop insurance premium rates. For the 85% coverage level, the premium rate is 4.98% under simple average APH. However, it decreases when we correct for the weather effect and further decreases to 4.91% when there is no weather effect and autocorrelation (Table 5). The effects in the premium rate in corn is not very discernible.

Table 5. Autocorrelation Effect on Premium Rates in Example County Cotton and Corn

Crop	Coverage level	Simple Average APH	Removing weather effect	Correcting auto correlation
Cotton	50	14.07%	13.83%	13.37%
	65	20.37%	20.23%	19.80%
	75	24.37%	24.27%	23.84%
	85	28.15%	28.10%	27.65%
Corn	50	0.06%	0.06%	0.06%
	65	0.78%	0.76%	0.75%
	75	2.28%	2.24%	2.23%
	85	4.98%	4.92%	4.91%

Conclusion

We examined the autocorrelation in county crop yield series for cotton, corn, and wheat in Texas, Illinois, and Kansas counties, respectively. Our results support the existence of autocorrelation in the large number of county yield series in Texas and Illinois. We speculate that the autocorrelation in county yield series is attributed to the cyclical nature of the weather. Therefore, we removed the weather effect by regressing yields on a drought index and temporal trend. After assessing the association with the weather, we analyzed error terms for existence of autocorrelation and simulated the crop insurance premium rates. Our results support the conclusion that there is variation in crop insurance rates when there is autocorrelation and weather association in the crop yield. The current premium rate is not the actuarially fair rate under the existence of autocorrelation. In our example counties, the autocorrelation in county crop yield are not strong which resulted in small effects on premium rates. But a potential for larger effects exists if there are crops and regions where autocorrelation is stronger. The primary implication of this research is that it could be useful for the RMA to examine whether there are crops and counties were APH yields are strongly autocorrelated and offer premium rates adjustment based on the magnitude and direction of the autocorrelation. Future research should also be directed to explore the potential sources of yield autocorrelation and possible solutions to either correcting it or making adjustments in the crop insurance premiums.

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