Applications of copulas to Analysis of Efficiency of Weather Derivatives as Primary Crop Insurance Instruments

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Introduction

Even though market for weather derivatives exists only for a little bit more than a decade, a considerable amount of academic work has been done on applications of weather derivatives to risk management in agriculture. Majority of researchers studying relationship between weather and agricultural yields conclude that economic evidence shows that weather derivatives can allow for effective management of volumetric risks in agriculture at both primary and reinsurance levels of aggregation (Musshoff, Odening, Wei Xu, 2009; Turvey, 2001; Norton, Osgood, Turvey, 2010; Turvey, Kong, Belltawn, 2009; Woodard, Garcia, 2008; Mahul, 2001; Vedenov, Barnett, 2004). At the same time there is still significant amount of the skepticism in the industry. Edward and Simmons (2004) note that although weather derivatives display advantages over traditional insurance, there is only a relatively small market for these products in agriculture. Among major factors hampering development of agricultural risk management tools based on weather indexes are farmers' unfamiliarity with weather derivatives, impacts of remaining price uncertainty, and diversification effects, inconsistency in practice of weather derivatives valuation methods, which doesn't allow for effective and fair pricing of contracts, and creates liquidity problems, and finally presence of spatial (or geographical) and technological (or technical) basis risk (risk that payoffs of a hedging instrument do not correspond to the underlying exposure), both spatial (or geographical) leads to situations, when problems of adverse selection and moral hazard have to be traded with problem of basis risk (Norton, Osgood, Turvey, 2010).

In theory, geographical basis risk could be significantly reduced using triangulated weather data, or providing insureds with the flexibility to choose and combine weather stations (Turvey, 2001); another approach is to perform spatial analysis techniques on weather data to provide a historical time series in varied geographic locations (Paulson and Hart 2006). Other researchers link microinsurance to microcredit and advocate for a central financial institution to aggregate index insurance contracts so as to average out basis risk for all actors (Miranda 2010, Woodard and Garcia 2008a). In addition to reduce the problem of basis risk, the hedger can use a number of “basis derivatives”, including basis swaps and basis options, to hedge basis risk (MacMinn, 1999; Considine, 2000). Turvey and Norton (2008) developed an internet based tool, which among its various capabilities allows for mitigation of spatial basis risk. All these approaches primarily focus on geographical basis risk.

Manfredo, and Richards (2009) showed that choosing hedging instruments with the ability to mitigate nonlinear risk exposure may be the most important factor in reducing overall residual basis risk when using weather derivatives. This suggests that spatial basis risk may be less important than technical basis risk when hedging volumetric risks with weather derivatives, what basically means that choice of weather stations may be less critical in managing basis risk than properly accounting for the relationship between yields and weather.

Review of the literature have shown that majority of researchers separate temperature and rainfall components of weather risk and use one of the two to construct weather indexes (Musshoff, Odening, Wei Xu, 2009; Manfredo, Richards, 2009; Berg, Schmitz, 2007; Woodard, Garcia, 2008; Mahul, 2001) while there have been just a few papers investigating effect of joint temperature-precipitation risk on crop yields (Turvey, 2001; Vedenov, Barnett, 2004). At the same time we were not able to find any research advocating for the best selection of time period, over which weather variables have to be recorded, in order to construct a weather index, characterized by high risk reducing ability. Usually researchers subjectively select calendar time period equal to one, or several month (Musshoff, Odening, Wei Xu, 2009; Vedenov, Barnett, 2004), or covering the whole season (Manfredo, Richards, 2009; Berg, Schmitz, 2007; Turvey, 2001; Woodard, Garcia, 2008; Mahul, 2001) to represent the period of time, which is most crucial for development of a plant, and hence which should be used to calculate values of weather variables. Given the obvious fact, that each year weather stochastically fluctuates around its normal conditions, what certainly affects planting time, and may change speed of development of a plant, and taking into account that in most cases crop yields are largely affected by short-term but relatively intensive weather events, we tend to believe that using approach, which would allow us to use shorter time periods for weather variables, and include both temperature and rainfall variables in the model, should provide us with opportunity to better capture weather risk and increase risk reducing ability of weather index contracts proposed in this paper.

Another concern to be addressed in this paper is selection of weather derivative type, which will be implemented in this research. Broll (2001) and Woodard (2008) note that since there is a general consensus about nonlinear dependence between weather and crop yields options may play an important hedging role while the relationship between the underlying variable and hedging instrument is nonlinear. Driven by this fact, we analyze performance of put and call options, written on specified weather index, and for specified location. Geographical basis risk is reduced by the means of using county level yields and weather data, obtained from the weather station centrally located in the given county.

Hence analysis presented here adds to the existing literature on agricultural applications of weather derivatives by deeper exploration of dependency structure between weather and crop yields, and incorporation of this structure into assessment of risk reducing efficiency of contracts, based on proposed weather indexes, by the means of copulas. More specifically, weather derivatives are designed for three different crops (corn, wheat, and cotton) grown in four geographically distinct areas of Texas. The efficiency of each instrument is then evaluated for typical crop producers in each county using Lower Partial Moment (LPM) measures.

Data and Methodology

Objective of the paper is to construct a county level weather derivative/crop insurance simulation model for the state of Texas. The model will be constructed on the basis of multivariate yield-weather distribution, built with the help of basic parametric copula functions and non-parametric marginal distributions. The model will estimate efficiency of weather derivatives contracts as a primary crop risk management tool in the state of Texas. We will start with three major crops (wheat, cotton, corn), produced in the region to the east from Pan Handle area (Haskell and Williamson counties), where water irrigation is not that spread, what allows to see better effect of weather fluctuations on yields variability. Future work will consider other possibly county combinations to prove the efficiency of insurance based on weather derivatives. Comparison of contracts, being developed in this paper, with the existing crop insurance policies will be done where possible.

Two major sources of data have been used for this paper. The first one is National Agricultural Statistical Service of USDA [13], which provided us with county level crop yield (corn, wheat, cotton) data, ranging from 1968 to 2009 in the area to the East of Panhandle (Haskell and Williamson counties); the second one is National Climatic Data Center of National Oceanic and Atmospheric Association [14], which provided daily weather data (precipitations and temperatures) for the same period of time as crop yields for weather stations, centrally located in the selected counties. An effort has been done to avoid any gaps in weather data.

The first stage of the analysis is to create a weather index, based on specified weather variables, which is capable to capture dependency between yield and weather and will be later on used as an object of insurance. To do this, we will largely rely on steps, proposed by Vedenov and Barnett (2004), but with changes in data and time windows used.

Construction of weather index starts with determination of the most critical time periods of the year, when weather anomalies can have largest effect on the future yield level. There are three possible approaches to determine these periods:

1. Consult with agronomist, and create a model based on their expertise. In this case we most likely will have to pick a period somewhere during the planting, periods of most active vegetation, maturation and finally during the harvesting to guarantee effective collection of the crops.
2. To regress the detrended yield data on weather variables (such as average temperature and precipitations) calculated in different periods during the year.
3. To write up a routine in one of the statistical software packages, and allow a model to pick any 5 best variables, which would generate a weather index with the best fit to the yield data.

While the first approach seems to be more logical, the second one is less subjective, but the third one gives an opportunity to test all possible combinations of precipitation and temperature variables, recorded over different time periods, and hence select the best combination, describing variability of yields most accurately.

To deviate from and hopefully improve assumptions, proposed in Vedenov and Barnett (2004), we decided to split the calendar year into 52 weekly periods (instead of original three monthly and one quarterly period), cumulative weekly cooling degree days (CDD, calculated as deviation of average daily temperature from 65F, if average daily temperature exceeds 65F), cumulative weekly heating degree days (HDD, calculated as deviation of average daily temperature from 65F, if average daily temperature falls below 65F), and finally cumulative weekly precipitations. Assuming that more continuous weather anomalies can have more substantial effect on yields, than just simple weekly average and cumulative values, we have constructed bi-weekly, tri-weekly, etc. up to 6 weeks cumulative weather variables.

To detrend the crops yield data, we have used the following formula:

$$Yield_{detr\_t} = Yield_t \times \hat{Y}ield_{2008} / \hat{Y}ield_t, \text{ where:}$$

$Yield_{detr\_t}$ – detrended values of yield in year t;

$Yield_t$ – value of yield in year t from the initial vector of yields;

$\hat{Y}ield_{2008}$ – the last value of yield in the vector of forecasted yields;

$\hat{Y}ield_t$ – value of yield in year t in the vector of forecasted yields;

This approach allows us to work with detrended yield values instead of detrended residuals, which is more convenient for the purposes of our research. Once detrended yield values have been obtained we run a series of model of the following type:

$$\ln(Yield) = \alpha + \beta_1 \times \ln(Weather_1) + \beta_2 \times \ln(Weather_2) + \beta_3 \times \ln(Weather_3) + \beta_4 \times \ln(Weather_4) + \beta_5 \times \ln(Weather_5) + e, \text{ where:}$$

$\ln(Yield)$ – detrended yield for each county;

β_i – regression coefficients;

$Weather_i$ – weather variable (either precipitation or temperature index variables, recorded over specified period of time).

We assume that natural logarithms of detrended yields and weather variables will be able to pick non-linearity between these variables, and will allow avoiding square terms and cross products to minimize the number of independent variables in the model, which is crucial when only 40 yield observations are available.

To calculate a risk reduction effectiveness of contracts, based on proposed indexes, we have to estimate a distribution of possible profits of a representative farmer with and without a contract. To do this, first, we'll have to make our detrended yields stochastic, and multiply them by the expected price of a crop to get a distribution of profits without a contract per 1 acre. To obtain a distribution of profits with a contract the following formula will be used:

$$\tilde{\pi} = \tilde{Y}ield \times Price + Indemnity - Premium, \text{ where:}$$

$\tilde{\pi}$ – stochastic profit of a representative farmer with a contract;

$\tilde{Y}ield$ – stochastic yield drawn from a joint yield-weather index distribution;

Price – expected price of a crop in the given county (we used expected prices reported by Risk Management Agency of USDA under their Group Risk Income Protection insurance plan).

Indemnity – indemnity payments, calculated as - $\max(Guaranteed\ index - Index\_stoch, 0) \times Guaranteed\ price$, where:

$Index\_stoch$ - stochastic weather index drawn from a joint yield-weather index distribution;

$Guaranteed\ index$ – guaranteed weather index equal to 85% of average of a historical weather index in the given county.

$Guaranteed\ price$ – guaranteed by the Federal Crop FCIC price (we assumed 85% protection level for the purposes of our research, i.e. guaranteed price was equal to 85% of the price guaranteed by the FCIC)

Premium – premium on a contract equal to fair premium on a proposed index contract calculated as - $1/10000 \times \sum_1^{10000} Indemnity_i$, where indemnity is calculated according to the formula described above.

To generate stochastic values of yields for the case without a contract and stochastic values of a weather index to estimate fair premium on a proposed contract an inverse transform method has been used. First distributions of historical detrended yields and weather index have been estimated using epanechnikov kernel density functions, with bandwidth equal to 0.5 of an optimal for a Gaussian kernel.

To generate stochastic values of yields and weather index for the case with the contract multivariate joint distribution has to be used, since values have to be drawn simultaneously. Trivial approach for this problem would be to use MVE distribution. But for the purposes of this research we are using two types of basic parametric copulas: Gaussian and t-copula, based on Epanechnikov kernel density distributions of marginals.

Once distributions of stochastic profits of a representative farmer without and with the contract (constructed with Gaussian and t-copula) are generated using methods of Monte-Carlo simulation, the risk reducing efficiency of the proposed contracts can be estimated using lower partial moments.

Lower partial moment of degree 2 (LPM_2) is a measure of downside risk computed as the average of the squared deviations below a target return. This measure of downside risk is more general than semi-variance and for the case without a contract is calculated according to the following formula:

$$\int_{-\infty}^{\bar{\pi}} (\tilde{\pi} - \bar{\pi})^2 \, g(\pi) d\pi, \text{ where:}$$

$\tilde{\pi}$ – distribution of stochastic profits without a contract;

$\bar{\pi}$ – threshold, after which a decision maker is indifferent about risk, associated with the risky alternative.

For the case with the contract LPM_2 is calculated according to the formula:

$$\iint_{-\infty}^{+\infty} \max([Yld\_\det\_stoch \times Price + Indemnity(Index\_stoch) - Premium] - \bar{\pi}, 0)^2 \, g(y, i) dy di, \text{ where:}$$

$Yld\_\det\_stoch$ - stochastic values of detrended yields drawn from joint yield-weather index distribution, based on parametric copula function;

$Price$ – expected price of a crop in given county;

$Indemnity(Index\_stoch)$ - stochastic values of indemnity payments, calculated according to the formula discussed above, given stochastic values of weather index drawn from joint yield-weather index distribution, based on parametric copula function;

$Premium$ – premium on a contract equal to a fair premium on a proposed index contract calculated according to the formula discussed above

To estimate the risk reduction effect, we calculate the difference of LPM_2 for a farmer with and without a contract. The higher the difference the bigger the degree of risk reduction in absolute terms.

Discussion of results

It is evident from tables 1, 2, and 3 that not only R-square for the models, based on weather variables recorded over shorter periods of time (e.g. 1 week) are higher, what indicates better fit and supports our assumption that weather over short period of time but with high intensity is more crucial for the development of a plant, but also delta values, measuring risk reduction effect are higher for 1_week models than for any other model, what again supports our assumption that for weather derivatives contracts to be efficient they must be based on a weather indexes recorded over shorter periods of time.

Table 1. Haskell county, wheat

	'1_week'	'2_weeks'	'3_weeks'	'4_weeks'	'5_weeks'	'6_weeks'	'seasonal'
R-sq	0.69	0.63	0.66	0.53	0.68	0.48	0.59
Delta (G_copula)	107.58	79.25	92.44	52.52	98.71	37.32	68.20
Delta (T_copula)	122.02	90.97	105.85	69.83	115.43	55.66	84.84

Table 2. Haskell county, cotton

	'1_week'	'2_weeks'	'3_weeks'	'4_weeks'	'5_weeks'	'6_weeks'	'seasonal'
R-sq	0.69	0.61	0.49	0.51	0.47	0.48	0.37
Delta (G_copula)	884.18	595.47	377.79	473.93	373.56	385.71	229.81
Delta (T_copula)	963.92	738.95	535.53	617.36	486.44	540.98	377.78

Table 3. Williamson county, corn

	'1_week'	'2_weeks'	'3_weeks'	'4_weeks'	'5_weeks'	'6_weeks'	'seasonal'
R-sq	0.63	0.47	0.46	0.42	0.42	0.39	0.24
Delta (G_copula)	982.46	452.62	519.98	412.21	431.64	348.32	72.87
Delta (T_copula)	1016.00	559.64	607.20	505.39	511.90	438.83	148.14

Conclusions

The efficiency of weather derivatives was analyzed for three crops grown in the area to the east from Pan Handle in Texas. For each crop, the relationship between yield and selected weather variables was estimated, and a weather derivatives contract was constructed based on the function which best fits the data. The constructed weather derivatives provided a considerable risk protection, and indicated that for weather derivatives to be efficient they should be constructed on the basis of weather variables recorded over relatively short periods of time in order to be able to capture relatively short, but intensive weather events, which has the highest effect on crop yields.

Potential discussion points

This is the one of the first paper discussing applications of copulas to risk management in agriculture through weather derivatives. Weather derivatives were thought to be quite powerful tool for management of weather related risks in agriculture in early 2000s, but high basis risk deteriorated their risk reducing efficiency. Copula approach, presented in the study, may help to decrease technological basis risk, and thus stimulate further research on application of weather derivatives. Consequently authors hope that this paper will instigate some interesting discussions about the approach implemented in this study. We also would like to encourage discussion about the approach being used to construct weather indexes (which weather variables and time periods to use, etc.), since they are the crucial part of the problem.

References

1. Oliver Musshoff, Martin Odening, Wei Xu. Management of climate risks in agriculture – will weather derivatives permeate? Applied economics, 2009, 1-11

2. Mark R. Manfredo, Timothy J. Richards. Hedging with weather derivatives: a role for options in reducing basis risk. Applied financial Economics, 2009, 19, 87-97

3. Calum Turvey. Weather derivatives for specific event risk in agriculture. Review of agricultural economics. 2001, 23, 333-351.

4. Ernst Berg, Bernhard Schmitz. Weather based instruments in the context of whole farm risk management. 101st EAAE Seminar "Management of Climate Risks in Agriculture", Berlin, Germany, July 5-6, 2007.

5. Michael Norton, Dan Osgood, Calum Turvey. Weather index insurance and the pricing of spatial basis risk. AAEA 2010 meeting, Denver, Colorado, July 25-27, 2010.

6. Calum Turvey, Rong Kong, Burgen C Belltawn. Weather Risk and the Viability of Weather Insurance in Western China. AAEA annual meeting 2009.

7. Joshua Woodard, Philip Garcia. Weather Derivatives, Spatial Aggregation, and Systemic Risk. Implications for Reinsurance Hedging.

8. Optimal insurance against climatic experience. Oliver Mahul. American Journal of Agricultural Economics, Vol 83, No. 3 (Aug., 2001), pp. 593-604.

9. An internet based tool for weather risk management. Calumn Turvey, Michael Norton. Agricultural and resource economics review. 37/1 (April 2008), 63-78.

10. Measuring Non-Catastrophic Weather Risk for Business. Juliusz Pres. The Geneva Papers, 2009, 34, 425-439.

11. Weather Derivatives and Weather Risk Management. Patrick Brockett, Mulong Wang, Chuanhou Yang. Risk Management and Insurance Review, 2005, Vol. 8, No. 1, 127-140.

12. Vedenov, D. V., B.J. Barnett. “Efficiency of Weather Derivatives as Primary Crop Insurance Instruments”. Journal of Agricultural and Resource Economics, 29 (December 2004): 387-403

13. USDA/NASS. "Quickstats, U.S. & States, Prices." National Agricultural Statistical Service, (2010). Available online at http://www.nass.usda.gov/Data_and_Statistics/Quick_Stats/index.asp.

14. NOAA/NCDC. “Surface Data, Daily” National Climatic Data Center, (2010). Available online at http://www7.ncdc.noaa.gov/CDO/cdo