On the Efficiency of Pseudo Risk Pools and Proxy yield data on Crop Insurance and Reinsurance in U.S

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Selected paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1

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Abstract

We empirically investigate the impact of aggregated county risk pools , used as proxy for a county with limited data, on premium rates and reinsurance needs for crop revenue insurance in the U.S. To quantify systemic risk, we employ nested Archimedean copula-based models which relaxes the exchangeability restriction and less prune to curse of dimensionality inherent in copula-based models. In the first stage of our analysis, employing irrigated and non-irrigated cotton yields from seven counties in Texas, we derive 'true' county-level rates using 'unlimited' data. In the second stage, we derive rates based on proxy data aggregated over county risk pools. Finally we compare the 'true' rates with those based on proxy data using root mean squared error ($rmse$) and diversification effect (DE). The results show substantial differences in systemic risk across risk pools. The risk pool use in practice was found to be far less efficient resulting to significantly high premiums rates and subsidies levels.

Key words: Proxy yields, Efficiency, Crop insurance, Systemic risk, Cotton.

JEL classification: G22, Q14.

1 Introduction

Agriculture is highly vulnerable to a variety of weather risks such as droughts, floods, hail, freezes, and windstorms. In developed countries, and increasingly in emerging economies, multi-peril and single peril crop insurance are major tools to manage farm risk. Unlike commercial insurance products such as life and auto, most crop insurance programs benefit from government subsidies to encourage participation.

In the U.S., crop insurance is administered by the Risk Management Agency (RMA) of the United State Department of Agriculture (USDA), with the main objective "to maximize participation in the Federal crop insurance program and to ensure equity for producers." The RMA heavily subsidizes premiums and fully covers the program's administration, operating, and reinsurance costs. Since inception in 1938, and the subsequent passage of the Crop Insurance Reform Act in 1994 and the Agricultural Risk Protection Act in 2000, total liabilities and subsidies for the program have increased substantially. In 2014, 295 millions acres were insured for a total liabilities and subsidies amounting to $123 billion and $7.3 billion, respectively, making it the most expensive agricultural commodity program (RMA., 2014) and a key fixture of U.S. agricultural policy.

The 2014 Agricultural Act further expands the program; extends coverage to many previously unserved counties with little or no historical data and authorizes several new county-level triggered insurance policies such as the Agricultural Risk Coverage (ARC) and Supplemental Coverage Option (SCO). The SCO is an optional policy that covers up to 20% deductible of a companion policy allowing growers to obtain close to full coverage from purchasing the two policies. Stacked Income Protection Plan (STAX) is a SCO that covers only upland cotton growers which unlike SCO can also be use as a stand alone policy. These insurances insure county-level revenues which can be triggered by low yields, low prices or a combination of the two.

While SCO/STAX cover county-level revenues "the geographical area that the expected and final area yields are based on, designated generally as a county, but may be a smaller or larger geographical area." In practice, data from nearby counties are aggregated to produce the require data for rating counties with limited historical yield data. In fact, 76% of the counties in the top five cotton producing states in the U.S. where STAX was available in 2015, data was aggregated from several (2 to 41) nearby counties to produce the require data for rating the counties; in Texas, data was aggregated from 2 to 24 counties to produce require data for 140 of the 176 counties; in Georgia, data was aggregated from 2 to 28 counties to produce require data for 80 of the 100 counties; in Arkansas, data was aggregated from 2 to 7 counties to produce require data for 11 of the 25 counties; in Mississippi, data was aggregated from 2 to 41 counties to produce require data for 55 of the 62 counties; and in North Carolina, data was aggregated from 2 to 15 counties to produce require data for 33 of the 58 counties.

Considering the extensive use of pooled data from nearby counties to rate premiums for a given county with limited data, it is fair to ask: (1) How accurate are the pooled data? (2) What effect does the current method have on price and participation? (3) Is there a better method for setting crop insurance rates? Several alternative pools with different sizes and spatial dependence are possible for any given county with insufficient data, and each with potentially different effects on premiums. In this case, selecting the most representative pool to be used as a proxy for the county will be central in obtaining accurate rates, and ensuring reasonable subsidy levels.

High premium rates and the inability of private insurers to compete in crop insurance markets is largely attributed to systemic risk inherent in agriculture (Miranda and Glauber, 1997) which is known to vary depending on the type of adverse weather condition, degree of severity, and the size of geographical area. Goodwin (2001) showed that correlation in crop yields tend to be stronger during years with severe drought than ones with normal weather, indicating a non-linear spatial dependence. Wang and Zhang (2003) using spatial analysis found that on average yields for wheat, soybeans, and corn in the U.S. are uncorrelated beyond 570 miles from one another. It is therefore likely that different county risk pools over which data are aggregated will be heterogenous in the degree of systemic risk. Thus, correctly quantifying systemic risk present in each pool is a *sine qua non* for obtaining reliable rates and selecting an optimal proxy risk pool for a county with insufficient data.

Until recently, Gaussian copulas were widely use in quantifying multiple dependent risks including rating revenue insurance by the the RMA. This copula assumes linear correlation with zero tail dependence, and tends to underestimate risk in the tails of a distribution resulting in lower premium rates. Goodwin and Hungerforth (2015) in a recent empirical study highlighted the importance of quantifying systemic risk in agriculture using non-Gaussian copulas. The authors found that average premium rates for corn and soybean in the U.S. differ between the D-vine copula and the Gaussian copula by -0.6% at the 95% coverage level, and 50% at the 75% coverage level.[1]

In this study, we investigate the impact of aggregated risk pools, used as proxy for a county with limited data, on premium rates and reinsurance of county-level revenue insurance in the U.S. Specifically, using Dickens county in Texas and six surrounding counties as an example, we empirically investigate systemic risk in upland cotton yield profiles obtained by aggregating data over 2 to 7 neighboring counties (including Dickens) and their effect on premium rates, subsidies, and reinsurance needs for Dickens county. To properly quantify cotton revenue (i.e., multiple dependent) risks, we employ Nested Archimedean Copula (NAC) models which relaxes the exchangeability restriction and circumvent the curse of dimensionality inherent in copula-based models. In the first step, we derive 'true' premium rates for cotton revenue insurance in Dickens county using 'unlimited' data. In the second step, we derive rates for Dickens county based on proxy data from potential county risk pools, including that used by RMA in rating 2015 SCO/STAX contracts. In the third step, we compare the 'true' rates in Dickens county with those derived with proxy data from risk pools using root mean squared error (*rmse*). To further gauge the degree to which the proxy pools are suitable, we estimate and compare the diversification effects (DE) of the

[1]Estimates derived using vine copula are not invariant with respect to the factoring (ordering of individual variables) of the multivariate density, thus resulting to a curse of dimensionality.

alternative risk pools used as proxy for Dickens. Finally, based on estimates of $rmse$ and DE, we determined optimal risk pools for rating premiums in Dickens county.

The results show substantial differences in systemic risk across risk pools and agricultural practices (irrigated and non-irrigated cotton). The risk pool used by RMA in rating SCO/STAX contracts for Dickens county administered in 2015 was found to be far less reliable, with premium rates up to 56% (169%) higher that the 'true' rate for a 90% (70%) coverage level. The rate differential based on RMA's total liability for Dickens county in 2015 implies that premiums for 90% (70%) coverage level are \$35,041 (\$25,607) higher than the true cost. On average, based on all counties rated with proxy data in 2015, this amounts to total premium excesses of \$14,752,130 and \$10,780,404 for the 90% and 70% coverage levels, respectively. We found alternative county risk pools significantly more efficient than the risk pool used in practce - producing rates that are only 1.5% lower than the 'true' rates and with minimum mean squared error.

The remainder of the paper is organized as follows. In the next section, we present the empirical strategy for our study. This includes trend estimation and detrending yields, specifying and estimating the Nested Archimedean Copula-based model, simulations, and premium rating. Section 3 presents an application of the empirical framework developed to quantify systemic risk in upland cotton production in the U.S. Finally, we conclude with main findings, implications on county-level revenue insurance and opportunities for future research.

2 Empirical Strategy

Indemnities for revenue insurance can be triggered by multiple dependent sources of risk; low yields, low prices or a combination of the two. Our empirical strategy is to estimate the joint distribution of yields and prices that allows us to generate revenue losses and calculate premium rates. We achieve this by employing Archimedean copula models. Copula-based models have widely been applied in risk management, insurance and finance literature and over the recent years gained strong appeal in rating crop insurance contracts due to its ability to capture nonlinear correlation in yields across space (and prices in the case of revenue insurance) in the wake of severe weather events.

A copula is multivariate distribution function with continuous marginal distribution uniformly distributed on [0,1].[2] A d-dimensional copula ($C(u_1, u_2, ..., u_d)$) is given as

$$C(u_1, u_2, ..., u_d) = G(G_1^{-1}(u_1), G_2^{-1}(u_2), ..., G_d^{-1}(u_d)), \tag{1}$$

where G is the joint distribution and $G_j,\ j\epsilon 1, ..., d$ is the marginal distribution. If the d-dimensional copula and the d marginal distributions $(G_1(x_1), G_2(x_2)..., G_d(x_d))$ are given, we can conveniently derive the corresponding density function $g(x_1, x_2, ..., x_d)$ as

$$g(x_1, ..., x_d) = c(G_1(x_1), G_2(x_2), ..., G_d(x_d)) \prod_{i=1}^{d} g_i(x_i), \tag{2}$$

where g_i is the marginal density function and $c(.)$ is the density of the copula. The later can be derived as:

$$c(u_1, u_2, ..., u_d) = \frac{G(G_1^{-1}(u_1), G_2^{-1}(u_2), ..., G_d^{-1}(u_d))}{\prod_{i=1}^{d} g_i(G_i^{-1}(u_i))}. \tag{3}$$

Elliptical and Archimedean are two main parametric families of copulas with extensive practical applications. Unlike elliptical copula (e.g., Gaussian), Archimedean copulas have explicit generating functions and are able to capture the dependency structure in the upper tail, lower tail or both tails of the distributions with a single parameter, allowing us to quantify systemic risk. A d-dimensional Archimedean copula with parameter θ can be specified as

$$C(u_1, u_2, ..., u_d; \theta) = \phi(\phi^{-1}(u_1), \phi^{-1}(u_2), ..., \phi^{-1}(u_d)), \tag{4}$$

where ϕ is a continuous, decreasing function on $[0,\infty]$ with $\phi(0) = 1$, $\phi(\infty) = 0$, with

[2]For a more background on copula, please see Joe (1996) and Nelsen (2006).

derivatives up to the order $d-2$ satisfying $(-1)^k \frac{d^k}{dt^k}\phi(t) \geq 0$ for all $k \epsilon \{0, ..., d-2\}, t \epsilon (0, \infty)$ (Kimberling, 1974; McNeil and Neslehova, 2009).

While copulas present a more flexible technique for multivariate analysis, the exchangeability feature inherent in an Archimedean copula implies that all margins of the same dimension are equal. This presents increasingly stronger assumption with increase in the dimension of the copula. To address this problems, more flexible approaches based on the Archimedean copula have been developed to handle high dimensional data without sacrificing the multivariate dependency structure. This includes Fischer copulas (Fischer and Kock, 2012), vine copulas (Kurowicka and Joe, 2011) and nested Archimedean copulas (Savu and Trede, 2010; McNeil and Neslehova, 2009; McNeil, 2008; Okrin et al., 2009). The later can either be fully nested or partially nested. This study employs a partially nested Archimedean copula (PNAC) where the multivariate dependency structure is modeled following a hierarchical structure in which an Archimedean copula is used as an entry for another at each level of hierarchy. If such entry is used alongside one additional dimension at a time, the resulting structure is fully nested. For an d-dimensional copula for which $d \geq 3$, if

$$C(u_1, u_2, ..., u_d; \theta_0, ..., \theta_{n-2}) = \phi_0(\phi_0^{-1}(u_1) + \phi_0^{-1}(u_2, ..., u_d; \theta_1, ..., \theta_{d-2})), \tag{5}$$

then C is a fully nested Archimedean copula with $d-1$ nesting hierarchies. Otherwise, the resulting structure is partially nested. For example, for a 3-dimensional copula specified as $C(u_1, u_2, u_3) = C(u_1, C(u_2, u_3; \theta_1); \theta_0)$, The copula generated by θ_1 is nested in the copula generated by θ_0. McNeil (2008) showed that in order for a NAC structure to be a proper cumulative distribution function, all nodes in the structure (of the form $\phi_i^{-1} \times \phi_j$) must have a completely monotone derivatives up to the order n. As illustrated by Savu and Trede (2010), this condition is met if the degree of dependency diminishes with increase in dimension of the copula from nesting a copula as an argument into another. This sufficient condition is easily met if all generators within the nested structure come from the same parametric family. We follow suit in this study, and use the same parametric family in all the margins.

3 Empirical Application

We apply the nested copula model developed above in rating county-level cotton revenue insurance, analogous to the Group Risk Income Protection (GRIP) available since 1999 and the Stacked Income Protection Plan (STAX) newly introduced and available this year (2015). We investigate two categories of revenue insurance; one based on the projected price of cotton (harvest price exclusion) and another based on the higher of the projected or harvest price. The demand for revenue insurance had significantly increase over the last decade and currently accounts for about 70% of the total liability of the Federal Crop Insurance program. As indicated above, indemnities for this insurance can be triggered by low yields, low prices or a combination of the two.

Annual county-level yield data for irrigated and non-irrigated upland cotton was obtained from the USDA's National Agricultural Statistics Service (NASS) databases while cotton prices were obtained from the New York Board of Trade (NYBT). Projected prices are taken as average daily (opening, high, low and closing) stock prices of December futures during the month of February and the harvest prices taken as average daily (opening, high, low and closing) stock prices of December futures during the month of November.

To investigate the impact of size of geographical area or county pool on the rates and viability of the program, we based our application on a clusters of 7 counties from three agricultural districts (Northern high plains, Northern low plains and Southern high plains) in Texas; Crosby, Dickens, Floyd, Garza, Hale, Lubbock, and Lynn. Texas is the number one cotton producing state in the U.S. followed by Georgia, Arkansas, Mississippi and North Carolina, and five (Crosby, Floyd, Hale, Lubbock, and Lynn) of the seven counties considered in this study are among the top 9 upland cotton producing counties in Texas. In addition, STAX/SCO was available to all 7 counties in 2015. However, due to missing data in Dickens for the recent 5 years, rates for Dickens county were based on data aggregated over Crosby and Dickens.

Our analysis aim to determine (1) the effect of using data aggregated over Dickens and nearby counties (including Crosby) on premium rates, and (2) which county pool gives the least biased rate estimate for Dickens county. To accomplish this, we utilize upland cotton yields in the 7 counties and price data from 1996 to 2009 during which period no data was missing.

In the first stage of our analysis, we estimate the joint distribution of irrigated upland cotton, non-irrigated upland cotton, projected price, and harvest price, and proceeded to simulate data and calculate premiums for each county. Prior to estimating the joint distribution with copula-based models, we adjust for the general upward trend in yields associated to improved technology. To accommodate outliers present in the data, we follow Goodwin and Hungerforth (2015) and estimate a quadratic trend nonparametrically using a local regression and then recenter the yields on 2009 by adding the deviations to the 2009 predicted yields using equation (6) and equation (7), respectively.

$$y_t = h(t) + \epsilon_t, \tag{6}$$

$$\hat{y}_t = \hat{y}_{2009} + \epsilon_t. \tag{7}$$

Figure 1 presents the regression estimates along with 95% confidence band.

We transform detrended yields into uniformly distributed variates on [0,1] for fitting copula structure, using the empirical distribution of the detrended yield and price data. As highlighted by Goodwin and Hungerforth (2015), this approach is preferred to using estimated cumulative distribution function (CDF) because the asymptotic distribution of the copula estimates are not affected by limitations in fitting the parametric marginal distribution (Chen and Fan, 2006) resulting to less variation around parameter estimates

(Charpentier et al., 2011). The 16-dimensional NAC structure was estimated using maximum likelihood.[3] To capture dependency in both tails of the distribution and for comparison purposes, we investigate three types of Archimedean copulas; Frank, Gumbel and Clayton. The later captures lower tail dependency and thus suitable in estimating the joint losses in this study. On the contrary, Gumbel exhibits upper tail dependency while Frank exhibit radial symmetry. Figure 1 presents the 16-dimension nested Clayton copula structure derived with upland cotton yields and price data from the 7 counties in Texas. This include irrigated cotton yields from 7 counties, non-irrigated cotton yields from 7 counties, projected price, and harvest price for cotton. The parameter estimates of the copula structure are depicted in table 4.

Next, we separately estimate parametric marginal distributions for each yield and price data, known to provide a more explicit representation than non-parametric yield distributions. For simplicity and based on results in past studies, we fitted a Weibull distribution on irrigated and non-irrigated cotton yields and a lognormal distribution on projected and harvest prices.

With the estimated structure of NAC and estimates of parametric marginal distributions of each yield and price data, we proceed to simulate the joint distribution of yields and prices and estimate premium rates. First, using the estimated 16-dimension copula structure, we draw 10,000 correlated uniform variates , and next use each simulated draw (as probabilities) with the corresponding (estimated) parametric distribution to derived quantiles of the distributions. With the simulated yields for county i and cotton type j ($y_{ij}, i = 1, ..., 7$ and $j = 1, 2$) and prices ($P_k, k = 1, 2$)), we proceeded to derive corresponding revenue distributions, $R_{ijk} = y_{ij} \times P_k$, and expected revenue, $\hat{R}_{ijk} = E(R_{ijk})$, where E is the expectation operator. The losses (L_{ijk}) for a given coverage level (c) are obtained as

$$L_{ijk} = max(\hat{R}_{ijk} \times c - R_{ijk}, 0), \tag{8}$$

[3] Estimation was done in R using the "copula" package (Hofert et al., 2015). For more details on its application see Hofert and Machler (2011).

and actuarially fair premium rates at coverage level c in each county are derive as

$$PR_{ijk} = \frac{E(L_{ijk})}{\hat{R}_{ijk} \times c}. \tag{9}$$

In the second stage, we randomly select and delete 5 observations in Dicken county between 2009 and 1989, creating missing data for the county. Next, we replace the whole data in Dickens county with data aggregated over the county and one or more neighboring counties and repeated the analysis. Based on the number of counties considered in this study, we investigated all possible aggregated county risk pools (ranging from 1 to six nearby counties) and conducted the analysis for each. We repeated the second step 500 times, in each case, creating a different series of missing values and replacing the data with a different aggregated data from the risk pools, and estimating new rates. Finally, we compare the rates generated in the second stage with those in the first stage, assumed to be the 'true' rates, using root mean squared error ($rmse$).

Note that the above analysis do not include the loading surcharge usually added on to the fair premium rates to enable insurers cover large losses. Acknowledging that this value can vary across the risk pool, we further investigate the degree to which the tail risk in the aggregated risk pools differ from that in the individual county risk profiles which constitute the pool, by estimating and comparing the diversification effects (DE) of the county risk pools using 'unlimited' data (without any missing) as in the first stage. Following Wang and Zhang (2003), the DE from aggregating n counties is

$$DE = \frac{BL_n^*}{n^{-1}(\sum_{i=1}^{n} BL_i)}, \tag{10}$$

where BL_i is the buffer load for county i and BL_n^* is the buffer load based on the entire geographical area created from pooling n counties. The BL is a derivative of the Buffer fund

(BF), the value at risk (VaR) of total net losses given as

$$BF = inf\{l\varepsilon R : p(\sum_{i=1}^{n} w_i.(L_{ijk} - \psi_{ijk}) \geq l) = 1 - \lambda\}, \tag{11}$$

where L_{ijk} is the indemnity, ψ_{ijk} is the corresponding actuarially fair premiums, w_i the weight of the the ith insurance policy and $1-\lambda$ is the ruin probability.[4] With the above information and ignoring loading associated with administration cost without lost of generality, $BL = BF/n$. We expect risk pools with tail risk similar to those of the individual counties in the pool to have a DE close to 1 and vice versa.

3.1 Results and Discussion

Table 2 reports 90% and 70% premium rates with projected price and higher of projected/harvest price for irrigated cotton in each county. Table 3 presents similar results for non-irrigated cotton.

Results show higher variation in rates for irrigated cotton compared to non-irrigated cotton. For example under Clayton copula, irrigated cotton rates for 90% (70%) coverage range from 4.6% (0.7%) in Lynn county to 34.8% (23.1%) in Floyd while rates for 90% (70%) coverage for non-irrigated cotton range from 9.2% (3.2%) in Lynn to 14.0% (6.4%) in Garza. Results also show that 90% (70%) premium rates for Crosby county is about 32% (52%) higher than rates in Dickens suggesting that the risk profiles for the two counties differ from one another, thus less likely to be a good proxy pool for Dickens. Recall that data was aggregated over Crosby and Dickens to rate 2015 STAX/SCO premiums for Dickens county. On average, rates based on projected prices are 1% to 14.8% (6% - 11%) higher than those based on higher of projected or harvest price for irrigated (non-irrigated) cotton. The rates estimated based on the three copulas shows high degree of similarities.

Table 4 present summary of premium rate estimates for irrigated cotton derived with

[4] We investigate two types of weights (w_i); first, we assume uniform weights across all regions and countries. Second, we weighted each county based on the proportion of planted acreage in 2014.

aggregated data from selected risk pools created by aggregating data over 2 to 7 counties. Similar results for non-irrigated cotton are presented in table 5. Estimates from each pool is a potential rate for Dickens county which had limited data.

Comparing the rates from each pool with the 'true' premium rate for Dickens county in tables 2 and 3 reveals that most of the estimates are highly different from one another. The mean rate for irrigated cotton based on the Crosby-Dickens pool (currently in effect) and the projected price using the Clayton copula is 38% (119%) higher that the 'true' rate at the 90% (70%) coverage level. Similar comparison using higher of projected/harvest price shows the rate based on the Crosby-Dickens pooled data to be 56% (169%) higher that the 'true' rate at the 90% (70%) coverage level. The county risk pool with the least biased rate is the Dickens-Crosby-Garza-Lynn pool (with 6.7% and 1.7% rate for 90% and 70% coverage, respectively) followed by the Dickens-Garza-Lynn pool (with 6.4% and 1.5% for 90% and 70% coverage, respectively). Similarly and for completeness, the mean rate for non-irrigated cotton based on the Crosby-Dickens pool and the projected price using the Clayton copula is 19% (26%) lower that the 'true' rate at the 90% (70%) coverage level. Similar comparison using higher of projected/harvest price shows the rate to be 15% (21%) lower that the 'true' rate at the 90% (70%) coverage level. The non-irrigated cotton risk pool with rate estimates apparently most similar to the the 'true' value is the Dickens-Crosby-Garza-Floyd-Lubbock-Lynn pool with 11.8% and 5.1% premium rate for a 90% and 70% coverage, respectively which is 12%-15% lower than the 'true' rate.

To shed more light on the practical implications of the results, based on recently release business summary by RMA, the total liability for STAX plans from its first year (2015) of implementation in Dickens county, rated with pooled data from Crosby and Dickens, amount to $1,347,719. Applying the rate differential implies that the 2015 STAX premiums in Dickens county only for 90% and 70% coverage levels are $35,041 and $25,607 higher than the 'true' cost, respectively. Considering these amounts to be the average differential in each of the 421 counties in 2015 where SCO/STAX is administered, results to total premium excesses of \$14,752,130 and \$10,780,404 for 90% and 70% coverage levels, respectively, with corresponding high levels of subsidies and reinsurance.

Estimates of root mean squared error under projected price ($rmse_{pp}$) and higher of projected/harvest price ($rmse_{hp}$) based on the Clayton copula reported in table 6 indeed confirm that for irrigated cotton the Dickens-Crosby-Garza-Lynn risk pool is the most efficient at the 90% coverage ($rmse_{pp}$=0.007, $rmse_{hp}$=0.008) followed by the Dickens-Crosby-Garza-Lynn pool ($rmse_{pp}$=0.012, $rmse_hp$=0.016). At the 70% coverage, the Dickens-Garza-Lynn pool is the most efficient under the projected price ($rmse_{pp}$=0.004, $rmse_{hp}$=0.006) while the Dickens-Crosby-Garza-Lynn risk pool leads under the higher of projected/harvest price ($rmse_{pp}$=0.005, $rmse_{hp}$=0.003). On the other hand, *rmse* estimates based on non-irrigated cotton reveal the Dickens-Crosby-Garza-Floyd-Lubbock-Lynn risk pool as the most efficient both at the 90% and 70% coverage levels (90%: $rmse_{pp}$=0.037, $rmse_hp$=0.041; 70%: $rmse_{pp}$=0.022, $rmse_{hp}$=0.025) followed by Dickens-Crosby-Garza-Floyd-Lynn pool (90%: $rmse_{pp}$=0.042, $rmse_{hp}$=0.048; 70%: $rmse_{pp}$=0.026, $rmse_{hp}$=0.030). These results suggest that county risk pools that are dynamic with respect to coverage level may well be needed as proxy for irrigated cotton in a given county.

Overall, the results in tables 4 and 5 show stronger dependence in the left tail than the center and right tail of the distribution, and an even greater strength in irrigated cotton than non-irrigated cotton. On average, premium rate estimates for irrigated cotton at the 90% coverage are (slightly) 1.4% higher under Frank and 0.9% higher under Gumbel than Clayton copula, whereas at the 70% coverage the rates based on Clayton copula are 10.8% and 12% higher than those based on the Frank and Gumbel copula, respectively. On the other hand, rate estimates for non-irrigated cotton at the 90% coverage are 2.4% higher under Frank and 2.3% higher under Gumbel than Clayton copula, whereas at the 70% coverage the rates based on Clayton copula are 4.8% and 5.7% higher than those based on the Frank and Gumbel copula, respectively. These results show that irrigated cotton are more risky under adverse weather conditions than non-irrigated cotton.

Overall and contrary to the above results where the rates based on projected price are generally higher, the mean premium rates based on projected price and higher of projected/harvest price are very similar to one another.

Table 7 present 90% and 70% premium rates based on projected price and higher of projected/harvest price and their corresponding diversification effects for selected aggregated county pools for irrigated cotton. Table 8 report similar results for non-irrigated cotton.

The results show that the Dickens-Crosby risk pool, with the highest DE, has the tail risk profile most similar to the two counties in the pool while the Dickens-Crosby-Garza-Floyd-Lubbock-Lynn risk pool has the least similar tail risk profile compared to each county's profile within the pool. Note that the latter pool is the most diversified pool and would have been preferred if this was a complete risk pool whereby each county in the pool is charged the same rate derived with the pooled data. Risk pool 6 (Dickens-Crosby-Garza-Lynn) and 7 (Dickens-Crosby-Garza-Lynn) which on average produce the most efficient proxy rates are respectively about 8.5% and 10.5% more diversified than risk pool 2 (Dickens-Crosby) suggesting that adding the full loading in the above analysis, which is less likely the case in practice, may produce different results. However, with non-irrigated cotton, risk pool 11 (Dickens-Crosby-Garza-Floyd-Lubbock-Lynn) selected above as the most efficient proxy to Dickens county has high DE (0.97), which is only 1% more diversified than risk pool 2 (Dickens-Crosby). Thus indicating that the ruin probability and loading of the pool is very similar to those of the constituents counties making it a more reliable proxy.

4 Conclusion

There has been substantial shift toward the demand of revenue insurance over the last decade. These programs have further been expanded under the 2014 farm bill by extending coverage to counties previously unserved with limited historical data and also introducing new county-level plans which include Supplemental Coverage Options (SCO) and Stacked

Income Protection Plan (STAX) for upland cotton growers. Due to insufficient data, premium rates for most counties where SCO/STAX is currently available are derived using proxy data, i.e., data aggregated over several counties. This study employs nested Archimedean copula-based models to investigate systemic risk across aggregated county risk pools for upland cotton in U.S and their suitability for serving as a proxy for an individual county with limited data.

Our results show substantial differences in systemic risk and premium rates across county risk pools with various geographical sizes. Premium rates based on the risk pool used by RMA in rating irrigated upland cotton in Dickens county were found to be far less reliable, with premium rates up to 56% (169%) higher that the 'true' rate for a 90% (70%) coverage level, costing about $35,000 ($26,000) more. Alternative county pools with larger geographical areas were found to be more efficient producing rates that 1.5% lower than the 'true' rates and with minimum mean squared error. These results are mostly driven by differences in systemic risk across risk pools and agricultural practices.

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Table 1: Parameter estimates of Nested Archimedean Copula

Parameter	Clayton	Frank	Gumbel
θ_0	0.103	0.457	1.000
θ_1	0.220	0.897	1.110
θ_2	2.333	6.483	2.167
θ_3	3.056	8.048	2.528
θ_4	4.067	10.172	3.033
θ_5	7.100	16.371	4.550
θ_6	11.000	24.235	6.500
θ_7	13.167	28.588	7.583

Figure 1: Local linear regression for cotton yields in Texas Counties

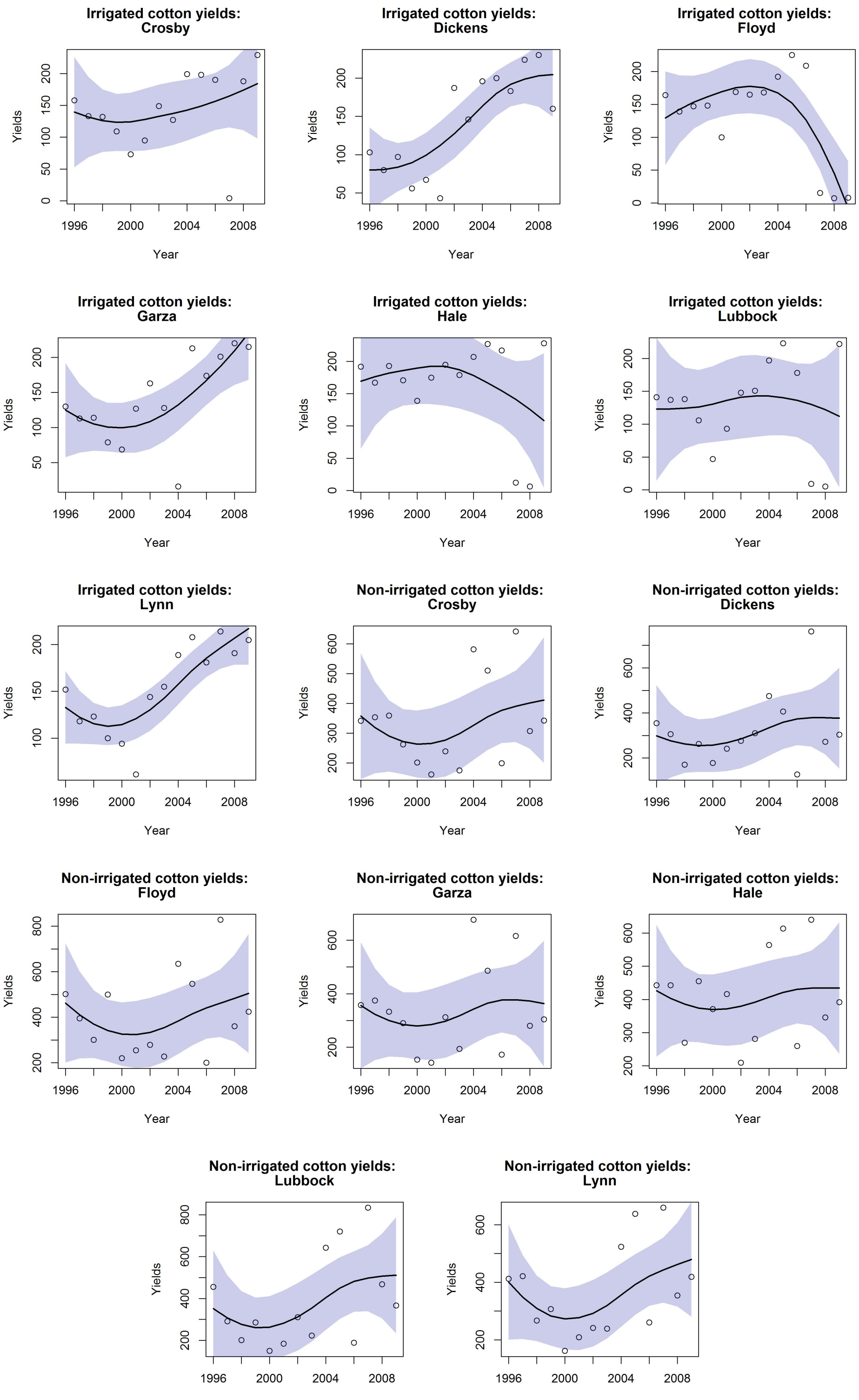

Table 2: County-level premium rates for irrigated cotton revenue insurance

	Clayton		Frank		Gumbel	
County	PR90	PR70	PR90	PR70	PR90	PR70
	Projected price					
Crosby	0.099	0.036	0.099	0.034	0.100	0.035
Dickens	0.068	0.016	0.068	0.015	0.069	0.016
Floyd	0.348	0.231	0.351	0.233	0.356	0.236
Garza	0.064	0.014	0.065	0.014	0.061	0.012
Hale	0.220	0.127	0.225	0.129	0.226	0.128
Lubbock	0.237	0.140	0.241	0.142	0.243	0.142
Lynn	0.054	0.010	0.055	0.009	0.055	0.008
Higher of projected/harvest price						
Crosby	0.092	0.032	0.092	0.030	0.091	0.030
Dickens	0.060	0.013	0.059	0.011	0.058	0.011
Floyd	0.345	0.228	0.347	0.230	0.350	0.231
Garza	0.057	0.012	0.057	0.010	0.052	0.009
Hale	0.216	0.123	0.219	0.125	0.219	0.124
Lubbock	0.233	0.137	0.236	0.138	0.237	0.138
Lynn	0.046	0.007	0.045	0.005	0.043	0.005

PR90 = Premium rate for 90% coverage, PR70 = Premium rate for 90% coverage
DE90 = Diversification effect for 90% coverage

Table 3: County-level premium rates for non-irrigated cotton revenue insurance

	Clayton		Frank		Gumbel	
County	PR90	PR70	PR90	PR70	PR90	PR70
	Projected price					
Crosby	0.116	0.047	0.118	0.047	0.116	0.045
Dickens	0.134	0.060	0.136	0.060	0.138	0.061
Floyd	0.116	0.048	0.120	0.049	0.119	0.047
Garza	0.140	0.064	0.142	0.065	0.141	0.063
Hale	0.102	0.038	0.102	0.036	0.103	0.036
Lubbock	0.120	0.050	0.123	0.051	0.122	0.050
Lynn	0.099	0.036	0.100	0.035	0.099	0.034
Higher of projected/harvest price						
Crosby	0.109	0.043	0.111	0.043	0.108	0.040
Dickens	0.128	0.056	0.129	0.055	0.129	0.056
Floyd	0.110	0.044	0.112	0.044	0.110	0.043
Garza	0.134	0.061	0.135	0.061	0.133	0.059
Hale	0.095	0.034	0.095	0.032	0.093	0.032
Lubbock	0.113	0.046	0.115	0.046	0.113	0.045
Lynn	0.092	0.032	0.093	0.031	0.091	0.029

PR90 = Premium rate for 90% coverage, PR70 = Premium rate for 90% coverage
DE90 = Diversification effect for 90% coverage

Table 4: Summary of irrigated cotton premium rates by aggregated county risk pool

	Clayton		Frank		Gumbel	
Pool	90%: mean(std)	70%: mean(std)	90%: mean(std)	70%: mean(std)	90%: mean(std)	70%: mean(std)
Projected price						
2	0.094 (0.025)	0.035 (0.016)	0.097 (0.028)	0.033 (0.017)	0.096 (0.027)	0.032 (0.017)
3	0.195 (0.063)	0.108 (0.049)	0.199 (0.064)	0.110 (0.050)	0.202 (0.066)	0.110 (0.052)
4	0.072 (0.006)	0.020 (0.004)	0.073 (0.007)	0.017 (0.004)	0.072 (0.007)	0.016 (0.004)
5	0.119 (0.031)	0.050 (0.021)	0.120 (0.030)	0.049 (0.022)	0.121 (0.030)	0.050 (0.022)
6	0.064 (0.004)	0.015 (0.002)	0.064 (0.004)	0.012 (0.002)	0.064 (0.004)	0.013 (0.002)
7	0.067 (0.003)	0.017 (0.002)	0.067 (0.004)	0.014 (0.002)	0.066 (0.004)	0.013 (0.002)
8	0.088 (0.005)	0.030 (0.003)	0.090 (0.007)	0.028 (0.004)	0.089 (0.006)	0.027 (0.004)
9	0.080 (0.004)	0.025 (0.002)	0.081 (0.004)	0.022 (0.003)	0.080 (0.005)	0.021 (0.002)
10	0.077 (0.003)	0.024 (0.002)	0.078 (0.003)	0.020 (0.002)	0.078 (0.003)	0.021 (0.002)
11	0.090 (0.004)	0.032 (0.003)	0.092 (0.005)	0.028 (0.003)	0.091 (0.005)	0.027 (0.003)
12	0.093 (0.004)	0.033 (0.003)	0.094 (0.004)	0.030 (0.003)	0.094 (0.004)	0.030 (0.003)
13	0.081 (0.003)	0.026 (0.002)	0.082 (0.004)	0.022 (0.002)	0.082 (0.003)	0.022 (0.002)
Higher of projected/harvest price						
2	0.094 (0.025)	0.035 (0.015)	0.097 (0.026)	0.033 (0.016)	0.096 (0.025)	0.032 (0.015)
3	0.195 (0.065)	0.108 (0.050)	0.199 (0.065)	0.110 (0.051)	0.202 (0.067)	0.110 (0.052)
4	0.072 (0.006)	0.020 (0.004)	0.073 (0.007)	0.017 (0.004)	0.072 (0.007)	0.016 (0.003)
5	0.119 (0.032)	0.050 (0.022)	0.120 (0.033)	0.049 (0.022)	0.121 (0.033)	0.050 (0.023)
6	0.064 (0.002)	0.015 (0.001)	0.064 (0.003)	0.012 (0.001)	0.064 (0.002)	0.013 (0.001)
7	0.067 (0.003)	0.017 (0.002)	0.067 (0.003)	0.014 (0.001)	0.066 (0.004)	0.013 (0.002)
8	0.088 (0.005)	0.030 (0.003)	0.090 (0.006)	0.028 (0.004)	0.089 (0.006)	0.027 (0.004)
9	0.080 (0.004)	0.025 (0.003)	0.081 (0.004)	0.022 (0.002)	0.080 (0.004)	0.021 (0.002)
10	0.077 (0.003)	0.024 (0.002)	0.078 (0.003)	0.020 (0.002)	0.078 (0.003)	0.021 (0.001)
11	0.090 (0.004)	0.032 (0.003)	0.092 (0.005)	0.028 (0.003)	0.091 (0.005)	0.027 (0.003)
12	0.093 (0.004)	0.033 (0.003)	0.094 (0.005)	0.030 (0.003)	0.094 (0.005)	0.030 (0.003)
13	0.081 (0.003)	0.026 (0.002)	0.082 (0.004)	0.022 (0.002)	0.082 (0.003)	0.022 (0.002)

2=Dickens-Crosby, 3=Dickens-Floyd, 4=Dickens-Garza, 5=Dickens-Floyd-Hale, 6=Dickens-Garza-Lynn, 7=Dickens-Crosby-Garza-Lynn, 8=Dickens-Crosby-Lubbock-Hale, 9=Dickens-Crosby-Garza-Floyd-Lnn, 10=Dickens-Crosby-Lubbock-Lynn-Hale, 11=Dickens-Crosby-Garza-Floyd-Lubbock-Lynn, 12=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd, 13=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd-Garza, std = standard deviation.

Table 5: Summary of non-irrigated cotton premium rates by aggregated county risk pool

	Clayton		Frank		Gumbel	
Pool	90%: mean(std)	70%: mean(std)	90%: mean(std)	70%: mean(std)	90%: mean(std)	70%: mean(std)
	Projected price					
2	0.108 (0.025)	0.044 (0.017)	0.112 (0.025)	0.042 (0.018)	0.111 (0.027)	0.042 (0.019)
3	0.112 (0.017)	0.045 (0.012)	0.114 (0.018)	0.044 (0.013)	0.114 (0.019)	0.044 (0.014)
4	0.115 (0.033)	0.049 (0.023)	0.118 (0.034)	0.048 (0.024)	0.119 (0.036)	0.048 (0.025)
5	0.079 (0.010)	0.023 (0.006)	0.079 (0.011)	0.022 (0.006)	0.080 (0.011)	0.022 (0.006)
6	0.110 (0.011)	0.045 (0.008)	0.113 (0.011)	0.044 (0.008)	0.114 (0.011)	0.043 (0.008)
7	0.114 (0.008)	0.048 (0.005)	0.117 (0.009)	0.046 (0.007)	0.117 (0.009)	0.045 (0.006)
8	0.091 (0.006)	0.032 (0.004)	0.094 (0.007)	0.030 (0.005)	0.093 (0.007)	0.029 (0.005)
9	0.116 (0.007)	0.049 (0.005)	0.118 (0.007)	0.047 (0.005)	0.119 (0.007)	0.047 (0.004)
10	0.093 (0.006)	0.034 (0.004)	0.095 (0.005)	0.031 (0.003)	0.095 (0.005)	0.031 (0.003)
11	0.118 (0.006)	0.051 (0.004)	0.123 (0.007)	0.049 (0.005)	0.121 (0.006)	0.048 (0.004)
12	0.099 (0.004)	0.037 (0.003)	0.101 (0.005)	0.035 (0.003)	0.101 (0.004)	0.034 (0.003)
13	0.104 (0.004)	0.041 (0.002)	0.106 (0.005)	0.038 (0.003)	0.106 (0.004)	0.038 (0.003)
	Higher of projected/harvest price					
2	0.108 (0.025)	0.044 (0.016)	0.112 (0.025)	0.042 (0.017)	0.111 (0.026)	0.042 (0.017)
3	0.112 (0.019)	0.045 (0.012)	0.114 (0.019)	0.044 (0.013)	0.114 (0.020)	0.044 (0.014)
4	0.115 (0.034)	0.049 (0.023)	0.118 (0.035)	0.048 (0.024)	0.119 (0.035)	0.048 (0.023)
5	0.079 (0.009)	0.023 (0.005)	0.079 (0.010)	0.022 (0.005)	0.080 (0.009)	0.022 (0.005)
6	0.110 (0.011)	0.045 (0.007)	0.113 (0.011)	0.044 (0.008)	0.114 (0.011)	0.043 (0.008)
7	0.114 (0.009)	0.048 (0.006)	0.117 (0.009)	0.046 (0.006)	0.117 (0.010)	0.045 (0.006)
8	0.091 (0.006)	0.032 (0.004)	0.094 (0.007)	0.030 (0.004)	0.093 (0.007)	0.029 (0.005)
9	0.116 (0.007)	0.049 (0.005)	0.118 (0.007)	0.047 (0.005)	0.119 (0.007)	0.047 (0.005)
10	0.093 (0.006)	0.034 (0.003)	0.095 (0.006)	0.031 (0.003)	0.095 (0.006)	0.031 (0.003)
11	0.118 (0.006)	0.051 (0.004)	0.123 (0.007)	0.049 (0.005)	0.121 (0.006)	0.048 (0.004)
12	0.099 (0.005)	0.037 (0.003)	0.101 (0.005)	0.035 (0.003)	0.101 (0.004)	0.034 (0.003)
13	0.104 (0.004)	0.041 (0.003)	0.106 (0.005)	0.038 (0.003)	0.106 (0.004)	0.038 (0.003)

2=Dickens-Crosby, 3=Dickens-Floyd, 4=Dickens-Garza, 5=Dickens-Floyd-Hale, 6=Dickens-Garza-Lynn, 7=Dickens-Crosby-Garza-Lynn, 8=Dickens-Crosby-Lubbock-Hale, 9=Dickens-Crosby-Garza-Floyd-Lnn, 10=Dickens-Crosby-Lubbock-Lynn-Hale, 11=Dickens-Crosby-Garza-Floyd-Lubbock-Lynn, 12=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd, 13=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd-Garza, std = standard deviation.

Table 6: Root mean squared error premium rates by aggregated county risk pool

	Clayton		Frank		Gumbel		Clayton		Frank		Gumbel	
Pool	$rmse_{pp}$ 90%	$rmse_{pp}$ 70%	$rmse_{pp}$ 90%	$rmse_{pp}$ 70%	$rmse_{pp}$ 90%	$rmse_{pp}$ 70%	$rmse_{hp}$ 90%	$rmse_{hp}$ 70%	$rmse_{hp}$ 90%	$rmse_{hp}$ 70%	$rmse_{hp}$ 90%	$rmse_{hp}$ 70%
	Irrigated cotton											
2	0.077	0.053	0.085	0.053	0.081	0.049	0.075	0.047	0.079	0.048	0.075	0.043
3	0.310	0.228	0.321	0.235	0.325	0.235	0.313	0.223	0.322	0.230	0.325	0.230
4	0.015	0.012	0.018	0.010	0.016	0.008	0.012	0.009	0.016	0.008	0.015	0.007
5	0.130	0.088	0.131	0.088	0.130	0.087	0.137	0.088	0.138	0.090	0.141	0.090
6	0.012	0.004	0.011	0.007	0.013	0.009	0.016	0.006	0.015	0.007	0.016	0.008
7	0.007	0.005	0.008	0.005	0.011	0.007	0.008	0.003	0.008	0.004	0.010	0.006
8	0.046	0.032	0.051	0.030	0.046	0.025	0.045	0.028	0.048	0.027	0.047	0.024
9	0.029	0.021	0.030	0.016	0.026	0.013	0.026	0.017	0.028	0.014	0.026	0.012
10	0.022	0.018	0.024	0.012	0.021	0.011	0.020	0.013	0.022	0.010	0.023	0.010
11	0.050	0.036	0.054	0.031	0.050	0.026	0.048	0.031	0.052	0.027	0.050	0.025
12	0.056	0.039	0.059	0.034	0.057	0.031	0.055	0.034	0.057	0.030	0.058	0.030
13	0.030	0.023	0.032	0.017	0.029	0.014	0.029	0.018	0.030	0.014	0.030	0.014
	Non-irrigated cotton											
2	0.077	0.049	0.074	0.053	0.080	0.056	0.081	0.052	0.080	0.053	0.087	0.059
3	0.061	0.041	0.062	0.044	0.066	0.047	0.066	0.044	0.068	0.045	0.073	0.051
4	0.078	0.053	0.080	0.056	0.084	0.057	0.082	0.054	0.083	0.055	0.084	0.057
5	0.125	0.084	0.129	0.086	0.132	0.089	0.125	0.081	0.131	0.083	0.131	0.086
6	0.058	0.038	0.055	0.040	0.058	0.043	0.068	0.044	0.064	0.044	0.068	0.049
7	0.047	0.029	0.046	0.034	0.050	0.038	0.054	0.034	0.052	0.035	0.053	0.039
8	0.096	0.062	0.096	0.068	0.102	0.072	0.101	0.065	0.103	0.069	0.106	0.074
9	0.042	0.026	0.042	0.031	0.045	0.033	0.048	0.030	0.047	0.033	0.048	0.036
10	0.093	0.059	0.092	0.066	0.097	0.068	0.100	0.063	0.098	0.067	0.099	0.070
11	0.037	0.022	0.032	0.026	0.039	0.030	0.041	0.025	0.038	0.027	0.043	0.033
12	0.078	0.051	0.079	0.057	0.083	0.060	0.084	0.054	0.086	0.058	0.086	0.062
13	0.067	0.043	0.067	0.050	0.072	0.052	0.074	0.046	0.075	0.051	0.075	0.054

$rmse_{pp}$ = Root mean squared error with projected price,
$rmse_{hp}$ = Root mean squared error with higher of projected/harvest price, 90% = 90% coverage, 70% = 70% coverage,
2=Dickens-Crosby, 3=Dickens-Floyd, 4=Dickens-Garza, 5=Dickens-Floyd-Hale,
6=Dickens-Garza-Lynn, 7=Dickens-Crosby-Garza-Lynn, 8=Dickens-Crosby-Lubbock-Hale,
9=Dickens-Crosby-Garza-Floyd-Lnn, 10=Dickens-Crosby-Lubbock-Lynn-Hale,
11=Dickens-Crosby-Garza-Floyd-Lubbock-Lynn, 12=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd,
13=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd-Garza, std = standard deviation.

Table 7: Premium rates and diversification effect of county risk pools for irrigated cotton

	Clayton				Frank				Gumbel			
Pool	PR90	DE90	PR70	DE70	PR90	DE90	PR70	DE70	PR90	DE90	PR70	DE70
Projected price												
2	0.079	0.95	0.023	0.91	0.078	0.94	0.02	0.81	0.079	0.94	0.02	0.81
3	0.079	0.88	0.022	0.66	0.08	0.89	0.02	0.62	0.081	0.89	0.021	0.62
4	0.058	0.88	0.011	0.7	0.057	0.87	0.009	0.66	0.055	0.85	0.008	0.61
5	0.113	0.86	0.043	0.68	0.116	0.87	0.04	0.64	0.117	0.86	0.04	0.62
6	0.055	0.88	0.009	0.7	0.054	0.87	0.008	0.65	0.053	0.86	0.007	0.61
7	0.06	0.86	0.012	0.68	0.059	0.84	0.01	0.59	0.058	0.84	0.009	0.56
8	0.121	0.9	0.049	0.76	0.123	0.9	0.045	0.71	0.123	0.89	0.045	0.69
9	0.063	0.83	0.013	0.59	0.062	0.82	0.011	0.51	0.061	0.81	0.01	0.48
10	0.099	0.87	0.034	0.68	0.1	0.87	0.03	0.61	0.1	0.86	0.03	0.59
11	0.074	0.79	0.019	0.53	0.075	0.79	0.016	0.46	0.074	0.78	0.015	0.43
12	0.102	0.86	0.036	0.67	0.103	0.86	0.032	0.6	0.103	0.85	0.031	0.58
13	0.085	0.8	0.024	0.54	0.086	0.79	0.021	0.48	0.085	0.78	0.02	0.45
Higher of projected/harvest price												
2	0.071	0.95	0.02	0.9	0.069	0.93	0.015	0.77	0.068	0.93	0.015	0.75
3	0.071	0.87	0.018	0.61	0.071	0.88	0.015	0.55	0.07	0.87	0.015	0.54
4	0.049	0.84	0.008	0.64	0.048	0.83	0.006	0.53	0.044	0.8	0.005	0.48
5	0.107	0.86	0.039	0.65	0.108	0.86	0.035	0.59	0.107	0.85	0.034	0.57
6	0.046	0.85	0.007	0.63	0.044	0.83	0.004	0.5	0.041	0.81	0.004	0.45
7	0.052	0.83	0.009	0.61	0.05	0.81	0.006	0.45	0.047	0.79	0.005	0.41
8	0.114	0.89	0.045	0.74	0.115	0.89	0.041	0.68	0.113	0.88	0.039	0.65
9	0.054	0.8	0.01	0.52	0.053	0.78	0.007	0.39	0.05	0.76	0.006	0.35
10	0.092	0.86	0.03	0.64	0.092	0.86	0.025	0.55	0.089	0.84	0.023	0.52
11	0.066	0.77	0.015	0.47	0.066	0.76	0.011	0.36	0.063	0.74	0.01	0.32
12	0.095	0.85	0.031	0.63	0.095	0.85	0.027	0.54	0.093	0.83	0.025	0.51
13	0.077	0.77	0.02	0.49	0.077	0.77	0.016	0.4	0.074	0.75	0.014	0.36

PR90 = Premium rate for 90% coverage, PR70 = Premium rate for 90% coverage
DE90 = Diversification effect for 90% coverage, DE70 = Diversification effect for 70% coverage
2=Dickens-Crosby, 3=Dickens-Floyd, 4=Dickens-Garza, 5=Dickens-Floyd-Hale, 6=Dickens-Garza-Lynn, 7=Dickens-Crosby-Garza-Lynn, 8=Dickens-Crosby-Lubbock-Hale, 9=Dickens-Crosby-Garza-Floyd-Lnn, 10=Dickens-Crosby-Lubbock-Lynn-Hale, 11=Dickens-Crosby-Garza-Floyd-Lubbock-Lynn, 12=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd, 13=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd-Garza.

Table 8: Premium rates and diversification effect of county risk pools for non-irrigated cotton

	Clayton				Frank				Gumbel			
Pool	PR90	DE90	PR70	DE70	PR90	DE90	PR70	DE70	PR90	DE90	PR70	DE70
Projected price												
2	0.121	0.98	0.052	0.97	0.123	0.97	0.05	0.93	0.122	0.97	0.049	0.92
3	0.121	0.97	0.051	0.97	0.123	0.97	0.05	0.94	0.123	0.97	0.049	0.92
4	0.133	0.97	0.06	0.97	0.135	0.97	0.059	0.94	0.135	0.97	0.058	0.92
5	0.096	0.83	0.034	0.7	0.098	0.83	0.031	0.64	0.097	0.81	0.03	0.62
6	0.117	0.96	0.049	0.95	0.119	0.96	0.046	0.89	0.118	0.95	0.045	0.87
7	0.116	0.96	0.048	0.95	0.118	0.96	0.045	0.9	0.116	0.95	0.044	0.88
8	0.1	0.85	0.036	0.75	0.102	0.85	0.033	0.68	0.1	0.84	0.032	0.67
9	0.115	0.97	0.048	0.96	0.117	0.96	0.045	0.9	0.116	0.95	0.043	0.88
10	0.098	0.87	0.035	0.77	0.1	0.86	0.032	0.7	0.098	0.85	0.031	0.68
11	0.116	0.97	0.048	0.96	0.118	0.96	0.045	0.91	0.116	0.96	0.044	0.88
12	0.101	0.88	0.037	0.8	0.102	0.88	0.034	0.74	0.101	0.87	0.033	0.72
13	0.104	0.89	0.039	0.82	0.106	0.89	0.037	0.76	0.104	0.88	0.035	0.74
Higher of projected/harvest price												
2	0.115	0.97	0.048	0.97	0.116	0.97	0.045	0.92	0.113	0.96	0.043	0.9
3	0.115	0.97	0.048	0.97	0.116	0.97	0.045	0.92	0.114	0.96	0.044	0.9
4	0.128	0.97	0.057	0.97	0.128	0.97	0.054	0.93	0.126	0.96	0.052	0.91
5	0.089	0.81	0.03	0.67	0.089	0.8	0.026	0.59	0.086	0.78	0.024	0.56
6	0.111	0.96	0.045	0.94	0.111	0.96	0.042	0.88	0.109	0.94	0.039	0.85
7	0.11	0.96	0.044	0.95	0.11	0.96	0.041	0.88	0.107	0.94	0.038	0.86
8	0.093	0.83	0.032	0.72	0.093	0.83	0.028	0.64	0.09	0.81	0.026	0.61
9	0.109	0.96	0.044	0.95	0.11	0.96	0.041	0.89	0.107	0.95	0.038	0.86
10	0.091	0.85	0.031	0.75	0.091	0.85	0.027	0.65	0.088	0.83	0.025	0.62
11	0.109	0.97	0.044	0.96	0.11	0.96	0.041	0.89	0.107	0.95	0.038	0.87
12	0.094	0.87	0.033	0.78	0.094	0.87	0.029	0.7	0.091	0.85	0.027	0.66
13	0.097	0.88	0.036	0.8	0.098	0.88	0.032	0.72	0.095	0.86	0.029	0.69

PR90 = Premium rate for 90% coverage, PR70 = Premium rate for 90% coverage
DE90 = Diversification effect for 90% coverage, DE70 = Diversification effect for 70% coverage
2=Dickens-Crosby, 3=Dickens-Floyd, 4=Dickens-Garza, 5=Dickens-Floyd-Hale,
6=Dickens-Garza-Lynn, 7=Dickens-Crosby-Garza-Lynn, 8=Dickens-Crosby-Lubbock-Hale,
9=Dickens-Crosby-Garza-Floyd-Lnn, 10=Dickens-Crosby-Lubbock-Lynn-Hale,
11=Dickens-Crosby-Garza-Floyd-Lubbock-Lynn, 12=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd,
13=Dickens-Crosby-Lubbock-Lynn-Hale-Floyd-Garza.