Covariate Risk and Viability of Weather Index-Insurance: The Case of African Risk Capacity

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Abstract

We investigate spatial dependence of drought and the potential for risk diversification through risk pools of countries in Africa, established by the African Risk Capacity. To model and simulate distribution of losses, we employ a two-stage process that involves a Vector autoregressive model (VAR) and Nested Archimedean Copulas (NAC). Finally, using a regional-wide rainfall insurance, we derive Buffer load (BL) and pooling effect (P.E), and investigate the viability of the risk pools. We find stronger dependence of losses in the tails, and heterogenous benefits in the risk pool, driven by covariate risk, and choice of season, rainfall index and coverage level.

Key words: Weather-index Insurance, Covariate risk, Risk pool, Africa Risk Capacity.

1 Introduction

Over the last decade, drought has been a major cause of natural disaster, and on average cost the World Food Program (WFP) about 36% for their expenses. In 2009, 2.5 billion U.S Dollars, about 63% of WFP annual budget was spend on relief efforts in Sub Saharan African. The economies of most countries in this region is agrarian with predominantly rain-fed agriculture, making this region highly vulnerable to weather risk such as drought, floods and erratic rainfall, predicted to intensify due to climate change. In addition, insurance and financial markets in this region are still in the nascent stage with less than 3% of the population having access to any form of insurance. International aid which is the main ex-post risk management mechanism, is ineffective and often trickle in several weeks after a disaster strike. These inefficiencies coupled with the absence of insurance fuels asset depletions, increase food insecurity and poverty, and threaten to roll back gains in economic development in this region.

In an effort to better manage extreme weather risk using insurance and reinsurance from international financial markets, In November of 2012, the African Union (AU) established the African Risk Capacity (ARC) Agency to pool extreme risk due to drought, floods, earthquakes and cyclone across African countries. The initial phase of the project is limited to developing a regional-wide rainfall index insurance to pool extreme drought risk across six African countries; Ethiopia, Kenya, Somalia, Niger, Senegal and Malawi. Index insurance resolves the problem of moral hazard inherent in traditional insurance but however induces basis risk which increases mismatch in payouts. Even though a cost-benefit analysis based on a set of assumptions by Clarke and Hill (2013) depicts ARC as potentially economically beneficial, little is known about its actuarial soundness. Covariate risk is inherent in agriculture and tend to exhibit stronger spatial correlation during extreme weather, resulting to significantly higher premiums and ruin probability of (re)insurer
(Cummins and Trainer, 2009). It is worth noting that surprising low participation rates and underinsurance in small scale index insurance pilots in India and Africa have been linked to

high premium rates (Giné et al., 2008; Cole et al., 2013).

While pooling risk across countries could lower premium rates for individual rated countries, the viability of the pool depends on the tail behavior of joint losses from all countries in the pool. Other factors such as agronomic traits of crops, type of weather variable, and location of crop influence the degree of correlation between weather and yields. However, stronger spatial correlation between the two tend to occur under extreme drought conditions.

In this study we investigate the spatial dependence of (extreme) rainfall in Sub-Sahara Africa, the corresponding losses based on rainfall index insurance for three crop growing seasons, and the potential effect on the solvency of risk pools established by ARC. Specifically, we investigate the effectiveness of risk pools involving five countries; Kenya, Ethiopia, Malawi, Niger and Senegal, and how the inclusion of each in the pool affects its viability. Following Wang and Zhang (2003) and Okhrin et al. (2013), we estimate and compare the required buffer fund (BF) and pooling effect (P.E) of each risk pool and how it varies with its size. Buffer Fund are reserves required to be set aside by insurers to cover losses under extreme events. This in turn affects how much additional money is charged unto fair premium (loading factor), thus the gross premium paid by the policy holder.

To model decadal rainfall amounts and capture the tail behavior of the joint loss distribution across the countries, we respectively employ a vector autoregressive model (VAR) and a copula based model. Copulas have been widely use in risk management, and are becoming popular in modeling weather patterns and pricing crop insurance. Their popularity stems from the fact that they are invariant to monotonic transformation, and the dependency structure only depends on the type of copula use and not on the distributions of its components. More so, non-Gaussian copulas can allow for lower tail dependency, upper tail dependency, or both to be capture in the model. The lower tail expresses the joint probability of drought-related losses in all countries.

While copulas present a more flexible technique for multivariate analysis, the exchangeability feature inherent in Archimedean copula implies that all margins of the same dimension are equal. This presents increasingly stronger modeling assumption with increase in the dimension of the copula. To overcome this challenge, we use nested Archimedean copulas (NAC) (Savu and Trede, 2010; McNeil and Neslehova, 2009; McNeil, 2008; Okrin et al., 2009) that allows for the construction of flexible high dimensional copulas in a hierarchical approach. In the final step, we derive draws of insurer losses from the estimated copula structures and their marginal distributions, based on specific coverage levels using a Monte Carlo simulation, estimate and compare buffer fund, loading factor, actuarially fair premiums, and pooling effect of risk pools made up of two to five countries.

The remainder of the paper is organize as follows. We proceed with a brief background on ARC. In the next section, we present the conceptual framework for the risk pool viability, the VAR model for decadal rainfall and nested Archimedean copula (NAC) for modeling spatial dependency. Data and summary of rainfall indices use to price contracts is presented in section four. The results and discussion are presented in section five, and finally we conclude with main findings, implications for the ARC and opportunities for future research.

2 Background on the African Risk Capacity (ARC)

The African Risk Capacity (ARC) Agency established by the African Union (AU) in November of 2012 is composed of two entities: the Specialized Agency and a financial affiliate company, ARC Insurance Company Limited. The Agency provides general oversight and supervise development of ARC capacity and services which include capacity building of individual countries, approving contingency plans and monitoring their implementation. The company carries out commercial insurance functions of risk pooling and risk transfer with the main objective to harness the natural diversification of weather risk across Africa, allowing countries to manage their risk as a group more timely and efficiently at a reduced cost, preventing humanitarian crises. To become a member, the national government collaborates with ARC to develop and submit an Operation Plan and a Final Implementation Plan (FIP) that would be submitted shortly before payout, which provide details on how the ARC payout would be deployed in a given situation. Upon completion, member states pay a one-time contribution to join the insurance pool, after which ARC works with them to calculate country wide premiums and allocate payout based on predetermined and transparent rules for payment. Each country chooses her coverage level, and ARC indemnity payout are targeted to reach national treasuries 2-4 weeks after harvest. Countries selected for the pilot risk pool include Ethiopia, Somalia, Kenya, Malawi, Niger, and Senegal.

3 Conceptual Framework

Covariate risk ubiquitous in crop insurance is evaluated via the required BF following Wang and Zhang (2003). This is the value at risk (VaR) of total net losses (total indemnity payout - total insurance premiums received) experienced by the insurer.

$$BF = inf\{l\varepsilon R : p(\sum_{i=1}^{n} w_i.(L(I_i) - \psi_i) \geq l) = 1 - \lambda\}, \tag{1}$$

where $L(I_i)$ is the indemnity based on the rainfall index I_i in country i, ψ_i is the corresponding actuarially fair premiums, w_i the weight of the the ith insurance policy, n=number of policies sold and $1 - \lambda$ is the ruin probability.[1] The required loading on actuarially fair premiums is derive as $BL = BF/n$. Without lost of generality, we ignore loading associated with administration cost. The risk reduction effect achieved through risk pooling across countries is evaluated using the pooling effect (PE) as

$$PE = \frac{BL_n^*}{n^{-1}(\sum_{i=1}^{n} BL_i)}, \tag{2}$$

where BL_n^* is the buffer load based on all countries in the pool while BL_i is the buffer load for country i.

[1] We investigate two types of weights (w_i); first, we assume uniform weights across all regions and countries. Second, we weighted each country's based on the proportion of arable farm land in the country

We calibrate and use two rainfall indices which we call the expected seasonal precipitation index (ESPI) and the seasonal standardized precipitation index (SSPI), i.e. $I_i = ESPI, SSPI$. The ESPI is given as

$$ESPI_{ji} = Max(\bar{R}_{ji} - R_{jit}, 0), \tag{3}$$

where $\bar{R}_{ij}$ is mean cumulative rainfall for crop growing season j in country i and R_{jit} is the observed amount at time t. Indemnity payout based on $ESPI_{ji}$ is derived as follow:

$$L_{ESPI_{jit}} = Max(G_{ESPI_{ji}} - ESPI_{ji}, 0), \tag{4}$$

where $G_{ESPI_{ji}}$ is the guaranteed level of the index or the strike point below which indemnity is triggered. In this study we investigate three different strike points; the 85, 65 and 50 percent quantile of the index distribution. On the other hand, the SSPI is given as

$$SSPI_{ji} = Max(\frac{(\bar{R}_j i - R_j it)}{sd_{R_{ji}}}, 0), \tag{5}$$

where $sd_{R_{ji}}$ is the standard deviation of cumulative rainfall for crop growing season j in country i. Indemnity payout based on $SSPI_{ji}$ is derive as follows:

$$L_{SSPI_{jit}} = Max(G_{SSPI_{ji}} - SSPI_{ji}, 0), \tag{6}$$

where $G_{SSPI_{ji}}$ is the strike point below which indemnity is triggered. We also evaluate three different strike points; the 85, 65 and 50 percent quantile of the index distribution.

Note that $ESPI_{ji}$ and $SSPI_{ji}$, and thus $L_{ESPI_{jit}}$ and $L_{SSPI_{jit}}$ are derive using jointly simulated decadal rainfall across countries in the pool. The multisite decadal rainfall model and the NAC structure estimated and use for the simulations are specified in the next section.

3.1 Multisite decadal rainfall model

We model decadal rainfall ($y_{i,t}$) observed in country (region) i at time t during a given growing season as a vector autoregressive model (VAR) in which the amounts of rainfall in each country is explain solely by their own history. In its basic form, a VAR(p)-process is define as:

$$\mathbf{y_t} = A_1\mathbf{y_{t-1}} + ... + A_p\mathbf{y_{t-p}} + B\mathbf{t} + \mathbf{v_t}, \tag{7}$$

where $\mathbf{y_t} = (y_{1t}, y_{2t}, ..., y_{Kt})$, A_i are $(K \times K)$ matrices of coefficients to be estimated for $i = 1, ..., p$, and $\mathbf{v_t}$ is a K-dimensional process with $\mathbf{E}(\mathbf{v_t}) = 0$ and a time invariant covariance matrix $E(\mathbf{v_t}\mathbf{v_t}^T) = \Sigma_{\mathbf{v_t}}$. To account for data frequency, seasonal indicator variables ($\mathbf{t}$) are included and B are their corresponding coefficients. We estimate several classes of models with different lag-order (p), and including a constant, a time trend or both. The best model is selected based on Akaike information criteria (AIC), Hannan-Quinn (HQ), Schwarz (SC) and forecast prediction error (FPE). The best and final model estimated (using ordinary least squares) is a VAR(1) that include both a time trend and a constant term. However, note that the final model does not account for spatial correlation in the data, thus the residuals from this model still contain information about on the spatial dependence of rainfall across the countries.

The joint distribution of the residuals, $v = (v_1, v_2, ..., v_n)'$ can be specify as

$$F(v) = C\{F_1(v_1), F_2(v_2), ..., F_n(v_n)\}, \tag{8}$$

where C denotes a copula (multivariate distribution) function that describes the dependency structure between $v_1, v_2, ..., v_n$, and $F_i(v_i)$ is the marginal distribution of v_i uniformly distributed on 0 and 1. Hence we can conveniently derive uniform variates (u_i) between 0 and 1 using $u_i = F_i(v_i)$ and the copula as $C(u_1, u_2, ..., u_n)$. We transform residuals at each location to uniform variates between 0 and 1 using their respective empirical cumulative distribution.

The multivariate density $f(v)$ is given as

$$f(v) = c\{F_1(v_1), F_2(v_2), ..., F_n(v_n)\} \times f_1(v_1) \times f_2(v_2) \times ... \times f_n(v_n), \tag{9}$$

Where $f_1(v_1), ..., f_n(v_n)$ are marginal densities and $c.$ is the density of $C(.)$. Our analysis dwell on exchangeable multivariate Archimedean copulas, which are widely use due to their flexibility and tractability. An n-dimensional Archimedean copulas with parametr θ can be specify as

$$C(u_1, u_2, ..., u_n; \theta) = \phi(\phi^{-1}(u_1), \phi^{-1}(u_2), ..., \phi^{-1}(u_n)), \tag{10}$$

where ϕ is a monotone decreasing generator function with $\phi(0) = 1$, $\phi(\infty) = 0$, and ϕ^{-1} is its inverse. To capture dependency in both tails of the distribution and for comparison purposes, we use three types of Archimedean copulas; Frank, Gumbel and Clayton. The later captures lower tail dependency, Gumble exhibits upper tail dependency while Frank exhibit radial symmetry. While copulas present a more flexible technique for multivariate analysis, the exchangeability feature inherent in Archimedean copula implies that all margins of the same dimension are equal. This presents increasingly stronger assumption with increase in the dimension of the data. To address this problems, more flexible approaches have been develop to handle high dimensional data without sacrificing the multivariate dependency structure using Archimedean copula. This include 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. If such entry is used alongside one additional dimension at a time, the resulting structure is fully nested.

For an n-dimensional copula for which $n \geq 3$, if

$$C(u_1, u_2, ..., u_n; \theta_0, ..., \theta_{n-2}) = \phi_0(\phi_0^{-1}(u_1) + \phi_0^{-1}(u_2, ..., u_n; \theta_1, ..., \theta_{n-2})), \tag{11}$$

then C is a fully nested Archimedean copula with $n-1$ 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 when investigating each of the three copula types considered. Thus the three structures separately considered in this study are partially nested Frank copula, partially nested Gumble copula, and partially nested Clayton copula. Figure **??** presents the nested structure derived with data from 19 regions across the five countries by rowing season. The structure for April to July and July to October seasons is each compose of 9 hierarchies with partially nested copulas of dimension 2, 4 and mostly 3. While that for December to March is made up of 7 hierarchies with partially nested copulas of dimension 2, 3 and mostly 4.

Figure 1 about here

4 Data

Observed decadal rainfall data from the first dekad of December 1999 to the 3rd dekad of May 2015 is obtained from a high spatial resolution (10 km x 10 km) famine early warning satellite system, from the National Oceanic and Atmospheric Administration (NOAA). This system was developed primarily to monitor drought in Sub-Saharan Africa, Asia, Central America and the Caribbean, and is currently use by ARC in their rate making process. Country-wide spatial data was downloaded for Kenya, Ethiopia, Malawi, Niger and Senegal. We select these countries because they constitute 5 of the 6 countries in the ARC pioneer risk pool. We are unable to obtain data for the sixth country, Somalia. To avoid dealing with extremely high dimensionality that come with grided data without sacrificing to much variability in the data, we opt to aggregate the grided data into 'sub-climatic' regions within each country. Using a hierarchical cluster, we grouped data in each country into arbitrary number of clusters and then aggregated the data in each cluster. Clustering data by season was found to produce more consistent clusters than using data for the entire year. We thus separated the data in three crop growing seasons prior to clustering. This first season runs from the first dekad in April to the 3rd Dekad in July, the second covers the first dekad of July to 3rd dekad of October, and the the third runs from the first dekad of December to the 3rd dekad of March. The number of clusters was taken as the number of main rainfall climatic zones in the country published by FAO, resulting to a total of 19 clusters and cluster-level data points; data in Kenya is grouped and aggregated into 5 clusters, Ethiopia and Senegal into 4 clusters each, and Malawi and Niger into 3 clusters each. Table 1 presents summary of the rainfall indices for each cluster, also numbered 1 to 19. We use the corresponding numbers to identify each cluster subsequently.

The results in table 1 shows that data points are heterogenous both within and across country and seasons, indicating that the clusters are distinct and can be use as proxies for climatic regions in each country. The mean ESPI for April-July, July-October, and December-March range from 2 to 188, 2 to 87, and 0.6 - 168, respectively. On the other hand, Mean SSPI for April-July, July-October, and December-March range from 0.3 to 0.5, 0.2 to 0.6, and 0.1 - 0.5, respectively. More so, the results confirm the presence of drought with a varied degree of severity within and across countries as well as seasons indicating potential for an insurance scheme and a risk pool based on the rainfall indices.

Table 1 about here

We are interested in finding out how the risk premium varies as we increase the number of countries in the risk pool. Following Okhrin et al. (2013), an initial country-wide risk pool is chosen, and subsequent (and larger) risk pools are created by adding other countries to the initial pool. However, contrary to the authors, we chose to add countries to the risk pool following their proximity to the country recently added. In addition, we also chose to use the same risk pool to evaluate both ESPI and SSPI in order to better compare the indices as the size of the pool increases. Table 1 depicts five incremental risk pools beginning with Ethiopia, and consecutively adding Kenya, Malawi, Niger and Senegal. With a viable risk pool, we expect the risk premium (buffer load) of the pool to decrease with increase in the size of the pool. The reduction in the risk premium of the risk pool relative to the risk premium of the individual countries in the pool is captured by the pooling effect (P.E). We therefore expect more viable risk pools to have both lower risk premium and P.E. compared to others.

Table 1: Country-wide Incremental Risk Pools

Risk pool ID	*Risk pool*
1	Ethiopia
2	Ethiopia, Kenya
3	Ethiopia, Kenya, Malawi
4	Ethiopia, Kenya, Malawi, Niger
5	Ethiopia, Kenya, Malawi, Niger, Senegal

5 Results and Discussion

Results of PNAC structure in figure 1 and their corresponding parameter estimates in table 3 show that locations closer to one another tend to exhibit stronger spatial dependence, however the relationship between distance and spatial dependence is not uni-directional and varies by season. For example, the strongest level of dependency between any two locations

(θ_8: April to July and July to October, and θ_6: December to March) is exhibited by locations in the same country. In the case of July to October season, we have location 17 and 19 both in Senegal. However, at the next (higher) level of the hierarchy, the strongest dependency exist between two locations in Ethiopia. On the other hand, in April to July and December to March seasons, the strongest level of dependency occurs between locations in Kenya and Niger, respectively. Okhrin et al. (2013) reported similar findings using temperature data from weather stations in China.

Figure 2 and figure 3 presents estimated BL for three coverage levels by season across the five risk pools based on ESPI and SSPI, respectively.[2]

The results show that the BL can be significantly reduced by increasing the number of countries in the pool. However, the change in BL following the addition of new members in the risk pool based on proximity, is not monotone and also depend on the season and the coverage level. Increasing the size of the risk pool based on this criteria appears to be most beneficial when the rainfall index (ESPI and SSPI) is derived for the July to October growing season, and least beneficial to the December to March growing season.

In addition, the results show some variation in BL across seasons and (expectedly) coverage level under both ESPI and SSPI. On average, the BL is highest During the July to October season and lowest in the December to March season, across all three coverage levels and risk pools. However, while the BL during July to October season drops by over 50% across all risk pools with decrease in the index-insurance strike point, the BL for December to March season remains fairly constant. At the 50% strike point across all seasons under both ESPI and SSPI, BL is minimal, thus suggesting strong potentials for gross premium reduction insuring extreme drought.

Comparing results obtain with the three copulas indicate that, overall, each type of Archimedean copula slightly under estimate and over estimate the BL in some seasons or coverage levels more than the others, and predictions from all three tend to be most similar

[2]The BL is taken as 1 percent quantile of the distribution of total net losses, meaning this loss is not exceeded 99 percent of the time.

for ESPI and SSPI based on July to October season. In addition, results depicted by ESPI and SSPI overall differ the most at the 85% insurance strike point, and tend to be more supportive with decrease in the strike point. In all, the results remain robust to the findings revealed in this study.

Tables 4, 5 and 6 presents estimates of actuarially fair premiums, buffer loads, loading factor and pooling effect based on ESPI and SSPI for April to July, July to October and December to March seasons for a risk pool of all five countries, respectively.[3] As expected, fair premiums are highest at the 85% strike point and drastically decrease with decrease in the insurance strike point for all seasons and rainfall indices. In addition, the BL for the entire risk pool significantly decreases with decrease in the insurance strike point for both ESPI and SSPI. However, the loading factor based on ESPI follows suit from the 85% strike point to the 65% strike point but blows right back up at the 50% strike point. Thus revealing stronger dependence in the tails of the distribution than the center based on ESPI.

Overall, estimates of the pooling effect show that pooling is effective in significantly diversifies risk based on ESPI and SSPI in all three seasons, however with unequal effect across seasons and most effective at the 50% trike points. Notice that the gains from pooling are least (up to 3 times less) for contracts to insure the July to October growing season. In addition, based on the P.E. estimate derived with SSPI for a 50% strike point during the July to October season, the gains in pooling measured by the proportion by which the BL for the pool is lower relative to those obtained from insuring individual countries, suggest the presence of covariate risk in the pool.[4]

Table 3 about here

Figure 2 about here

Figure 3 about here

[3]The loading is calculated as 0.06×99 percent quantile of the index.

[4]Under i.i.d losses, we expect the BL of the entire pool to decrease by 0.229 ($\frac{1}{\sqrt{19}}$). Any reduction less than this amount supports the presence of covariate risk (Okhrin et al., 2013).

Table 4 about here

Table 5 about here

Table 6 about here

6 Conclusion

In an attempt to better manage extreme weather risk in Sub Saharan Africa using insurance and reinsurance from international financial markets, the African Risk Capacity (ARC) was recently established by the African Union (A.U) to pool extreme weather risk across countries in Africa. An initial risk pool made up of five countries to insure against extreme drought risk is ongoing. However, the viability of the pool in the face of covariate risk is still unknown.

In this study, we take small but major step to investigate spatial dependence of rainfall and potential gains, if any, in diversifying risk in the pool. We employed a two-stage approach that involves modeling decadal rainfall with a VAR model, and subsequently using its residuals in a nested Archimedean copula-based model to capture joint dependence of losses in the tail, and derive estimates for buffer load and pooling effect, use to assess the viability of the pool.

We find strong spatial dependence in rainfall across regions in the pool which is however non directional with significant differences across growing seasons. Overall, we find remarkable non monotonic reduction in BL with increase in pool membership with considerable differences across seasons and coverage levels. More importantly, we find stronger dependence in the tail of the distribution than at the center at the 50% insurance strike point. Overall, P.E estimates reveal that the entire risk pool is highly effective in diversifying risk. However the benefits also vary by season, and at the 50% strike point during July to October season, we find strong presence of covariate risk in the entire pool. We also find considerable differences between the ESPI and SSPI, and some in the type of copula used.

Thus it is fair to say that there is a good potential for ARC to achieve BL and gross premium reduction by insuring the risk pool against extreme drought conditions using rainfall index insurance depending on the choice of season, coverage and weather index use in designing the contracts. In this case, insuring the entire pool from extreme drought risk during the December to March growing season at a coverage level between 65% and 50% appears to make sense.

In the future, investigating other indices such as the water requirement satisfaction index, and examining an insurance portfolio that combines different coverage levels and growing seasons will be interesting.

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