CHALLENGES OF INSURING WEATHER RISK IN AGRICULTURE

Martin Odening

Department of Agricultural Economics, Humboldt-Universität zu Berlin

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Motivation

NatCatSERVICE

Weather catastrophes worldwide 1980 – 2010
Number of events with trend

Number
1200
1100
1000
900
800
700
600
500
400
300
200
100
0


Munich RE

- Meteorological events (Storm)
- Hydrological events (Flood, mass movement)
- Climatological events (Extreme temperature, drought, forest fire)

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Outline

1. Covariate Risk
due to Systemic Weather Risk

2. Non-stationary loss distributions
due to Climate Change

3. Model Risk
due to Data Scarcity
Challenge 1: Systemic Weather Risk

Problem:

- Systemic risk can lead to a breakdown of a private crop insurance market (e.g. Duncan & Myers)

Remedies:

- Spatial diversification (Wang & Zhang)
- Time diversification (Chen & Goodwin)
- Product diversification
- Reinsurance
- Securitization (Barieu & El Karoui)
Case Study: Weather Risk in China

- Quantification of the dependence structure of weather events at different locations by means of copulas
- Is spatial diversification of systemic weather risk possible?
- Weather risk indicators: Growing Degree days; Frost Index
- Insurer‘s risk exposure: Buffer Fund
Buffer Fund

\[ BF = VaR_\alpha(NTL) \]

\[ NTL = \sum_{i=1}^{n} w_i \cdot \{L_i - \pi_i\} \]

\[ L_i = f(I_i, K_i) \cdot V \]

\[ \pi_i = E(L_i) \]

- \( BF \) = buffer fund;
- \( w \) = weight;
- \( \alpha \) = confidence level;
- \( NTL \) = net total loss;
- \( I \) = weather index;
- \( i \) = region;
- \( L \) = loss;
- \( K \) = trigger level;
- \( \pi \) = fair premium;
- \( V \) = tick value;
Flow Chart of the Computational Procedure

1. Daily temperature records
2. Standardized residuals
3. Copula
4. Simulated dependent standardized residuals of daily temperature
5. Temperature models
6. Simulated daily temperature
7. Simulated weather index for each weather station
8. Net total losses for several aggregation levels

Source: Okhrin, Odening, Xu (2012)
Location of Selected Weather Stations
Structure of Hierarchical Archimedean Copula

Source: Okhrin, Odening, Xu (2012)
Buffer Loads for Different Regional Aggregation Levels: GDD

Source: Okhrin, Odening, Xu (2012)
Conclusions

- Copulas allow a flexible modeling of the dependence structure of joint weather risks
- Significant stochastic dependence of temperature related insurance losses in China
- Systemic weather risk can be mitigated by regional diversification but is still high
- Supplementary tools for risk reduction are required
(Time) Diversification of insurance losses by multi-year insurance contracts

**Argument:** Multi-year insurance contracts can be offered at lower premia than single-year contracts due to time diversification (e.g. Chen & Goodwin 2010)

**But:** The fallacy of time diversification (e.g. Samuelson 1969); Multi-year insurance contracts are more expensive than single-year contracts due to loss of flexibility of premium adjustments

**Question:** What are the benefits of multi-year insurance contracts, if any?
Insurance Market Model
(adapted from Kleindorfer et al. 2012)

- Competitive insurance market; area yield insurance; two-period model
- Risk averse farmers; differ in basis risk
- Risk averse insurers specialized on single-year or multi-year contracts
  - MY: price constant, compensation in each period
  - SY: price in period 2 depends on loss in period 1
- Choice set farmers: MY, SY in one or both years, no insurance
- Optimal decision rule by dynamic programming
Results:
- SY and MY contracts co-exist
- choice of optimal contract depends on basis risk and risk aversion
- more farmers demand insurance if both contract types are offered

Extension:
- multiple periods
- shifting loss distribution
Challenge 2: Increasing Weather Risk

Problem:
Climate change
→ increasing weather risk
→ non-stationary loss distribution
→ historical loss models underestimate risks and rate risks incorrectly
→ insurance contract adjustment required

Remedies:
- Risk projections using climate models
- Local tests
### Classification of Statistical Tests for Changing Weather Risk

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Characteristics</th>
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<tbody>
<tr>
<td>Subject of risk measurement</td>
<td>Mean of extreme weather indices</td>
</tr>
<tr>
<td></td>
<td>Quantiles of basic weather variables</td>
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<tr>
<td>Time increment</td>
<td>Global</td>
</tr>
<tr>
<td></td>
<td>Local</td>
</tr>
<tr>
<td>Kind of change</td>
<td>Continuous</td>
</tr>
<tr>
<td></td>
<td>Jump</td>
</tr>
<tr>
<td>Statistical test procedure</td>
<td>Mann-Kendall test</td>
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<td></td>
<td>Change point test</td>
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<td></td>
<td>t-test</td>
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<td>Quantile regression</td>
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<td>Extreme value theory</td>
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</tbody>
</table>
Local versus Global Test of Changes in Monthly Rainfall (Berlin)

![Graph showing precipitation changes over time (1948-2008)]

- Observations
- 1948-2008
- 1948-1962
- 1963-1977
- 1978-1992
- 1993-2007

Precipitation (mm/month)

Time

- 1948
- 1958
- 1968
- 1978
- 1988
- 1998
- 2008
Local Test Results for GDD (Mason, Iowa)

Source: Wang et al. (2013)
Trends of Indices
C = change point test, M = Mann-Kendall Test, T = t-test

<table>
<thead>
<tr>
<th>Indices</th>
<th>GDD</th>
<th>FDI</th>
<th>CRI</th>
<th>PFI</th>
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<td>Sign</td>
<td>Test</td>
<td>From-To</td>
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<td>-</td>
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<td>1988-1989</td>
<td>+</td>
<td>M,T</td>
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</tbody>
</table>

Source: Wang et al. (2013)
10% Quantile CRI
Mason (upper panel) and Berlin (lower panel)

Source: Wang et al. (2013)
Conclusions

- The „Increasing-Weather-Risk-Hypothesis“ has to be qualified
- Local test procedures:
  → more detailed information when changes of weather conditions occur;
  → facilitate the adjustment of insurance contracts
Challenge 3: Data Scarcity

Problem:
- limited yield data
  → parameter uncertainty may increase risk loadings

Remedies:
- (daily) weather data
- crop yield models
- bootstrapping procedures
- expert knowledge
Bayesian Copula Estimation with Expert Knowledge (Arbenz & Canestraro 2012)

\[ f(\theta, \psi | O, \mathcal{E}) \propto f(\theta) \prod_{i=1}^{d} f(\psi_i) \]

prior

\[ \prod_{n=1}^{N} \left[ c(F_{\psi_1}(x_{1,n}), \ldots, F_{\psi_d}(x_{d,n}) | \theta) \prod_{i=1}^{d} f_i(x_{i,n} | \psi_i) \right] \]

likelihood of observation

\[ \times \prod_{k=1}^{K} g(\hat{\theta}_k | \theta) \]

likelihood of experts' opinions

\( \theta \): copula parameters
\( \psi \): parameters of marginal distributions
\( O \): observation set
\( \mathcal{E} \): set of expert knowledge
Area Yield Insurance for Rice Producers in China

China

Heilongjiang

Jilin

Liaoning
Elicitation of joint probabilities from insurance experts

„What is your estimate of the joint probability that a shortfall of average rice yield, which occurs less than once in a decade, is simultaneously observed in Heilongjiang and in Jilin?“
Estimation of Buffer Loads with Different Data Sets

a) estimation with regional data

1. Expert knowledge → Dependence parameters
2. Regional crop yield data → Copula → Posterior distribution of parameters → Simulated aggregated loss distribution → Buffer fund, buffer load

b) estimation with sub-regional data

1. Disaggregated crop yield data → Resampling → Empirical aggregated loss distribution → Buffer fund, buffer load

Source: Shen, Odening, Okhrin (2013)
Estimated Loss Distributions

Source: Shen, Odening, Okhrin (2013)
Estimated Loss Distributions

Source: Shen, Odening, Okhrin (2013)
Conclusion

- Expert knowledge can be combined with yield data in a Bayesian framework.
- Inclusion of expert knowledge corrects risk premia (in our application)
- Generalization of the “treatment effect” is difficult
- Increased model complexity

