Potential for Weather-Indexed Insurance in Northern China

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INTRODUCTION

- Farmers in China face various weather risks, but have few options to offset them. Weather-indexed insurance is a financial weather derivative that has promise. Compared with traditional crop insurance, it links crop yields with weather records and avoids moral hazard.
- Studies show farmers in China are interested in weather-indexed insurance, but little research focuses on constructing weather-indexed insurance in China. Crop yield and weather data are a major obstacle.
- This study estimates the effects of weather on crop yields, simulates yields using the estimated model, and constructs weather-indexed insurance according to relationship between weather records and crop yields.

STUDY AREA

- China's main corn production area, including ten districts of Inner Mongolia and two districts of Shaanxi Province in Northern China.

METHODS

- Flexible fractional polynomial (FP) method is used to capture nonlinear relation between growing degree days and corn yields. (1) \( W(G, p, \text{time}, D) = y_j = b_0 + F(G) + a_i z_{ij} + D_i + \epsilon_j \).
- Where \( F(G) \) is FP for growing degree days, \( a_i \) are other factors (precipitation, technology, fertilizers) that affect crop growth in region \( j \) during \( t \); \( b_0 \) are parameters to be estimated; \( D_i \) are time-invariant, district fixed-effects; and \( \epsilon_j \) are iid.
- Monte Carlo methods are utilized to predict average yields ('Results').
- Probability Distribution Function of corn yields is employed to construct weather-index insurance pricing function [4].

RESULTS and CONCLUSIONS

- Coefficients of gdd for the first 3 models are not significant; coefficients for #4 and #5 are significant at 1% level. Deviance differences of the two models are significant under 1% and 10% levels, and they explain 80% and 82% variation in corn yields, respectively. Among models, the FP models #4 and #5 best explain corn yields.
- In #4, precipitation in July, August and September, and time (representing technology), have significant effects on corn yields. Results for #5 are similar regarding precipitation, July precip is insignificant. Remaining variables in #4 and #5 also explain crop yield variation.
- Predicted yields from models #4 and #5 match actual average district yields quite closely (Fig. 2). Predicted yields from model 4 fit better than those from #5.
- Model 4 could be used to construct a weather-indexed insurance price function. In #4, time and July and August precipitation positively affect corn yields, but September precipitation lowers it (because crops are ripe at that time and dry weather aids harvests).
- The relation between gdd and corn yield is illustrated in Fig 3.

REFERENCES:


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Table: Estimated Model (not all variables shown)

<table>
<thead>
<tr>
<th>Model</th>
<th>( R^2 )</th>
<th>( \text{Dev.dif} )</th>
<th>Power(G)</th>
<th>( F(p) )</th>
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<tr>
<td>#1</td>
<td>0.7762</td>
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<td>1.05</td>
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</tbody>
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Fig 2: Actual average and predicted yields, 12 districts

Fig 3: Relationship between gdd and corn yields