The Development of a Weather-based Crop Disaster Program

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Motivation

- Recent efforts to provide disaster programs have been implemented through FSA (LFP, LIP, ELAP, NAP).

- Past efforts to provide area products have been unpopular.

- Crop disaster program may still provide safety net at a substantially lower cost.
  - Insurance to guard against only systemic drought risk.
  - Monitoring and administrative cost reduction.
  - Indemnity payments made earlier to reduce timing inefficiencies.
Outline

1. Introduction
2. Data
3. Yield Regressions
4. Disaster Program Efficiency
5. Concluding Remarks
Past Studies

- Weather and yields fitted to examine impacts of predicted climate change (Deschenes and Greenstone, 2007; Schlenker, Hanemann, and Fisher, 2006; Schlenker and Roberts, 2009).

- Fitted relationship to examine the impact from drought on yields (Westcott and Jewison, 2013; Yu and Babcock, 2010).

- Use weather outcomes to inform yield distributions (Cai et al., 2014; Rejesus, et al., 2015).

- Comparison of “free area insurance” versus individual insurance policies (Paulson and Babcock, 2009).
Weather and Yield Data

- Weather station data collected through NOAA’s Daily Global Historical Climatology Network (GHCN) dataset.
  - Data are aggregated to the county level.
  - For counties with less than 3 stations, nearest stations are used.
- County-level detrended yields.
- Top 5 corn production states: Illinois, Indiana, Iowa, Minnesota, and Nebraska.
Summary plots for weather and production variables for McClean County, Illinois, 1950-2014

McCLean County, Illinois (1950 - 2014)
Detrended Yield (Bushels per acre)

Annual Growing Degree Days, Apr. 1 - Sept. 30

Annual Precipitation (In Inches), Apr. 1 - Sept. 30
Yield Regression

The following indices were computed for the county, agricultural district, and state:

\[ IP_{Git} = GDD_{Git} \times (-PRCP_{Git}) \]
\[ IS_{Git} = GDD_{Git} - PRCP_{Git} \]

where

\[ GDD_{dit} = \max \left( \frac{T_{\min} + T_{\max}}{2} - 50, 0 \right) \]
\[ GDD_{Gi} = \max \left[ \frac{\left( \sum_{d=1}^{D} GDD_{dit} \right) - \text{mean}(GDD_{Gi})}{\text{std}(GDD_{Gi})}, 0 \right] \]
\[ PRCP_{Gift} = \min \left[ \frac{\left( \sum_{d=1}^{D} PRCP_{dit} \right) - \text{mean}(PRCP_{di})}{\text{std}(PRCP_{di})}, 0 \right] \]

for \( G = \) two-month time period, \( i = \) county, \( d = \) day, \( t = \) year.
Yield Regression

\[ Y_{it} = \beta_0 + \beta_1 I S_{Git} + \beta_2 I S_{Git}^2 + \beta_3 I P_{Git} + \beta_4 I P_{it} + \beta_5 I P_{it}^2 \]
\[ + \beta_6 I P_{At} + \beta_7 I P_{At}^2 + \beta_8 I P_{St} + \beta_9 I P_{St}^2 + e_{it} \]

- \( Y_{it} \) is the standardized yield deviations for county \( i \) in year \( t \).
- Regressions run separately by state.
- \( i = \text{county}, \ A = \text{Agricultural district}, \ S = \text{State} \).
Regression Results, by State, 1980-2015 (Dependent Variable: Standardized Yields)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Illinois (n=79)</th>
<th>Indiana (n=66)</th>
<th>Iowa (n=99)</th>
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<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>Standard Error</td>
<td>T-stat</td>
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<tr>
<td>Intercept</td>
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<td>0.034</td>
<td>11.557 ***</td>
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<tr>
<td>IS_AM</td>
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<tr>
<td>IS_AS^2</td>
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<td>0.047</td>
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<td>IP_AM</td>
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<tr>
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<td>0.184</td>
<td>-7.200 ***</td>
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<tr>
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<td>0.138</td>
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<td>IP</td>
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<tr>
<td>Adjusted R^2</td>
<td>0.439</td>
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</table>
Plot of actual detrended versus predicted yields for McClean County, Illinois, 1980-2015

Model Results: McClean County, IL, 1980-2014

Deviations in Detrended Yield (in bushels per acre)

Actual

Predicted

<table>
<thead>
<tr>
<th>State</th>
<th>n</th>
<th>Adjusted $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Illinois</td>
<td>79</td>
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<tr>
<td>Indiana</td>
<td>66</td>
<td>0.400</td>
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<tr>
<td>Iowa</td>
<td>99</td>
<td>0.188</td>
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<tr>
<td>Minnesota</td>
<td>58</td>
<td>0.167</td>
</tr>
<tr>
<td>Nebraska</td>
<td>77</td>
<td>0.170</td>
</tr>
<tr>
<td>All States</td>
<td>379</td>
<td>0.202</td>
</tr>
</tbody>
</table>
Yu and Babcock (2010)

\[ Y_{it} = \beta_0 + \alpha_i + \sum_{r=1}^{R} \gamma_r (CRD_r \times T) + \beta_1 DI_{it} + \beta_2 DIT_{it} + \beta_3 DI_{it}^2 + \beta_4 DIDI_{it} + e_{it} \]

- DI uses Cooling Degree Days
- Index constructed at county-level (similar results with ag. district model)

Westcott and Jewison (2013)

\[ Y_t = \beta_0 + \beta_1 T + \beta_2 PlantProgmidMay + \beta_3 TEMP_{July} + \beta_4 PRCP_{July} + \beta_5 PRCP^2_{July} + \beta_6 PRCP_{June}I(< .10) + e_t \]

- Aggregates weighted by harvested corn acres.
- Data are used from 1988 - 2012.
Schlenker and Roberts (2009)

\[ y_{it} = \int_{low}^{high} g(h)\phi_{it}(h)dh + z_{it}\delta + c_{i} + e_{it} \]

- Includes weather between March to August for corn/soybeans.
- Finely scaled data from PRISM (2.5 mile squared).
- Weather data are aggregated to county-level to match yield data.

Deschenes and Greenstone (2007)

\[ V_{it} = \alpha_{i} + \alpha_{t} + \beta_{1}X_{it} + \sum_{h} \theta_{h}f_{h}(\bar{W}_{hi}) + \alpha_{i} + e_{it} \]

- Farmland values \((V)\) is the variable of interest.
- Use PRISM weather data and aggregate to county level.
- Soil quality data are included.
- \(h\) includes linear and quadratic terms for \(PRCP\) and \(TEMP\) in January, April, July, and October.
Farm-level Simulation Methodology

- Use a simulation model based on Cooper (2010) and Cooper and Delbecq (2014).
  - County based model generates representative producer yields and prices.
  - Each run consists of 10,000 draws of price and yield deviates.
  - Generate county yields and add variability to obtain representative producer yields based on crop insurance county base rates.
Farm-level Performance

- Each state utilizes its unique regression results with county covariates.

- Individual historic and actual yields are simulated using simulation procedure from Cooper (2010) and Cooper and Delbecq (2014).

- Indemnities are received when predicted county-level yields are below county-level trigger.

- Weather program is compared to Revenue Protection at 75% coverage level.
Preliminary Results

- Effective premium under disaster program is $19.53, relative to $34.64 for RP.

- Disaster program reduces revenue CV by 16.9%, relative to 29.7% for RP.
Future Endeavors

- Deeper analysis of farm-level simulation results.
- Out-of-sample examination of model fit excluding counties and years.
- Extend analysis to include top producing states of soybeans, wheat, and cotton.
- Include estimated administrative cost of programs into analysis.
Thank you for your time.

Questions?

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