Outline

1. Motivation
2. Strength of Empirical (Panel) Studies
3. Challenges for Empirical (Panel) Studies
   - Modeling Where Crops Will Be Grown
   - Price Feedbacks
   - Modeling Adaptation Using Panel Variation
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How Good Are Statistical Models?

- Recent forecasting exercise for wheat (Asseng et al, NCC 2014)
  - Researcher were given data at beginning and throughout growing season
    - 29 crop models / 1 statistical model
  - Asked to predict wheat yield at various stages
    - Subsequently compared to actual / measured yields

  Model mean performs better than any single model
  Most crop models perform less well for very high temperatures
  Simple statistical model performed very well!

Money ball: Parsimonious models can be very good predictors

Average predicted reduction in yields
- 6% for 1°C increase in temperature
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Source: Asseng et al. (2014): Table S4 - HSC experiment
How Good Are Statistical Models?

Source: Asseng et al. (2014): Table S5 - CIMMYT experiment
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Link between Weather and Yields

- Last decade has seen many new micro-level panel studies
  - Statistical advantages of using panel variation
    - Avoids omitted variable bias of time-invariant variables
  - Easy to conduct out-of-sample forecasts for different years
    - Models perform very well for years besides the ones used in estimation
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- Most models assume time separability
  - Trick: allows for highly nonlinear model of temperature
  - Number of variables given by nonlinear function, not days of year
    - Sum nonlinear function over all days of growing season
    - Example: restricted cubic splines (local third-order approximations)
    - Number of variables are given by knots (# of knots - 1)
US Corn Yields 1990-2014

Effect on Annual Log Corn Yield

Ozone Exposure for 100hrs

-0.7 -0.6 -0.5 -0.4 -0.3 -0.2 -0.1 0

Spline in Ozone Exposure  Linear Above 65ppb
Advances: Relaxing Separability

- Corn Yields in Africa [Slides]
- Rice Yields in Asia [Slides]
- Wheat Trials in Kansas [Slides]
- Error Correction Model [Slides]
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Adapting Crops to a Warmer Climate

- Seems difficult in a given location
  - Same results in panel and cross-section of Farmland Values
  - Same results in panel and when looking at trends (Burke and Emerick, 2015)
  - Comparable sensitivities in different climatic zones
  - Newer varieties seem more, not less sensitive to extreme heat

Changes in comparative advantage (Costinot, Donaldson & Smith, 2014)

- Soils not as good in higher latitudes
- Last glacial expansion scraped off good top soil
- Non-uniform warming (higher latitudes warm more)
- Sunlight restrictions

Wolfram Schlenker (Columbia and NBER)
Econometric Studies
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- More likely outcome
  - Shift where crops are grown
  - Change in comparative advantage (Costinot, Donaldson & Smith, 2014)
  - Forecasts for new areas difficult for panel model (what are fixed effects)?
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Emerging consensus that climate change will reduce output in existing areas
- Might actually be good for farmers, but bad for consumers!
- Nature achieves what government supply restrictions tried to achieve
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Price-feedbacks and consumer surplus
- Agricultural goods are a global market
- Aggregate supply and demand is what matters
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Price-feedbacks and consumer surplus
- Agricultural goods are a global market
- Aggregate supply and demand is what matters

We have more and more micro-level studies
- Aggregate them up to get combined response function
- Can be used to better model production shifts
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Adaptation to Extreme Heat

- Envelope theorem
  - First-order effect of climate = weather effect

- For non-marginal changes, need to “continuously” adjust first-order effect
  - Can do that in nonlinear panel model

- Thought experiment (Butler and Huybers, 2013)
  - Are hotter places less sensitive to extreme heat?
  - Can we assume that with climate change places will adapt?
    - Places that are currently cold will reduce sensitivity when they warm
    - But is reduction in sensitivity costless?
  - Can model adaptation cost in nonlinear panel models
Adaption to Extreme Heat: Changing Sensitivity

Yield vs. Extreme Heat

Schlenker, Roberts, and Lobell (2013)
Adaption to Extreme Heat: Changing Sensitivity

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Impact Without Adaptation
Modeling the Benefit of Adaptation

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## Impacts of 2°C Warming

### Panel A: Model using Log Yields as Dependent Variable

<table>
<thead>
<tr>
<th>Reference Model</th>
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<th>Weighted Impact (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Effect of Heat</td>
<td>Mean (1a) -16.5%</td>
<td>Min (1b) -67.6%</td>
</tr>
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</table>

Sensitivity to Heat Varies (Model 2)
- Impact without Adaptation
- Impact with Adaptation

Robustness vs Average Yield
- Costly Adaptation

### Panel B: Model using Yields as Dependent Variable

Reference Model
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4. Yields in Africa

5. Rice Yields in Asia

6. Kansas Wheat Trials

7. Cross-Section in US Farmland Values
Lobell, Bänzinger, Magorokosho, and Vivek (Nature Climate Change, 2011)

- Unique data set of field trials
  - 123 research stations
    - CIMMYT
  - Testing for drought conditions

- Matched with closest weather station
  - Better than gridded weather data
  - Authors split season into three phases (separate coefficients)

- Major results
  - Find nonlinearity effect of temperature on yield
  - Stronger under drought conditions
Location of Field Trials

Source: Lobell, Bänzinger, Magorokosho & Vivek (2011)
Regression Coefficients for Temperature

Source: Lobell, Bänzinger, Magorokosho & Vivek (2011)
Outline

4 Yields in Africa

5 Rice Yields in Asia

6 Kansas Wheat Trials

7 Cross-Section in US Farmland Values
Rice Yields in Asia

- Welch, Vincent, Auffhammer, Moya, Dobermann & Dawe (PNAS, 2010)
- Rice field trials through South-eastern Asia
- Matched with weather station
  - Authors split season into three phases (separate coefficients)
- Major results
  - Effect varies by growing phase
  - Maximum and minimum temperatures have opposite effects
    - Higher maximum temperatures are beneficial
    - Lower minimum temperatures are harmful
Location of Field Trials

Regression Coefficients for Temperature

Outline

4  Yields in Africa

5  Rice Yields in Asia

6  Kansas Wheat Trials

7  Cross-Section in US Farmland Values
Wheat in Kansas

- Tack, Barkley, and Nalley (PNAS, 2015)

- Unique data set of field trials
  - Kansas wheat variety field trials
    - 1985-2013
    - September - May growing season (split in fall, winter, spring)

- Matched with field-level weather data
  - Using full distribution between minimum and maximum temperature gives much better fit

- Major results
  - Biggest driver of yield losses: freezes and extreme heat
  - Climate change reduces freeze damage, increase damage from extreme heat
  - Newer varieties more sensitive to extreme heat than older varieties
Wheat in Kansas: Weather Effects

Wheat in Kansas: Warming Scenarios

Can crop switching save the day?

Cross-sectional analysis of farmland values
  - Accounting for extreme heat
  - Limit to Eastern United States

Similar results
  - Large negative effect of extreme heat
  - Robust to myriad of specification checks
    - Different census years
    - Permutations of other control variables
Predicted Changes under Hadley III

<table>
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<th>Variable</th>
<th>2020–2049 Average (%)</th>
<th>2070–2099 Average (%)</th>
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<tr>
<td>Degree days (8–32°C)</td>
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<td>Precipitation</td>
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<td>Std. error, total impact</td>
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<td>(4.85)</td>
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<td>Degree days (8–32°C)</td>
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<td>-67.67</td>
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<tr>
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<td>(4.75)</td>
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<td>-69.31</td>
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<td>(4.86)</td>
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<tr>
<td>Total impact</td>
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<td>-60.38</td>
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<tr>
<td>Std. error, total impact</td>
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<td>(5.61)</td>
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Predicted Changes under Hadley III - Yield Panel