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The Cumulative Costs of Climate Change

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London School of Economics

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Some Like It Cold: The Persistent Cost of Higher Temperatures in the Economic Sectors of Europe
Some Like It Cold: The Persistent Cost of Higher Temperatures in European Economic Sectors

Ben Groom (University of Exeter)
Manuel Linsenmeier (LSE)
Sefi Roth (LSE & IZA)

Climate Adaptation Research Symposium – UCLA
September 2021
• There is growing evidence that weather conditions can have significant implications to human health and well-being

• As temperatures are predicted to continue rising over this century, it is important to understand what are the effects of warmer weather on the economy
  • Bottom-Up
  • Top-Down

• Previous studies have documented a negative link between high temperature and changes in aggregate economic production (e.g. GDP growth)

• The design of adequate policies and more precise estimates of the costs of higher temperature require a more detailed understanding of the link between temperature and economic activity across different industries and subnational geographies
In this Paper

- We examine the effects of temperature fluctuations on the growth rate of Gross-Value Added (GVA) across different industries and subnational regions in Europe.

- Focus on heterogeneous responses to temperature shocks depending on the local climate and the persistence of these shocks.
  - We also look at spatial spillover effects, heterogeneity across seasons, and adaptation but I will not present it today.

- Use rich socioeconomic and climate data of more than one thousand small administrative districts in Europe across industries.

- We exploit year-to-year fluctuations of annual mean temperature within district across Europe.
We find negative effects of warmer-than-average years on total economic output in relatively cold districts (annual mean temperatures < 13 degrees C).

This effect is also persistent, reducing output in several consecutive years after an initial temperature shock.

We find little evidence for any effect of higher annual mean temperature on total economic output at annual mean temperatures above 13 degrees Celsius.

Examining individual industry groups, we show that the negative effect of higher annual mean temperatures on the growth rate of total is mainly coming from the following industries: manufacturing, construction, agriculture, and mining and utilities.
Outline

- Related Literature
- Data
- Empirical Strategy
- Main Results
- Conclusions
Related Literature

• Macro Level: Several studies have examined the effect of annual mean temperature on aggregate economic output (Dell et al., 2014; Burke et al., 2015; Kalkuhl and Wenz, 2020)

• Micro Level: this strand of literature has documented impacts of daily temperature levels on labour supply (Graff Zivin and Neidell, 2014), labour productivity (Behrer and Park 2020), health (Deschenes and Greenstone, 2011), and other socioeconomic outcomes (Carleton and Hsiang, 2016)

• Recently, evidence on the effects of temperature on productivity in China (Zhang et al., 2018) & India (Somanathan et al., 2018; Colmer, 2020), and a study on economic output across several industries in the US (Colacito et al., 2019)
Data

- We use data on GVA by industry from EUROSTAT and the OECD. The data is provided at the level of nuts-3 administrative districts in Europe (nuts-2 for Turkey) and the territorial 2 level of the OECD.

- For data on temperature and precipitation we use high-resolution reanalysis data. The data is based on reanalysis of the ECMWF and spatially refined using the model COSMO. The data has a resolution of about 6 km. We aggregate it to administrative districts using gridded population data from the Gridded Population of the World dataset.
Empirical Strategy

• We estimate fixed-effects models with the growth rate of gross-value added (either total or for a specific industry) as our outcome variable and use polynomials of annual mean temperature as our treatment.

• More formally, we estimate the following models:

\[
\log(y_{i,t}) - \log(y_{i,t-1}) = \sum_{j=1}^{k} \beta_j (T_{i,t})^j + \gamma_1 P_{i,t} + \gamma_2 (P_{i,t})^2 + \alpha_i + \theta_t + \epsilon_{i,t}
\]  

(1)

\[
\log(y_{i,t}) - \log(y_{i,t-1}) = \sum_{l=0}^{s} \sum_{j=1}^{k} \beta_j (T_{i,t-l})^j + \gamma_1 P_{i,t} + \gamma_2 (P_{i,t})^2 + \alpha_i + \theta_t + \epsilon_{i,t}
\]  

(2)
Main Results (1)

Predicted effect of annual mean temperature on

a. national GDP per capita

b. subnational GVA per capita for European countries

- Predicted effect of $T$
  - World
  - European countries

- Annual mean temperature (degree C)
Main Results (2)

Marginal effect of annual mean temperature on GVA per capita

[Map of Europe with color coding and graphs showing marginal effects and histograms]
Main Results (3)

**a.** Instantaneous effect

- Marginal effect of $T$
  - Annual mean temperature (degree C)
  - Quadratic model
  - Cubic model
  - Quartic model

**b.** Quadratic model

- Instantaneous effect
- Cumulative effect (6 lags)
Main Results (4)

(a) Instantaneous and (b) cumulative marginal effect (6 lags) at different levels of annual mean temperature (0, 10, 20 °C)
Conclusions

- We estimated the link between annual mean temperature and GVA across regions and industries in Europe.
- Our study shows that in Europe the most important dimension of the temperature - economy relationship is the cost of warming in cold regions.
- Importantly, we show that this effect is also persistent, reducing output in several consecutive years after an initial temperature shock.
- In Europe (at least), some like it cold.
Sandy Dall’erba
Professor, University of Illinois at Urbana-Champaign

U.S. Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit
U.S. INTERSTATE TRADE WILL MITIGATE THE NEGATIVE IMPACT OF CLIMATE CHANGE ON CROP PROFIT

Sandy Dall’erba, Zhangliang Chen, Noe Nava

Dept. of Agricultural and Consumer Economics & Center for Climate, Regional, Environmental and Trade Economics (CREATE), University of Illinois

(100% solar-powered presentation)

With financial support from USDA NIFA 2015-67023-23677
Motivations

- Climate change leads to more frequent and intense extreme weather events (IPCC, 2021) and growing world population => increasing concerns about food security

- Spillover effects in the Ricardian literature are often ignored

  Mendelsohn et al. (1994); Deschênes and Greenstone (2007); Le (2009); Schlenker and Roberts (2009); Schlenker et al. (2005, 2006): \( \frac{\partial y_i}{\partial C_i} = \beta \) and \( \frac{\partial y_i}{\partial C_j} = 0 \)

  Exceptions: Polsky (2004), Seo (2008), Dall’Erba and Dominguez (2015): \( \frac{\partial y_i}{\partial C_j} \neq 0 \) (geography, trade, surface water)

- Spatial econometric work with endogenous \( W \) still uncommon and focus on time-invariant \( W \)

  Kelejian and Piras (2014); Qu and Lee (2015); Bramoullé et al. (2009).

- Int’l trade allows impacted countries to offset their own production losses with imports

  (Costinot et al. 2016; Reimer and Li, 2009; Schenker, 2013) **but nothing at the domestic level**
What percentage of the U.S. agricultural production is exported?

a) 11.1%

b) 21.1%

c) 41.1%

What percentage of the U.S. intermediate and final demand for agricultural goods is imported?

d) 8.3%

e) 28.3%

f) 48.3%

2014 data, WIOD (2016)
Introduction: Preview of Methods and Results

• The First Question / First stage (the sensitivity of trade flows to drought)
  
  
  => Exports are negatively affected by droughts in the origin state.
  
  => Exports are positively affected by droughts in the destination state.

• The Second Question / Second stage (the sensitivity of agricultural profit to local and external droughts)
  
  o SLX model: \[ y_{it} = \alpha + \beta'X_{it} + \delta_1 D_{it} + \delta_2 \sum_j W_{jt} + \lambda + \eta_t + \epsilon_{it} \]
  
  o Ricardian approach (Mendelsohn et al. 1994, Deschênes and Greenstone, 2007; Fisher et al. 2012)
  
  ⇒ Profit increases when the trade partners experience a drought

Overall, trade more than offsets the negative impact of future weather conditions on profits.
Interstate Trade Flows: data sources and summary

- **Freight Analysis Framework Version 4 (FAF⁴)** of the Bureau of Transportation Statistics based on (CFS) Oak Ridge National Lab

- Focus on US interstate trade because:
  - **Crops, fruits and vegetables**: 18% of the production is exported; 13% of the intermediate and final consumption is imported (United Nations, 2017)
  - **All agricultural commodities**: 11.1% of the production is exported; 8.3% of the intermediate and final consumption is imported (WIOD, 2016) – 8.8% and 8.1% including food manufacturing.

### Summary Statistics (average over the period)

<table>
<thead>
<tr>
<th></th>
<th>Min.</th>
<th>1st.Qu</th>
<th>Median</th>
<th>Mean</th>
<th>3rd.Qu</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Export_ratio &lt;sup&gt;1&lt;/sup&gt;</td>
<td>0.2544</td>
<td>0.5189</td>
<td>0.5189</td>
<td>0.5150</td>
<td>0.5923</td>
<td>0.8894</td>
</tr>
<tr>
<td>Import_ratio &lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.1052</td>
<td>0.4273</td>
<td>0.5379</td>
<td>0.5120</td>
<td>0.6346</td>
<td>0.9592</td>
</tr>
</tbody>
</table>
Interstate Trade Flows: Trade Volume (in 2012 prices)
Interstate Trade Flows: Trade Partners
Interstate Trade Flows: focus on Nebraska

2007 Agricultural Trade Flows (NE)

2012 Agricultural Trade Flows (NE)
**Drought:** definitions and classifications

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Possible Impacts</th>
<th>Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>Palmer Drought Severity Index (PDSI)</strong></td>
<td><strong>CPC Soil Moisture Model (Percentiles)</strong></td>
</tr>
<tr>
<td>D0</td>
<td>Abnormally Dry</td>
<td>Going into drought:</td>
<td>-1.0 to -1.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• short-term dryness slowing planting, growth of crops or pastures</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Coming out of drought:</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• some lingering water deficits</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• pastures or crops not fully recovered</td>
<td></td>
</tr>
<tr>
<td>D1</td>
<td>Moderate Drought</td>
<td>Some damage to crops, pastures</td>
<td>-2.0 to -2.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Streams, reservoirs, or wells low, some water shortages developing or imminent</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Voluntary water-use restrictions requested</td>
<td></td>
</tr>
<tr>
<td>D2</td>
<td>Severe Drought</td>
<td>Crop or pasture losses likely</td>
<td>-3.0 to -3.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Water shortages common</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Water restrictions imposed</td>
<td></td>
</tr>
<tr>
<td>D3</td>
<td>Extreme Drought</td>
<td>Major crop/pasture losses</td>
<td>-4.0 to -4.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Widespread water shortages or restrictions</td>
<td></td>
</tr>
<tr>
<td>D4</td>
<td>Exceptional Drought</td>
<td>Exceptional and widespread crop/pasture losses</td>
<td>-5.0 or less</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Shortages of water in reservoirs, streams, and wells creating water emergencies</td>
<td></td>
</tr>
</tbody>
</table>

Short-term drought indicator blends focus on 1-3 month precipitation. Long-term blends focus on 6-60 months. Additional indices used, mainly during the growing season, include the USDA/NASS Topsoil Moisture, Keetch-Byram Drought Index (KBDI), and NOAA/NESDIS satellite Vegetation Health Indices. Indices used primarily during the snow season and in the West include snow water content, river basin precipitation, and the Surface Water Supply Index (SWSI). Other indicators include groundwater levels, reservoir storage, and pasture/range conditions.
July 31st drought maps (% of territory with PDSI <-3)

Intensity:
- Yellow: D0 Abnormally Dry
- Orange: D1 Moderate Drought
- Brown: D2 Severe Drought
- Red: D3 Extreme Drought
- Dark Red: D4 Exceptional Drought

2002: 63.26%
2007: 36.18%
2012: 70.85%
Drought: data (NARR)

From **monthly** PDSI data for each county \( c \) to **yearly** severe drought days of state \( s \)

\[
\text{Severe drought days}_s = \sum_{c \text{ in state } s} \left[ \left( \sum_{m : M_i} 1(PDSI_{c,m} < -3) \right) \times 30 \right] \times \frac{\text{cropland}_c}{\text{total cropland}_s}
\]

**This new variable** reflects:
- Extensiveness: captured by weighting scheme.
- Severity: use \((-3)\) as the cut-off to disregard moderate droughts.
- Timing: \( M_1 = \) all months; \( M_2 = \) months in growing season (April-Sept.); \( M_3 = 3 \) months before harvest
Structural Gravity Model: reduced-form specification (Head and Meyers 2014; Yotov et al. 2016)

\[ \text{EX}_{ijt} = \alpha_n + H_{ii} \beta + \text{BORDER}_{ij} \beta_1 + \text{TIME}_{ij} \beta_2 + Y_{it} \beta_3 + \Pi_{it} \beta_4 + E_{jt} \beta_5 + P_{jt} \beta_6 + DD_{it} \beta_7 + DD_{jt} \beta_8 + R_{it} \beta_9 + R_{jt} \beta_{10} + DGT_{it} \beta_{11} + DGT_{jt} \beta_{12} + \epsilon_{ijt} \]

with \( \epsilon_{ijt} = \gamma_{IJ} + \mu_t + \varepsilon_{it} \) or \( \epsilon_{ijt} = \gamma_{IJ} + \tau_{jt} + \partial_{It} + \varepsilon_{it} \)

\( t = \) year index (1997, 2002, 2007, 2012); \( n = 9,216 \)

- \( \text{EX}_{ijt} \) = bilateral trade flow of crops, fruits, veggies from \( i \) to \( j \) (FAF4)
- \( H_{ii} \) = home state fixed effect
- \( \text{BORDER}_{ij} = 1 \) if exporter and importer are contiguous;
- \( \text{TIME}_{ij} = \) travel time by road (log);
- \( Y_{it} = \) agricultural GDP in exporter \( i \) (BEA)
- \( \Pi_{it} = \) (MLRT) exporter \( i \)'s ease of market access to all \( j \);
- \( E_{jt} = \) food manufacturing GDP in importer \( j \) (BEA)
- \( P_{jt} = \) (MLRT) importer \( j \)'s ease of market access from all \( i \);
- \( \text{DD} = \) growing season degree days: April-September (NARR);
- \( \text{R} = \) growing season rainfall (NARR)
- \( \text{DGT} = \) severe drought days (NARR)
- \( I, J = \) exporter (importer) climate zone index
9 U.S. Climate Zones (Source: NOAA)
<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th></th>
<th>PPML</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Common border</td>
<td>1.611**</td>
<td>1.617**</td>
<td>1.015**</td>
<td>1.006**</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.15)</td>
<td>(0.23)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>Travel time</td>
<td>-1.920**</td>
<td>-1.911**</td>
<td>-0.607**</td>
<td>-0.631**</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.13)</td>
<td>(0.12)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Drought days (orig.)</td>
<td>-0.044+</td>
<td>-0.061+</td>
<td>-0.03</td>
<td>-0.029</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Drought days (dest.)</td>
<td>0.055*</td>
<td>0.002</td>
<td>0.069**</td>
<td>0.089*</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>GDP (orig.)</td>
<td>1.358**</td>
<td>1.366**</td>
<td>0.772**</td>
<td>0.781**</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.09)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>GDP (dest.)</td>
<td>1.026**</td>
<td>1.024**</td>
<td>0.456**</td>
<td>0.458**</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Remoteness index (orig.)</td>
<td>2.650**</td>
<td>2.694**</td>
<td>1.152*</td>
<td>1.189**</td>
</tr>
<tr>
<td></td>
<td>(0.41)</td>
<td>(0.42)</td>
<td>(0.46)</td>
<td>(0.46)</td>
</tr>
<tr>
<td>Remoteness index (dest.)</td>
<td>3.208**</td>
<td>3.291**</td>
<td>0.446</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>(0.42)</td>
<td>(0.45)</td>
<td>(0.64)</td>
<td>(0.73)</td>
</tr>
<tr>
<td>Degree days (orig.)</td>
<td>-0.021</td>
<td>0.019</td>
<td>0.15</td>
<td>0.117</td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td>(0.28)</td>
<td>(0.35)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Degree days (dest.)</td>
<td>0.874**</td>
<td>1.021**</td>
<td>0.535</td>
<td>0.597</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.27)</td>
<td>(0.36)</td>
<td>(0.38)</td>
</tr>
<tr>
<td>Precipitation (orig.)</td>
<td>-0.347*</td>
<td>0.008</td>
<td>-0.148</td>
<td>-0.144</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.20)</td>
<td>(0.17)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Precipitation (dest.)</td>
<td>0.199</td>
<td>0.419*</td>
<td>0.505**</td>
<td>0.723**</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.21)</td>
<td>(0.19)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Home by year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Climate zone dyadic FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Climate zone by year FE (exporter and importer)</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Num. of obs.</td>
<td>6,401</td>
<td>6,401</td>
<td>9,216</td>
<td>9,216</td>
</tr>
<tr>
<td>Adj. R squared</td>
<td>0.551</td>
<td>0.568</td>
<td>0.827</td>
<td>0.834</td>
</tr>
</tbody>
</table>

Note: The dependent variable is interstate trade flows of crops. Standard errors in parentheses.

*p < .10,

**p < .05,

***p < .01.
## Robustness checks

<table>
<thead>
<tr>
<th>Benchmark (from column 4 of table 2)</th>
<th>Drought days in the origin state</th>
<th>Drought days in the destination state</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimates</td>
<td>Standard error</td>
</tr>
<tr>
<td>(1) use USDA farm production region</td>
<td>0.03</td>
<td>(0.25)</td>
</tr>
<tr>
<td>(2) use one side exporter/importer-by-year FEIs</td>
<td>-0.03</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(3) trade flows for cereal grain only (SCTG02)</td>
<td>-0.03</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(4) trade flows for other crops only (SCTG03)</td>
<td>-0.03</td>
<td>(0.03)</td>
</tr>
<tr>
<td>(5) trade flows in volume measure (SCTG02)</td>
<td>-0.04</td>
<td>(0.05)</td>
</tr>
<tr>
<td>(6) trade flows in volume measure (SCTG03)</td>
<td>-0.03</td>
<td>(0.03)</td>
</tr>
<tr>
<td>(7) drought during growing season</td>
<td>-0.04</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(8) drought during last 3 months before harvest</td>
<td>-0.00</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(9) add total population and crop stock</td>
<td>-0.03</td>
<td>(0.04)</td>
</tr>
<tr>
<td>(10) add ethanol and biodiesel capacity</td>
<td>-0.04</td>
<td>(0.05)</td>
</tr>
</tbody>
</table>

Note: The dependent variable is interstate trade flows of crops. Details of the estimates appear in tables A1–A3.

+ $p < 0.10$,

* $p < .05$,

** $p < .01$
Extensive margin

A

drought
- 3 month before harvest
- full year

extensive margin (number of trade partner)
Intensive margin

B

intensive margin (million dollar per partner)

drought

- 3 month before harvest
- full year

EX_SCTG02  EX_SCTG03  IM_SCTG02  IM_SCTG03
Ricardian approach: Basic Principle

- Different from the production function of one type of crop (McCarl et al., 2008; Lobell et al., 2008; Schlenker and Roberts, 2009). (“Dumb farmer”, Upper bound)

- Ricardian approach (“Clairvoyant farmer”. Lower bound). It accounts for adaptation and adjustment costs without modeling them explicitly (Mendelsohn et al., 1994).

![Graph showing Ricardian approach with profits per acre on the y-axis and temperature on the x-axis. Points A, B, and C represent different activities, with Activity 2 having a peak profit function at C. The hedonic function is also shown.](image-url)
Ricardian approach: Basic Model

\[
\text{ag\_profit}_i = X_i'\beta + \sum \theta_j f_j(T_{ij}) + \epsilon_i \quad \epsilon_i \sim N(0, \sigma^2) 
\]

Dependent variable: agricultural profit
Can also be farmland value

Control variables:
Soil conditions and Human Intervention

Climate variables: many functional forms e.g. quadrics average temp. and rainfall, degree-days, temp. bins.

Vast literature on US agriculture only:

[Dep. Var.: Agricultural profit]
Kelly et al. (2005); Deschênes and Greenstone, (2007); Fisher et al. (2012).

[Dep. Var.: Farmland value]
Ricardian approach: specification

\[ y_{it} = \overline{EX}_{i,t} \beta + DGT_{it} \theta + W_{it} \delta + X_{it} \gamma + v_i + v_{it} + \epsilon_{it} \quad \epsilon_{it} \sim F(0, \sigma^2_{\epsilon}) \]

\( i = 48 \) states, \( l = 9 \) climate regions, \( t = 4 \) years (1997, 2002, 2007, 2012), \( n = 192 \)

\( y \) = agricultural profit from crop, fruits, veggies production before subsidy [Census of Agriculture] (sales - costs)

\( \overline{EX} \) = (log of) predicted export from the first step

DGT = severe drought days [NOAA]

W = other weather variables: growing season degree days (and squared value), growing season rainfall (and squared value) [NARR]

X = Other controls: (log of) per capita income, density, density^2 [BEA]

\( v_i \) = state FE

\( v_{it} \) = climate zone \( \times \) year FE
## OLS results

<table>
<thead>
<tr>
<th></th>
<th>(1) No trade</th>
<th>(2) No trade</th>
<th>(3) Trade</th>
<th>(4) Trade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drought</td>
<td>0.091</td>
<td>0.235</td>
<td>0.198</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.17)</td>
<td>(0.14)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>GDD</td>
<td>-0.062</td>
<td>-0.096</td>
<td>-0.186</td>
<td>0.135</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.29)</td>
<td>(0.16)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>GDD squared</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Precipitation</td>
<td>4.461</td>
<td>26.764*</td>
<td>4.905</td>
<td>25.098*</td>
</tr>
<tr>
<td></td>
<td>(9.04)</td>
<td>(14.10)</td>
<td>(8.46)</td>
<td>(13.14)</td>
</tr>
<tr>
<td>Precipitation squared</td>
<td>-0.174</td>
<td>-0.619</td>
<td>-0.131</td>
<td>-0.612*</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.38)</td>
<td>(0.27)</td>
<td>(0.35)</td>
</tr>
<tr>
<td>Per capita income</td>
<td>10.179</td>
<td>18.935</td>
<td>9.241</td>
<td>9.991</td>
</tr>
<tr>
<td></td>
<td>(12.83)</td>
<td>(16.48)</td>
<td>(12.01)</td>
<td>(15.51)</td>
</tr>
<tr>
<td>Per capita income squared</td>
<td>-0.123</td>
<td>-0.207</td>
<td>-0.141</td>
<td>-0.165</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.16)</td>
<td>(0.12)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Density</td>
<td>3.461*</td>
<td>4.216*</td>
<td>3.326*</td>
<td>3.392*</td>
</tr>
<tr>
<td></td>
<td>(1.50)</td>
<td>(1.77)</td>
<td>(1.41)</td>
<td>(1.66)</td>
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<tr>
<td>Density squared</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
<td></td>
<td>(-0.001)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td><strong>Total exports</strong></td>
<td>0.038**</td>
<td>0.045**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-298.014</td>
<td>-858.921</td>
<td>-147.364</td>
<td>-776.66</td>
</tr>
<tr>
<td></td>
<td>(450.80)</td>
<td>(718.06)</td>
<td>(423.31)</td>
<td>(669.57)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Climate zone by year FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>192</td>
<td>192</td>
<td>192</td>
<td>192</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.50</td>
<td>0.63</td>
<td>0.57</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is crop growers' profit. Standard errors in parentheses.

*p < .10

*p < .05

*p < .01
Ricardian approach: Marginal effects

- Marginal effects of drought on agricultural profits
  - without interstate trade:
    \[
    \frac{\partial y_i}{\partial DTG_i} = \theta \quad \text{and} \quad \frac{\partial y_i}{\partial DTG_j} = 0
    \]
  - with interstate trade:
    \[
    \frac{\partial y_i}{\partial DTG_i} = \theta + \beta \times \sum_j \frac{\partial \hat{X}_{ij}}{\partial DTG_i} \quad \text{and} \quad \frac{\partial y_i}{\partial DTG_j} = \beta \times \sum_j \frac{\partial \hat{X}_{ij}}{\partial DTG_j}
    \]
- Two benefits of introducing trade
  - Spatial heterogeneity: droughts have different impacts on different places.
  - Spatial spillover: drought in location \(i\) has an impact in other places \(j\).
Total effect on (local) profit / acre of one extra week of local severe drought: \( \frac{\partial y_i}{\partial DTG_i} = \theta + \beta \sum_j \frac{\partial X_{ij}}{\partial DTG_i} \)
Average effect on local profit /acre of one extra week of severe drought in the trade partners: \( \frac{\partial y_i}{\partial DTG_j} = \beta \times \sum_j \frac{\partial \hat{X}_{ij}}{\partial DTG_j} \)
For temperature and precipitation, we use 4 combinations of RCM-GCM: CRCM-CCSM, CRCM-CGCM, MM5I-CCSM and RCM3-GFDL.

- GCMs are: the Community Climate System Model; the Third Generation Coupled Global Climate Model; the Geophysical Fluid Dynamics Laboratory. All based on the 4th IPCC’s SRES A2 scenario: 870ppm CO2 and +3.5°C by 2100.
- RCMs are: the Canadian Regional Climate Model (v.4); the Hadley Centre Regional Model (v.3); the Pen. State University NCAR Mesoscale Model.

For drought, we use the future PDSI data of Dai and Zhao (2017). Have been used in Zhao and Dai (2017); Huang et al. (2017); Trenberth et al. (2017)

Ricardian approach:
future weather conditions (2038-2070 w.r.t. 1968-2000)
$14.5$ billion mitigation effects of domestic trade:
Projected change in profit with trade ($3.3$ billion profit) - Projected change in profit without trade ($11.2$ billion loss)
Conclusion and Discussions

- Domestic **food security** and **political isolationism** (e.g. 2019-2020 trade war with China)

- Study the role of interstate trade in a Ricardian model using a panel dataset of 48 continental US states and 4 census years.

- A gravity model predicts the interstate trade flows and allows some climate variables to have an **indirect effect** on local agricultural profit.

- Projections highlight that interstate trade more than compensate for the adverse effect of future weather conditions in the US ($14.5 billion effect).

- Corroborate the conclusions at the international level: Reilly and Hohmann (1993); Costinot *et al.* (2016); Dall’erba *et al.* (2021)
U.S. Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit

Sandy Dall’Erba, Zhangliang Chen, and Noé J. Nava

According to the current Intergovernmental Panel of Climate Change report, climate change will increase the probability of occurrence of droughts in some areas. Recent contributions at the international level indicate that trade is expected to act as an efficient tool to mitigate the adverse effect of future climate conditions on agriculture. However, no contribution has focused on the similar capacity of trade within any country yet. The U.S. is an obvious choice given that many climate impact studies focus on its agriculture and around 90% of the U.S. crop trade is domestic. Combining a recent state-to-state trade flow dataset with detailed drought records at a fine spatial and temporal resolution, this paper highlights first that trade increases as the destination state experiences more drought and inversely in the origin state. As a result, crop growers’ profits depend on both local and trade partners’ weather conditions. Projections based on future weather data convert the crop grower’s expected loss without trade into expected profit. As such, this paper challenges the estimates of the current climate impact literature and concludes that trade is expected to act as a $14.5 billion mitigation tool in the near future.

Key words: Agricultural profit, drought impact evaluation, intranational trade.

JEL codes: F14, F18, Q52.

Recent decades have witnessed an increase in the frequency and intensity of extreme weather events, and the latest report of the Intergovernmental Panel on Climate Change predicts that this trend should continue in the near future. Agriculture, the economic sector...
Pierre Mérel
Professor, UC Davis

Reckoning Climate Change Damages Along an Envelope
Reckoning Climate Change Damages Along an Envelope

Matthew Gammans†

Pierre Mérel‡

Emmanuel Paroissien*

† Agricultural, Food and Resource Economics, Michigan State University
‡ Agricultural and Resource Economics, University of California Davis
* INRAE-ALISS, France

Climate Adaptation Research Symposium
UCLA Luskin Center for Innovation
September 8–9, 2021
Identifying sectoral climate damages after adaptation

Since the 1990s, a rich literature has sought to estimate climate damages using historical data

**Empirical challenge:** adaptation may mitigate climate damages

- Examples in agriculture: crop/varietal selection, shift in growing season, irrigation infrastructure, multiple cropping
- So the impact of climate is conceptually different from the impact of weather

**Estimand:** Effect of climate inclusive of adaptation on an outcome

- Example: GDP, land value, agricultural production, etc.
- Without price changes (no trade adjustments)
- “What would be the impact of climate change on the value of US agricultural output, at current prices, after agents have adapted to the new climate?”
Emerging line of thought:
- Cross-sectional studies are irremediably plagued with OV bias
- Panels grant clean (and large) exogenous variation in weather
- But weather \( \neq \) climate

Envelope Theorem (ET): a central result of optimization theory
- Agents’ adaptation actions are taken \textit{with a purpose}
- ET then implies \textit{tangency} between
  - the (unobserved) \textit{value function} that allows for adaptation (outer envelope)
  - the (more easily observed) \textit{objective function} when actions are optimal

\[
\text{marginal climate impact} = \text{marginal weather impact}
\]
Marginal weather impacts are inclusive of adaptation if:

- Adaptation effects are continuous (Guo and Costello, 2013)
- In the long run, agents actually maximize the outcome at expected weather (i.e., climate)
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But agents plausibly maximize the expected outcome

\((\mathcal{P}_1) : \max_a \mathbb{E} y(X, a)\) instead of \((\mathcal{P}_0) : \max_a y(\mathbb{E} X, a)\)
Marginal weather impacts are inclusive of adaptation if:

- Adaptation effects are continuous (Guo and Costello, 2013)
- In the long run, agents actually maximize the outcome at expected weather (i.e., climate)

But agents plausibly maximize the expected outcome

\[(P_1) : \max_a E_y(X, a) \quad \text{instead of} \quad (P_0) : \max_a y(E_X, a)\]

We show that, under \((P_1)\):

- A systematic ET result still obtains if and only if the 2\(^{nd}\)-order effects of weather on the outcome \(y\) are independent of agents’ actions \((a)\), i.e.:

\[y(X, a) = \Gamma(X) + \Psi(a)X + \Phi(a)\]
Empirical implications

Any impact estimate $\hat{\beta}$ identified from weather fluctuations reflects, at best, the local (marginal) impact of climate after adaptation.

Consider a non-marginal climate change, say $\Delta \mu = +2^\circ C$

- $\Delta Y = \hat{\beta} \Delta \mu$ only if $Y$ is linear
- In general, $\Delta Y$ is the integral of $Y'$ from $\mu_0$ to $\mu_0 + \Delta \mu$

Estimating $\Delta Y$ thus requires a collection of estimates of $Y'$, i.e., marginal weather impacts $\hat{\beta}_\mu$, estimated at different climates $\mu$ (Hsiang, 2016)

Once the weather/climate variables (e.g., temperature) have been chosen, estimation of the long-run response is “model-free”
Agriculture is arguably the sector most impacted by climate change.

Ongoing discussion around the adaptation-inclusive impact of climate change on US agriculture (Mendelsohn et al., 1994; Schlenker et al., 2005; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Fisher et al., 2012; Deschênes and Greenstone, 2012; Burke and Emerick, 2016; Mérel and Gammans, 2021)

Our data:

- US county-level agricultural GDP (source: Bureau of Economic Analysis)
- Counties east of the 100th meridian, without irrigation
- Almost balanced panel of 1,308 counties, 2001–2017
- Weather data from PRISM
Joint estimation of local weather impacts

Model (1) assumes time-invariant locational climate $\mu(i)$:

$$y_{it} = \alpha_i + \alpha_t + f_{\text{state}(i)}(t) + \beta_{\mu(i)} x_{it} + \epsilon_{it}$$  \hspace{1cm} (1)

- $\beta_{\mu}$ is the local marginal effect of weather at $\mu$

Model (2) allows for time-varying locational climate $\mu(i, t)$:

$$y_{it} = \alpha_i + \alpha_t + f_{\text{state}(i)}(t) + \beta_{\mu(i,t)} x_{it} + \epsilon_{it}$$  \hspace{1cm} (2)

Model (3) adds state-specific weather slopes:

$$y_{it} = \alpha_i + \alpha_t + f_{\text{state}(i)}(t) + \beta_{\mu(i,t)} x_{it} + \gamma_{\text{state}(i)} x_{it} + \epsilon_{it}$$  \hspace{1cm} (3)

- Identification of $\beta_{\mu}$ relies on comparisons of counties with themselves under different climates as well as cross-comparison of counties but within states
Weather and climate variables

We consider 2 weather indicators measured over April–October:

- Average temperature
- Cumulative precipitation

Climate at any point in time is computed as

$$\mu_{it} = \frac{\sum_{s=t-30}^{t-1} x_{is}}{30}$$

For Model (1), climate is fixed and computed as

$$\bar{\mu}_i = \frac{\sum_{t=2001}^{2017} \mu_{it}}{17}$$

For each climate variable, we divide the spectrum of observed climates into 100 climatic intervals (bins)

- Each bin includes about 13 counties
Geographical distribution of climate bins in Model (1)

(a) Temperature

(b) Precipitation
Long-run responses to climate

Benchmark: quadratic in temperature and precipitation

(0) Benchmark  (1) Stat. climate  (2) Rolling climate  (3) State slopes

Legend:  
- 95% CI with state-clustered SEs  
- 95% CI with Conley SEs
Simulated impact of a $+2^\circ C$ scenario

(0) Benchmark  (1) Stat. climate  (2) Rolling climate  (3) State slopes

Each dot corresponds to a county. The gray segments represent 95% confidence intervals using Conley standard errors.

Aggregate estimates vary from -5% to -10% with SEs around 3.5
Estimates of weather effects may identify climate impacts if agents:

- follow \((P_0) : \max_a y(\mathbb{E}X, a)\)
- follow \((P_1) : \max_a \mathbb{E}y(X, a)\) and cannot alter 2nd-order weather impacts

In favorable cases:

- Only the local marginal effect of climate is identified
- Recovering the response function requires:
  - Estimates of the marginal effect at adjacent climates
  - Integrating these over the counterfactual range of climates

Our illustration on US Ag. GDP suggests a 10% drop under a +2°C warming scenario


Emerging Research on Financial Adaptations to Climate Impacts

Wading into the Economic Impacts of Climate Change on Water

Equitable Adaptation to Climate-Related Flood Risks: Part 2

Up next – 10:15-11:45am PT
Thanks for joining us!
The session will begin shortly.

Thanks for tuning in!