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The Cumulative Costs of Climate Change

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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

Introduction

- 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 centaury, 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

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In this Paper

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- 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

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Preview of Results

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- 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 form the following industries: manufacturing, construction, agriculture, and mining and utilities

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Outline

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- 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)

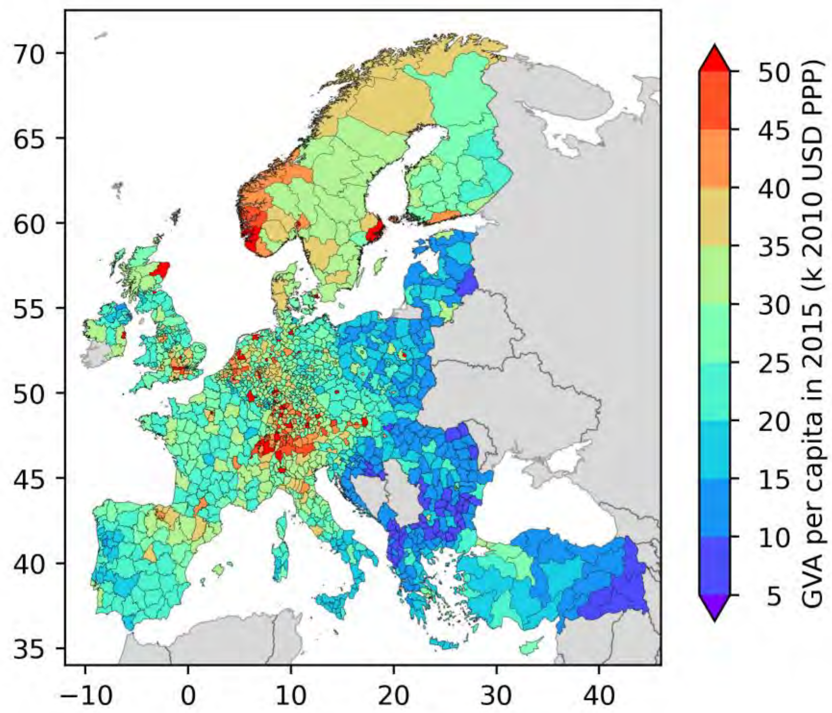
Data

- 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

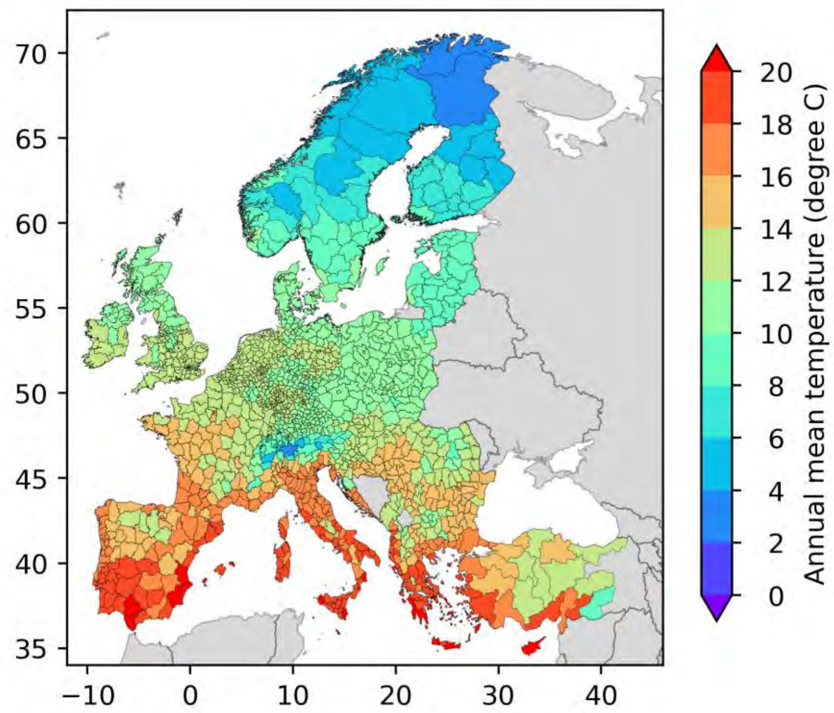
- For data on temperature and precipitation we use high-resolution reanalysis data. The data is based on reanalysis of the ECMWF and spatially refined using the model COSMO. The data has a resolution of about 6 km. We aggregate it to administrative districts using gridded population data from the Gridded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

Data

GVA Per Capita



Temperature (C)



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:

$$log(y_{i,t}) - log(y_{i,t-1}) = \sum_{j=1}^{k} \beta_j \left(\overline{T}_{i,t}\right)^j + \gamma_1 \overline{P}_{i,t} + \gamma_2 \left(\overline{P}_{i,t}\right)^2 + \alpha_i + \theta_t + \epsilon_{i,t} \quad (1)$$

$$log(y_{i,t}) - log(y_{i,t-1}) = \sum_{l=0}^{s} \sum_{j=1}^{k} \beta_j \left(\overline{T}_{i,t-l}\right)^j + \gamma_1 \overline{P}_{i,t} + \gamma_2 \left(\overline{P}_{i,t}\right)^2 + \alpha_i + \theta_t + \epsilon_{i,t} \quad (2)$$

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Main Results (1)

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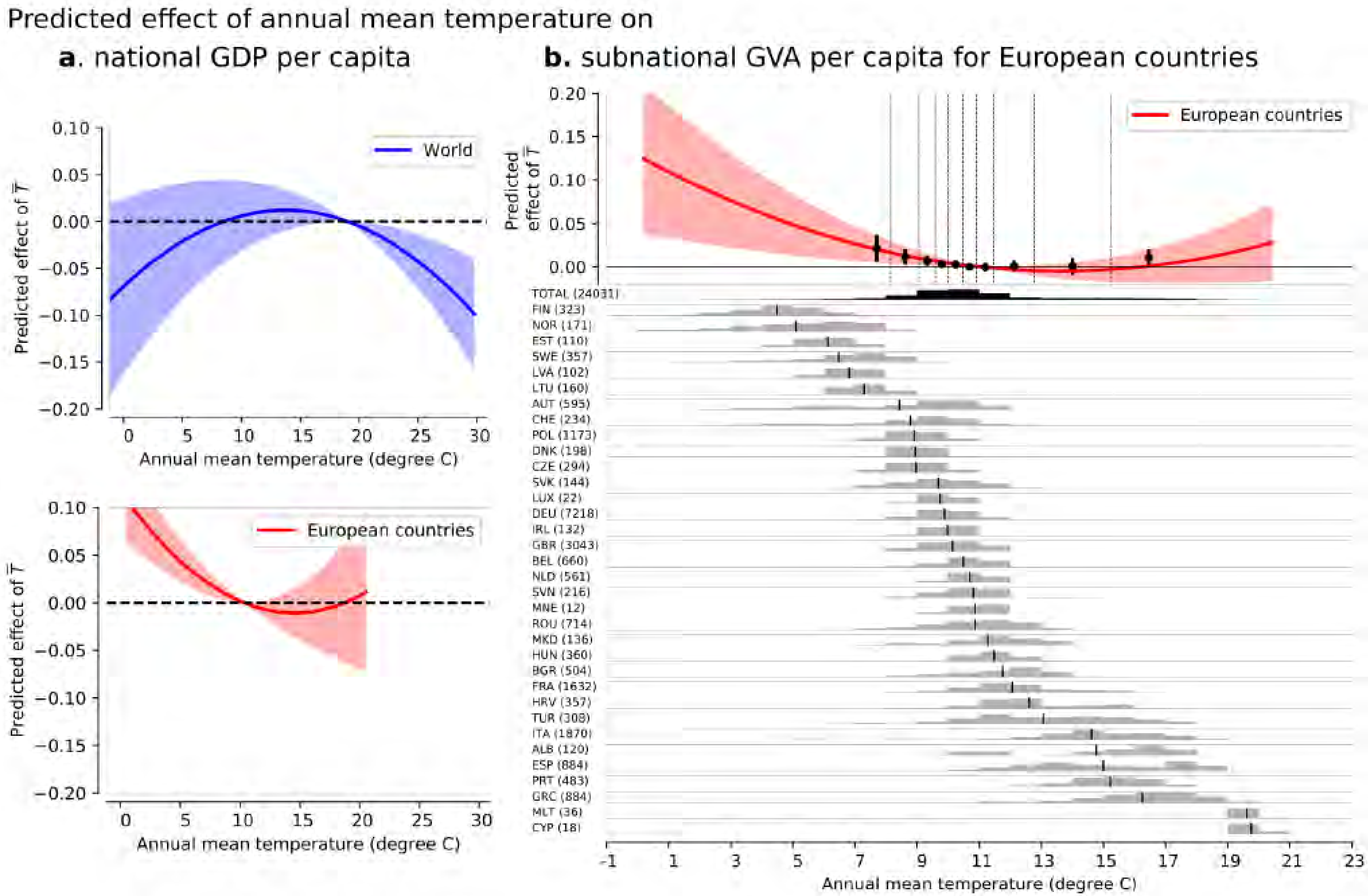

Main Results (2)

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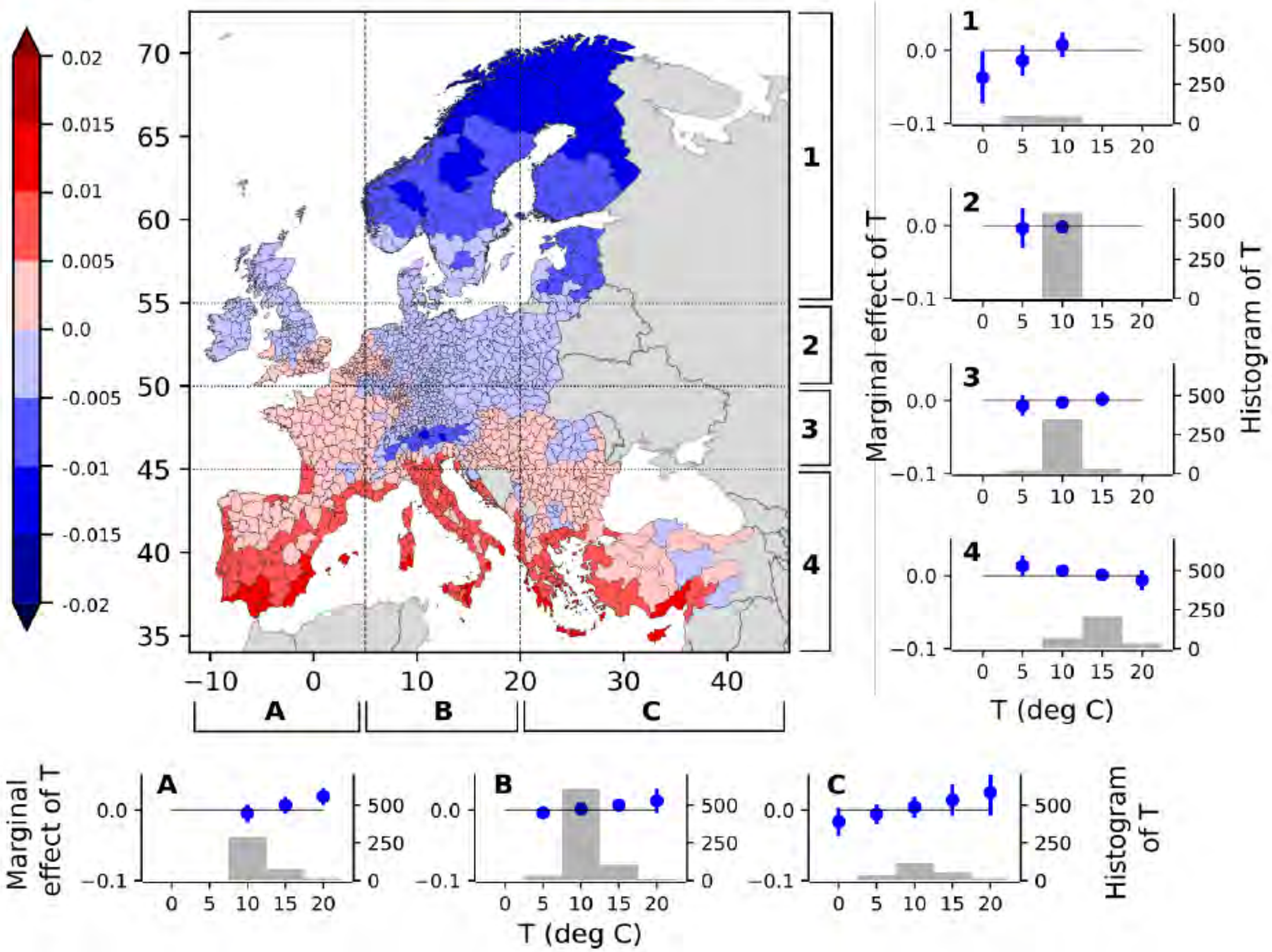
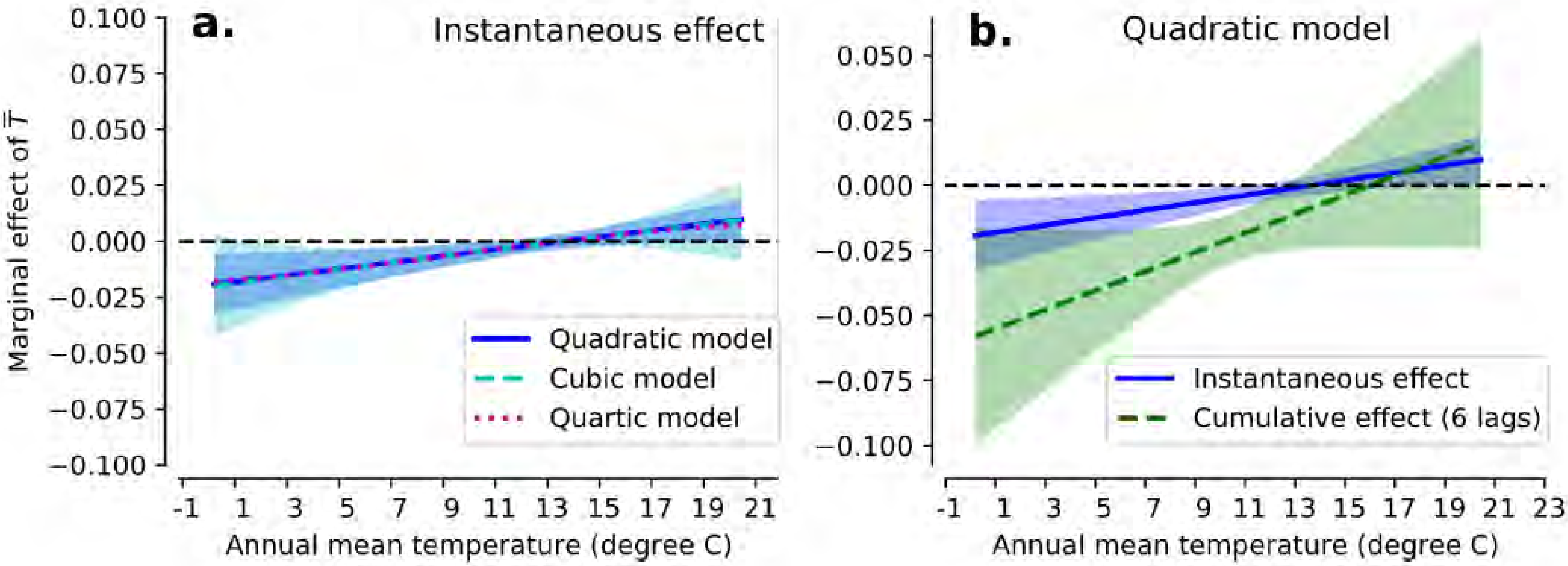
Marginal effect of annual mean temperature on GVA per capita

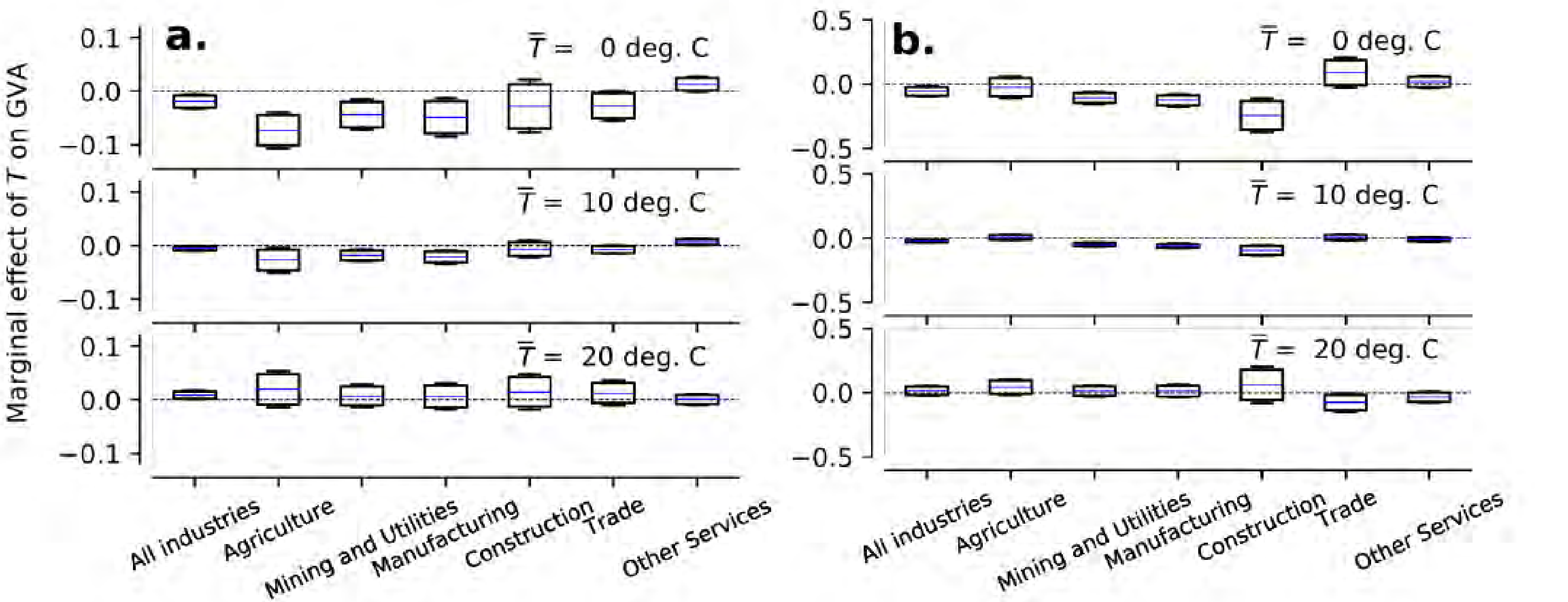


Main Results (3)



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

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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): $\partial \mathrm{y_i}/\partial \mathrm{C_i} = \beta$ and $\partial \mathrm{y_i}/\partial \mathrm{C_j} = 0$

Exceptions: Polsky (2004), Seo (2008), Dall'Erba and Dominguez (2015): $\partial \mathrm{y_i}/\partial \mathrm{C_j} \neq 0$ (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)
  - Structural gravity model (Anderson and Van Wincoop 2004, Eaton and Kortum 2003; Head and Meyers 2014; Yotov et al. 2016, Reimer and Li 2009, Ferguson and Gars, 2017)

  => 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)
  - SLX model: $y_{it} = \alpha + \beta' X_{it} + \delta_1 D_{it} + \delta_2 \sum_j \widehat{W_{jt}} + \lambda_i + \eta_t + \varepsilon_{it}$
  - Ricardian approach (Mendelsohn et al. 1994, Deschênes and Greenstone, 2007; Fisher et al. 2012)

  $\Rightarrow$ **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** (FAF^4) of the Bureau of Transportation Statistics based on (CFS) Oak Ridge National Lab
- Domestic trade flow data of major crops, fruits and vegetables (sum of SCTG section 2 and 3) measured in 1997, 2002, 2007, 2012

- 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)

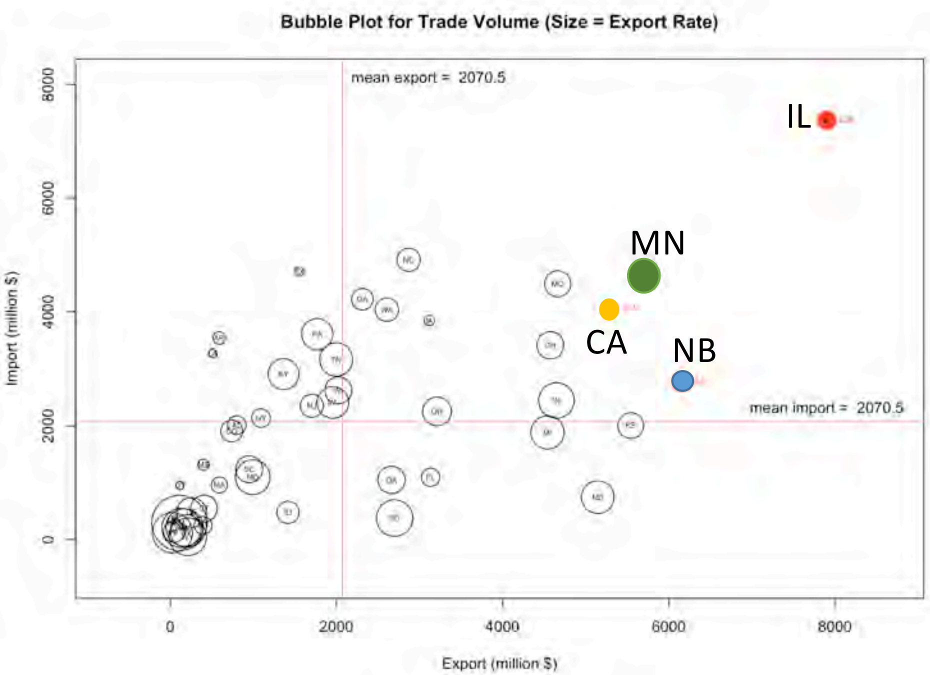
All agricultural commodities: 11.1% of the production is exported; 8.3% of the intermediate and final consumption is imported (WIOD, 2016) – 8.8% and 8.1% including food manufacturing.

Summary Statistics (average over the period)

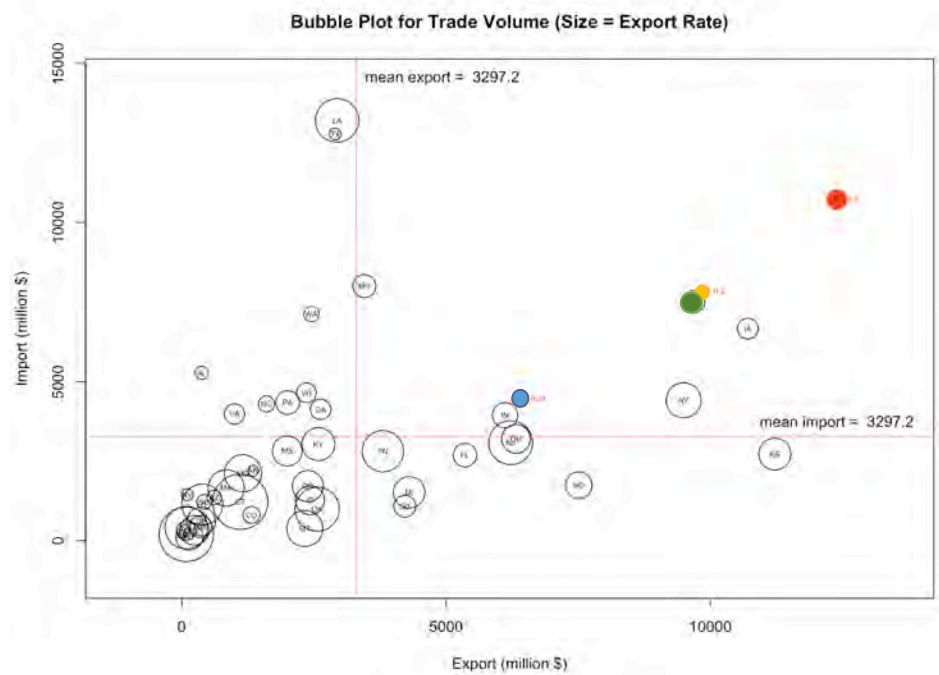
		Min.	1st.Qu	Median	Mean	3rd.Qu	Max.
Export_ratio	$\mathrm{ER_i} = 1 - \frac{\mathrm{T_{ii}}}{\sum_j \mathrm{T_{ij}}}$	0.2544	0.5189	0.5189	0.5150	0.5923	0.8894
		Min.	1st.Qu	Median	Mean	3rd.Qu	Max.
Import_ratio	$\mathrm{IR_i} = 1 - \frac{\mathrm{T_{ii}}}{\sum_j \mathrm{T_{ji}}}$	0.1052	0.4273	0.5379	0.5120	0.6346	0.9592

Interstate Trade Flows: Trade Volume (in 2012 prices)

2007 Agricultural Trade Flows

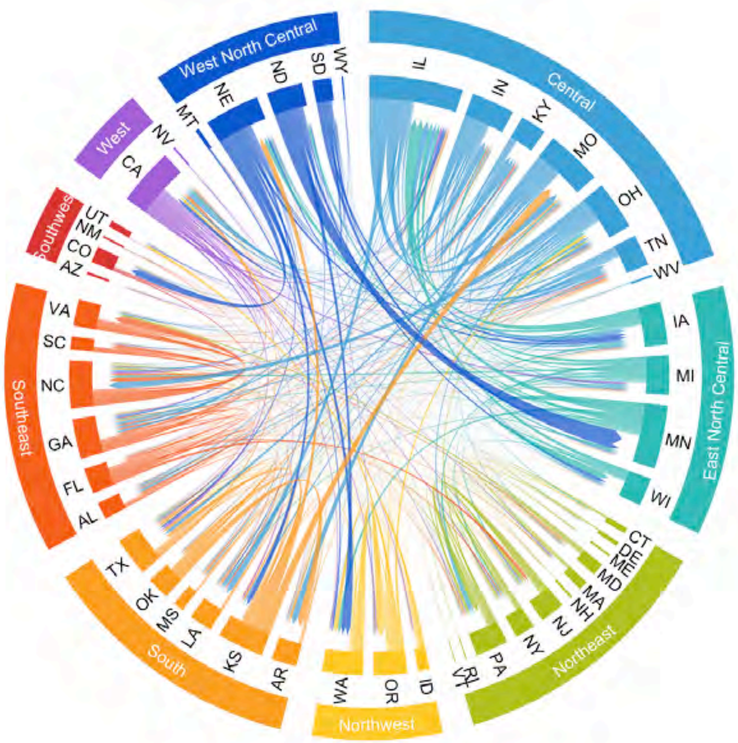


2012 Agricultural Trade Flows

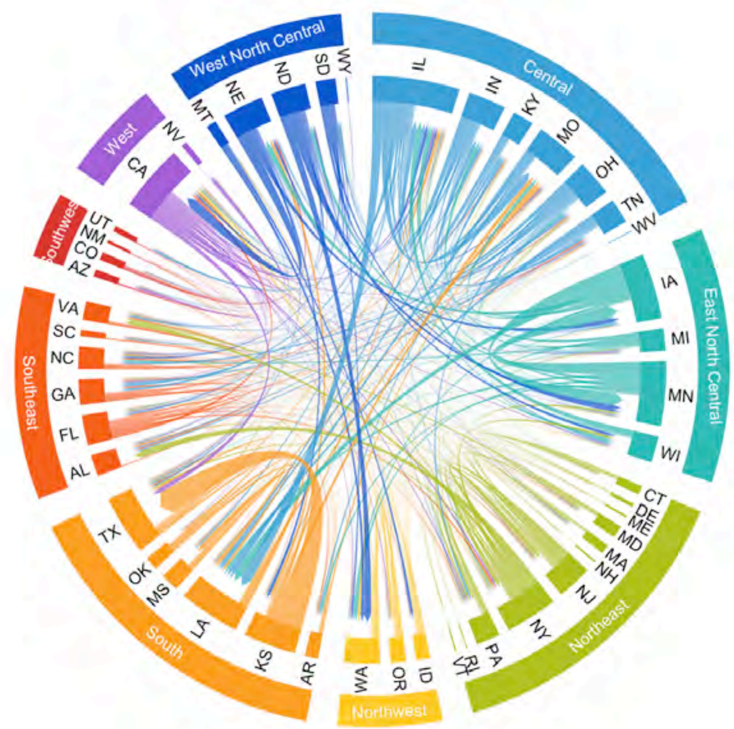


Interstate Trade Flows: Trade Partners

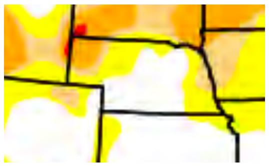
2007 Agricultural Trade Flows



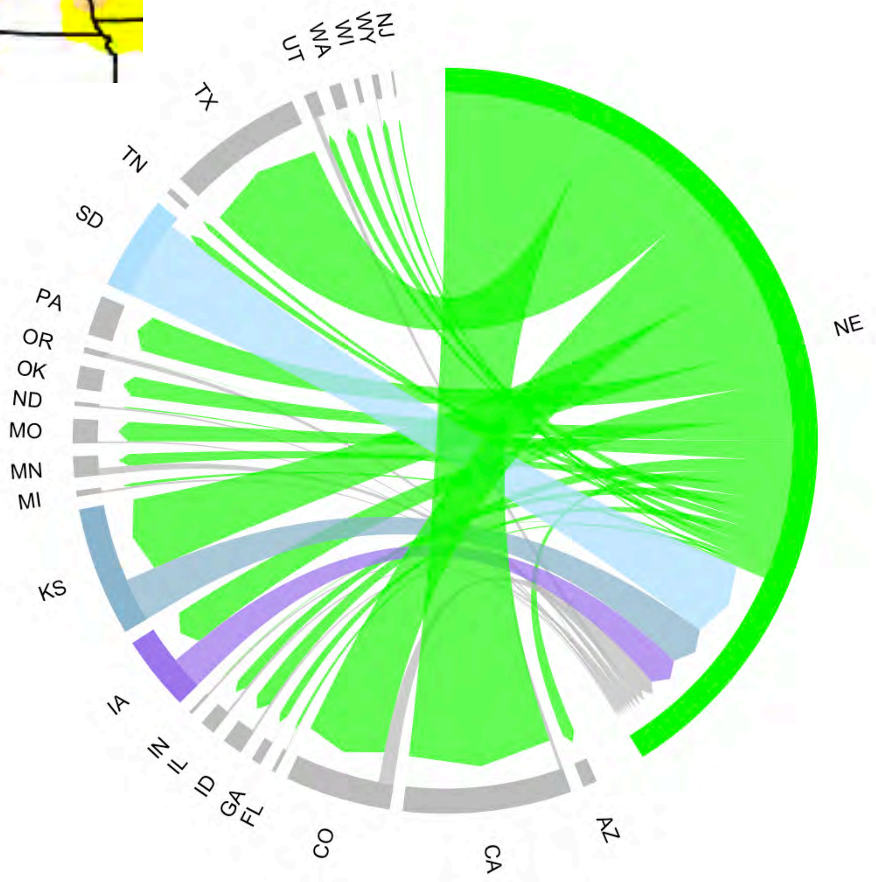
2012 Agricultural Trade Flows

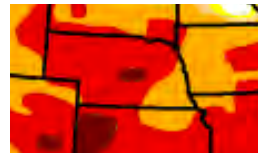


Interstate Trade Flows: focus on Nebraska

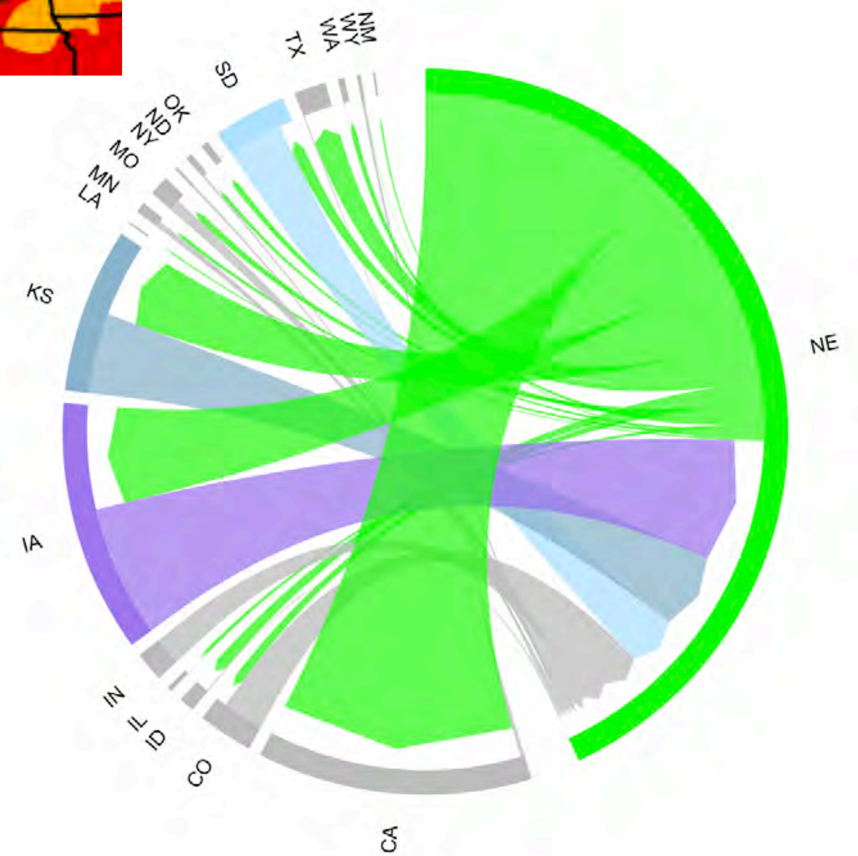


2007 Agricultural Trade Flows (NE)





2012 Agricultural Trade Flows (NE)



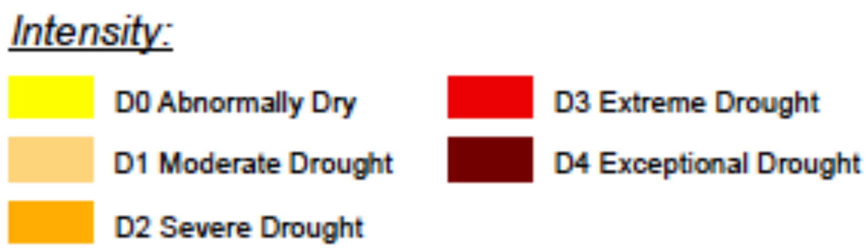
Drought: definitions and classifications

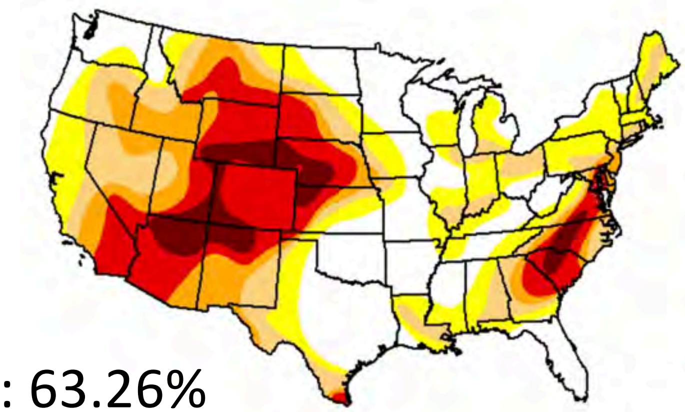
Drought Severity Classification

			Ranges				
Category	**Description**	**Possible Impacts**	**Palmer Drought Severity Index (PDSI)**	**CPC Soil Moisture Model (Percentiles)**	**USGS Weekly Streamflow (Percentiles)**	**Standardized Precipitation Index (SPI)**	**Objective Drought Indicator Blends (Percentiles)**
D0	Abnormally Dry	Going into drought: • short-term dryness slowing planting, growth of crops or pastures Coming out of drought: • some lingering water deficits • pastures or crops not fully recovered	-1.0 to -1.9	21 to 30	21 to 30	-0.5 to -0.7	21 to 30
D1	Moderate Drought	• Some damage to crops, pastures • Streams, reservoirs, or wells low, some water shortages developing or imminent • Voluntary water-use restrictions requested	-2.0 to -2.9	11 to 20	11 to 20	-0.8 to -1.2	11 to 20
D2	Severe Drought	• Crop or pasture losses likely • Water shortages common • Water restrictions imposed	-3.0 to -3.9	6 to 10	6 to 10	-1.3 to -1.5	6 to 10
D3	Extreme Drought	• Major crop/pasture losses • Widespread water shortages or restrictions	-4.0 to -4.9	3 to 5	3 to 5	-1.6 to -1.9	3 to 5
D4	Exceptional Drought	• Exceptional and widespread crop/pasture losses • Shortages of water in reservoirs, streams, and wells creating water emergencies	-5.0 or less	0 to 2	0 to 2	-2.0 or less	0 to 2

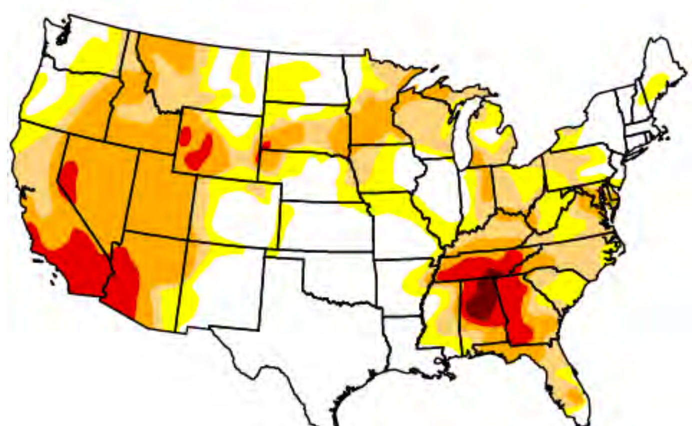
Short-term drought indicator blends focus on 1-3 month precipitation. Long-term blends focus on 6-60 months. Additional indices used, mainly during the growing season, include the USDA/NASS Topsoil Moisture, Keetch-Byram Drought Index (KBDI), and NOAA/NESDIS satellite Vegetation Health Indices. Indices 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)

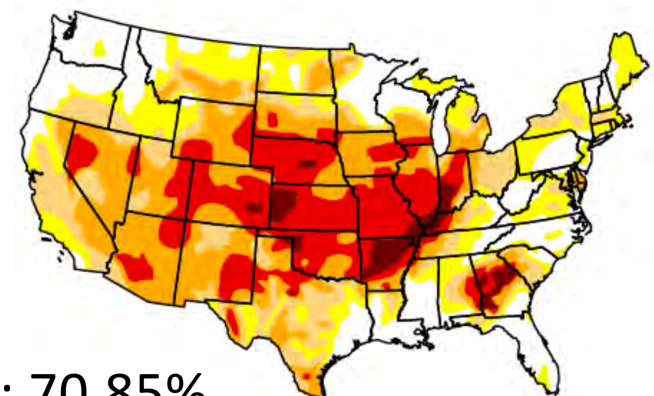




2002: 63.26%



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*

$$Severe\ drought\ days_s = \sum_{c\ in\ state\ s} \left\{ \underbrace{\left[\sum_{m:M_i} \mathbf{1}\left(PDSI_{c,m} < -3\right) \right]}_{count\ number\ of\ severe\ drought\ months} \underbrace{\times 30}_{convert\ months\ to\ days} \right\} \times \underbrace{\frac{cropland_c}{total\ cropland_s}}_{weighted\ by\ county\ c's\ cropland\ acreage}$$

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)

$$\mathrm{EX}_{\mathrm{ijt}} = \alpha\iota_n + \underbrace{H_{ii}'\beta + BORDER_{ij}'\beta_1 + TIME_{ij}'\,\beta_2}_{} + \underbrace{Y_{it}'\beta_3 + \Pi_{it}'\beta_4}_{} + \underbrace{E_{jt}'\beta_5 + P_{jt}'\beta_6}_{}$$

$$+ \underbrace{DD_{it}'\beta_7 + DD_{jt}'\beta_8 + R_{it}'\beta_9 + R_{jt}'\beta_{10} + DGT_{it}'\beta_{11} + DGT_{jt}'\beta_{12}}_{} + \epsilon_{\mathrm{ijt}}$$

with $\epsilon_{\mathrm{ijt}} = \gamma_{IJ} + \mu_t + \varepsilon_{it}$ or $\epsilon_{\mathrm{ijt}} = \gamma_{IJ} + \tau_{Jt} + \partial_{It} + \varepsilon_{it}$

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

EX_{ijt} = bilateral trade flow of crops, fruits, veggies from i to j (FAF4)

H_{ii} = home state fixed effect

$BORDER_{ij}$ = 1 if exporter and importer are contiguous;

$TIME_{ij}$= travel time by road (log);

Y_{it}= agricultural GDP in exporter *i* (BEA)

Π_{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;

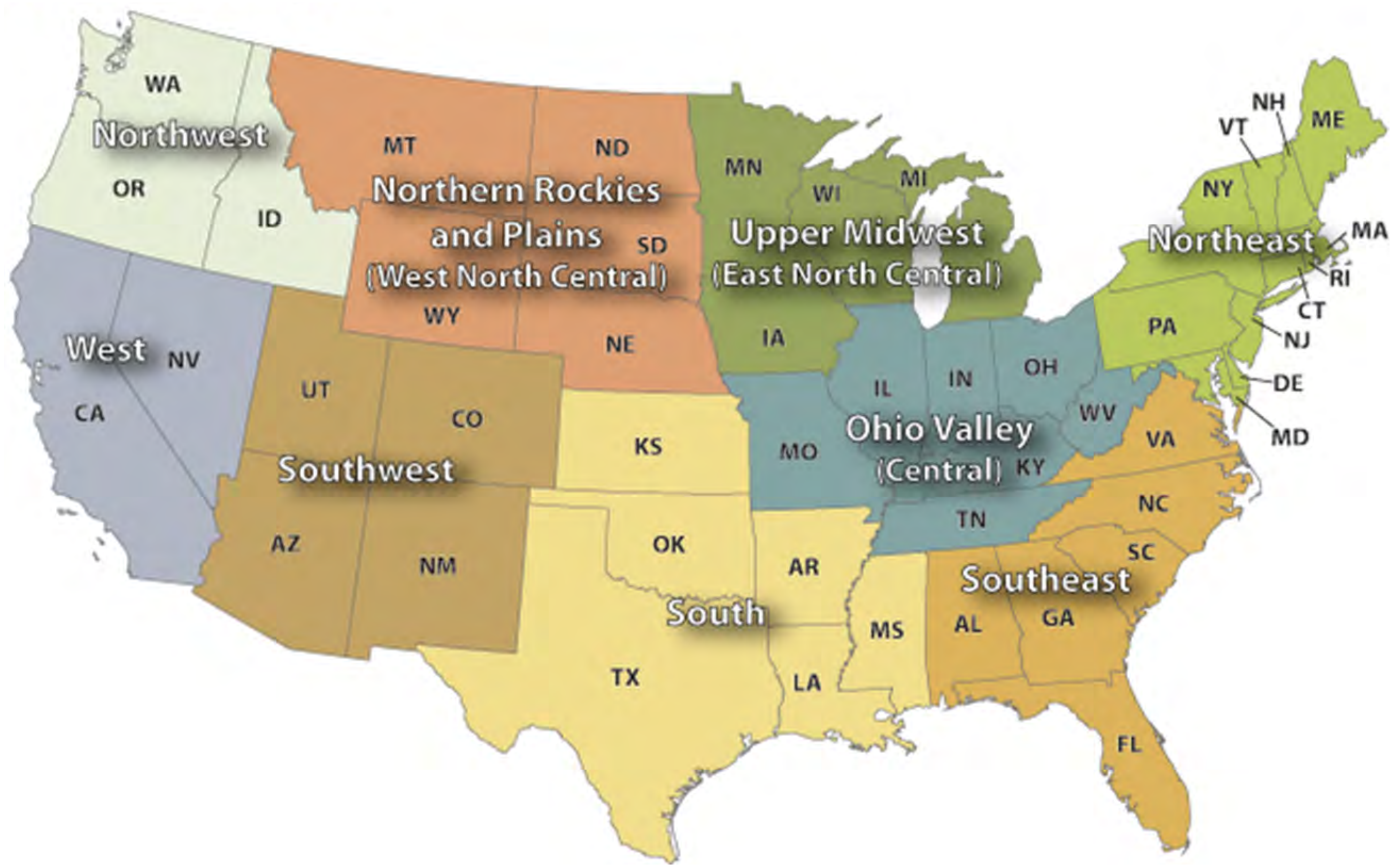
DD = growing season degree days: April-September (NARR);

R= growing season rainfall (NARR)

DGT = severe drought days (NARR)

I, J = exporter (importer) climate zone index

9 U.S. Climate Zones (Source: NOAA)



	OLS		PPML	
	(1)	(2)	(3)	(4)
Common border	1.611**	1.617**	1.015**	1.006**
	(0.15)	(0.15)	(0.23)	(0.23)
Travel time	−1.920**	−1.911**	−0.607**	−0.631**
	(0.13)	(0.13)	(0.12)	(0.12)
Drought days (orig.)	−0.044+	−0.061+	−0.03	−0.029
	(0.03)	(0.03)	(0.03)	(0.03)
Drought days (dest.)	0.055*	0.002	0.069**	0.089*
	(0.03)	(0.03)	(0.03)	(0.04)
GDP (orig.)	1.358**	1.366**	0.772**	0.781**
	(0.05)	(0.05)	(0.09)	(0.10)
GDP (dest.)	1.026**	1.024**	0.456**	0.458**
	(0.04)	(0.04)	(0.05)	(0.05)
Remoteness index (orig.)	2.650**	2.694**	1.152*	1.189**
	(0.41)	(0.42)	(0.46)	(0.46)
Remoteness index (dest.)	3.208**	3.291**	0.446	0.63
	(0.42)	(0.45)	(0.64)	(0.73)
Degree days (orig.)	−0.021	0.019	0.15	0.117
	(0.27)	(0.28)	(0.35)	(0.37)
Degree days (dest.)	0.874**	1.021**	0.535	0.597
	(0.26)	(0.27)	(0.36)	(0.38)
Precipitation (orig.)	−0.347*	0.008	−0.148	−0.144
	(0.15)	(0.20)	(0.17)	(0.26)
Precipitation (dest.)	0.199	0.419*	0.505**	0.723**
	(0.15)	(0.21)	(0.19)	(0.26)
Home by year FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Climate zone dyadic FE	Yes	Yes	Yes	Yes
Climate zone by year FE (exporter and importer)	No	Yes	No	Yes
Num. of obs.	6,401	6,401	9,216	9,216
Adj. R squared	0.551	0.568		
Pseudo R-squared			0.827	0.834

Note: The dependent variable is interstate trade flows of crops. Standard errors in parentheses.
$^{+}p < .10$,
$^{*}p < .05$,
$^{**}p < .01$.

Robustness checks

	Drought days in the origin state		Drought days in the destination state	
	Estimates	Standard error	Estimates	Standard error
Benchmark (from column 4 of table 2)	–0.03	(0.03)	0.09*	(0.04)
Robustness checks:				
(1) use USDA farm production region	0.03	(0.25)	0.07*	(0.02)
(2) use one side exporter/importer-by-year FEs	–0.03	(0.03)	0.09**	(0.03)
(3) trade flows for cereal grain only (SCTG02)	–0.03	(0.04)	0.12**	(0.05)
(4) trade flows for other crops only (SCTG03)	–0.03	(0.03)	0.07*	(0.05)
(5) trade flows in volume measure (SCTG02)	–0.04	(0.05)	0.10*	(0.05)
(6) trade flows in volume measure (SCTG03)	–0.03	(0.03)	0.09*	(0.04)
(7) drought during growing season	–0.04	(0.04)	0.09*	(0.04)
(8) drought during last 3 months before harvest	–0.00	(0.04)	0.09*	(0.05)
(9) add total population and crop stock	–0.03	(0.04)	0.09*	(0.05)
(10) add ethanol and biodiesel capacity	–0.04	(0.05)	0.13**	(0.05)

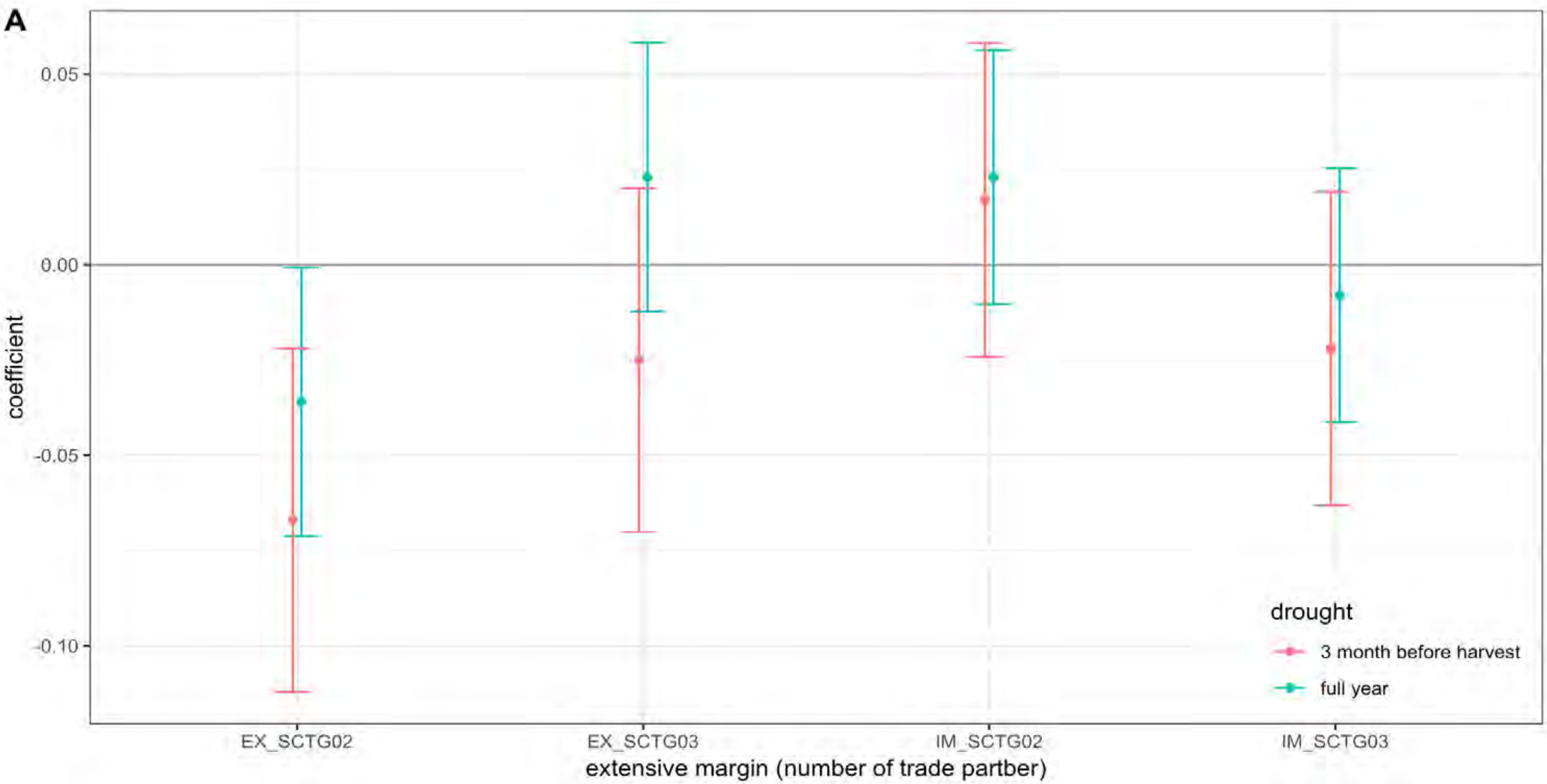
Note: The dependent variable is interstate trade flows of crops. Details of the estimates appear in tables A1–A3.

+ $p < 0.10$,

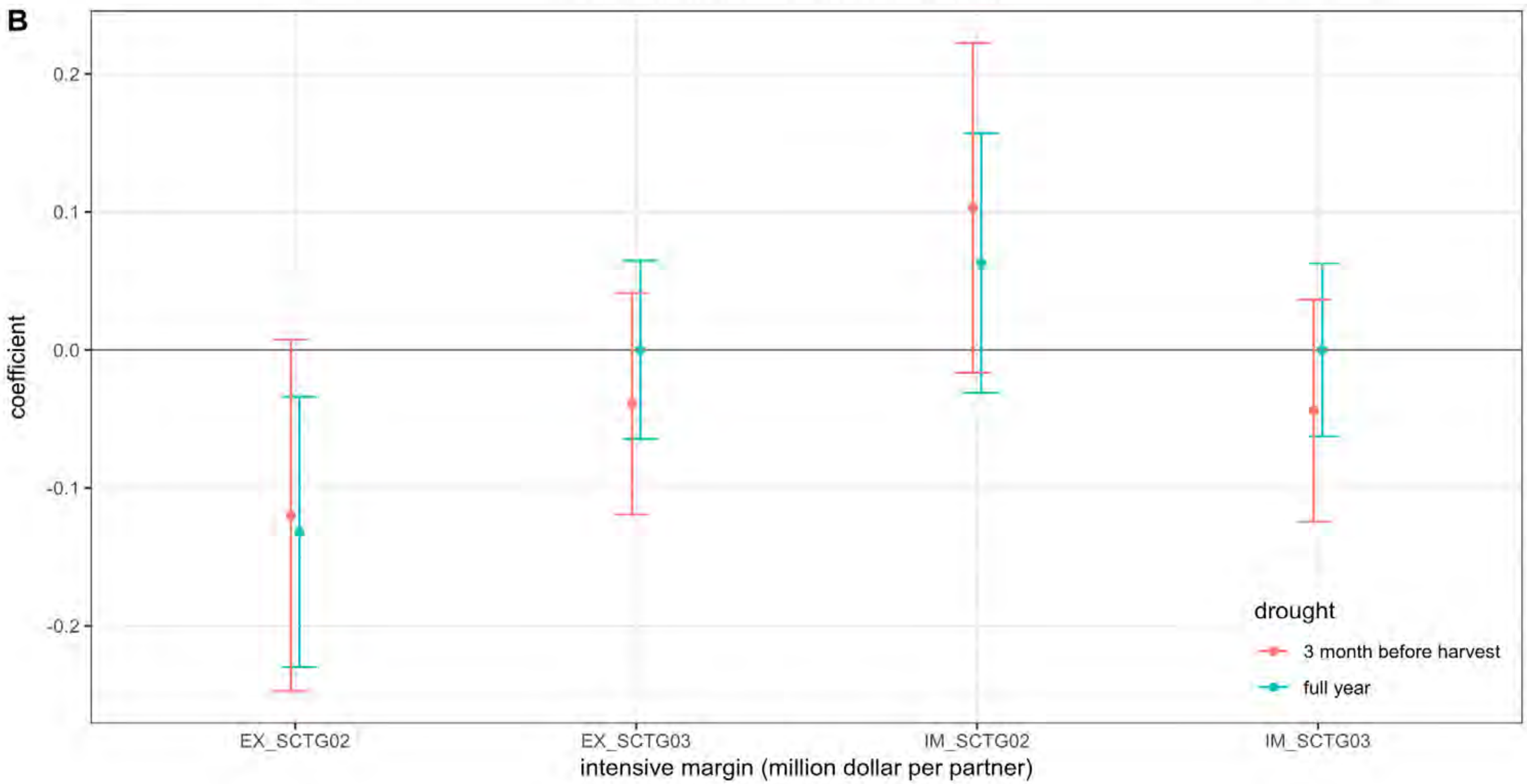
* $p < .05$,

** $p < .01$

Extensive margin



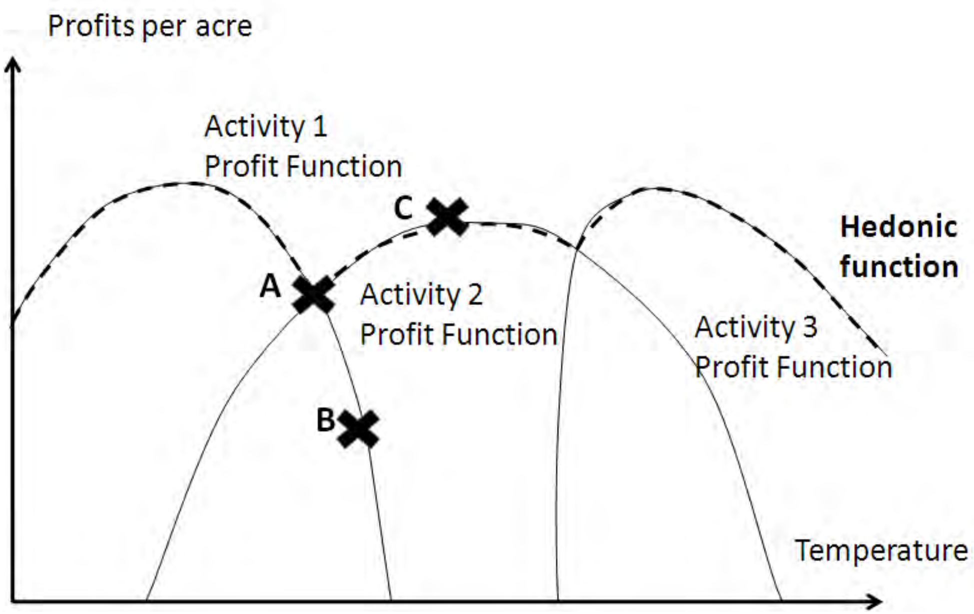
Intensive margin



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).**



Ricardian approach: Basic Model

$$\text{ag\_profit}_i = X_i'\beta + \sum \theta_j f_j(T_{ij}) + \varepsilon_i \qquad \varepsilon_i \sim N(0, \sigma_\varepsilon^2)$$

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]

Mendelsohn et al. (1994), Mendelsohn and Dinar (2003), Massetti and Mendelsohn (2011), Schlenker et al. (2005, 2006). With spillovers: Polsky (2004), Dall’erba and Dominguez (2016)

Ricardian approach: specification

$$\mathrm{y_{it}} = \widehat{\mathrm{EX}}'_{i.t}\boldsymbol{\beta} + DGT'_{it}\boldsymbol{\theta} + W'_{\mathrm{it}}\delta + \mathrm{X}'_{\mathrm{it}}\gamma + \nu_{\mathrm{i}} + \nu_{\mathrm{It}} + \epsilon_{\mathrm{it}} \qquad \epsilon_{\mathrm{it}} \sim \mathrm{F}(0, \sigma^2_\epsilon)$$

i = 48 states, I = 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)

$\widehat{\mathrm{EX}}$ = (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, $\mathrm{density}^2$ [BEA]

ν_{i} = state FE

ν_{It} = climate zone × year FE

OLS results

	(1) No trade	(2) No trade	(3) Trade	(4) Trade
Drought	0.091	0.235	0.198	0.38
	(0.15)	(0.17)	(0.14)	(0.17)
GDD	−0.062	−0.096	−0.186	0.135
	(0.17)	(0.29)	(0.16)	(0.27)
GDD squared	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Precipitation	4.461	26.764^{+}	4.905	25.098^{+}
	(9.04)	(14.10)	(8.46)	(13.14)
Precipitation squared	−0.174	−0.619	−0.131	−0.612^{+}
	(0.28)	(0.38)	(0.27)	(0.35)
Per capita income	10.179	18.935	9.241	9.991
	(12.83)	(16.48)	(12.01)	(15.51)
Per capita income squared	−0.123	−0.207	−0.141	−0.165
	(0.13)	(0.16)	(0.12)	(0.15)
Density	3.461*	4.216*	3.326*	3.392*
	(1.50)	(1.77)	(1.41)	(1.66)
Density squared	−0.001	0.000	0.000	0.000
	(−.001)	(0.00)	(0.00)	(0.00)
Total exports			0.038**	0.045**
			(0.008)	(0.011)
Constant	−298.014	−858.921	−147.364	−776.66
	(450.80)	(718.06)	(423.31)	(669.57)
Year FE	Yes	No	Yes	No
Climate zone by year FE	No	Yes	No	Yes
Observations	192	192	192	192
R-squared	0.50	0.63	0.57	0.68

Note: 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:

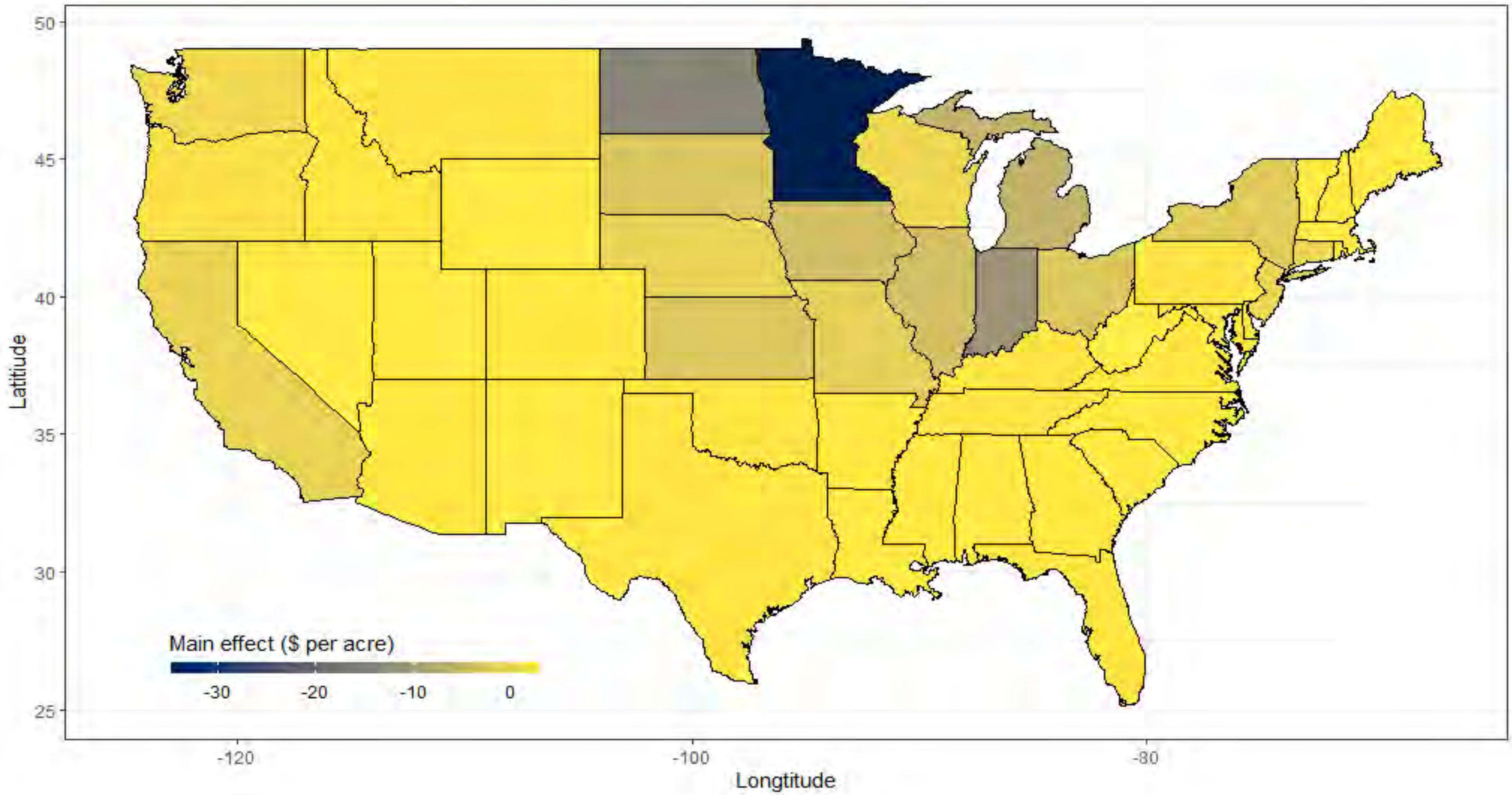
$$\partial \mathrm{y_i}/\partial \mathrm{DTG_i} = \theta \qquad \text{and} \qquad \partial \mathrm{y_i}/\partial \mathrm{DTG_j} = 0$$

  - with interstate trade:

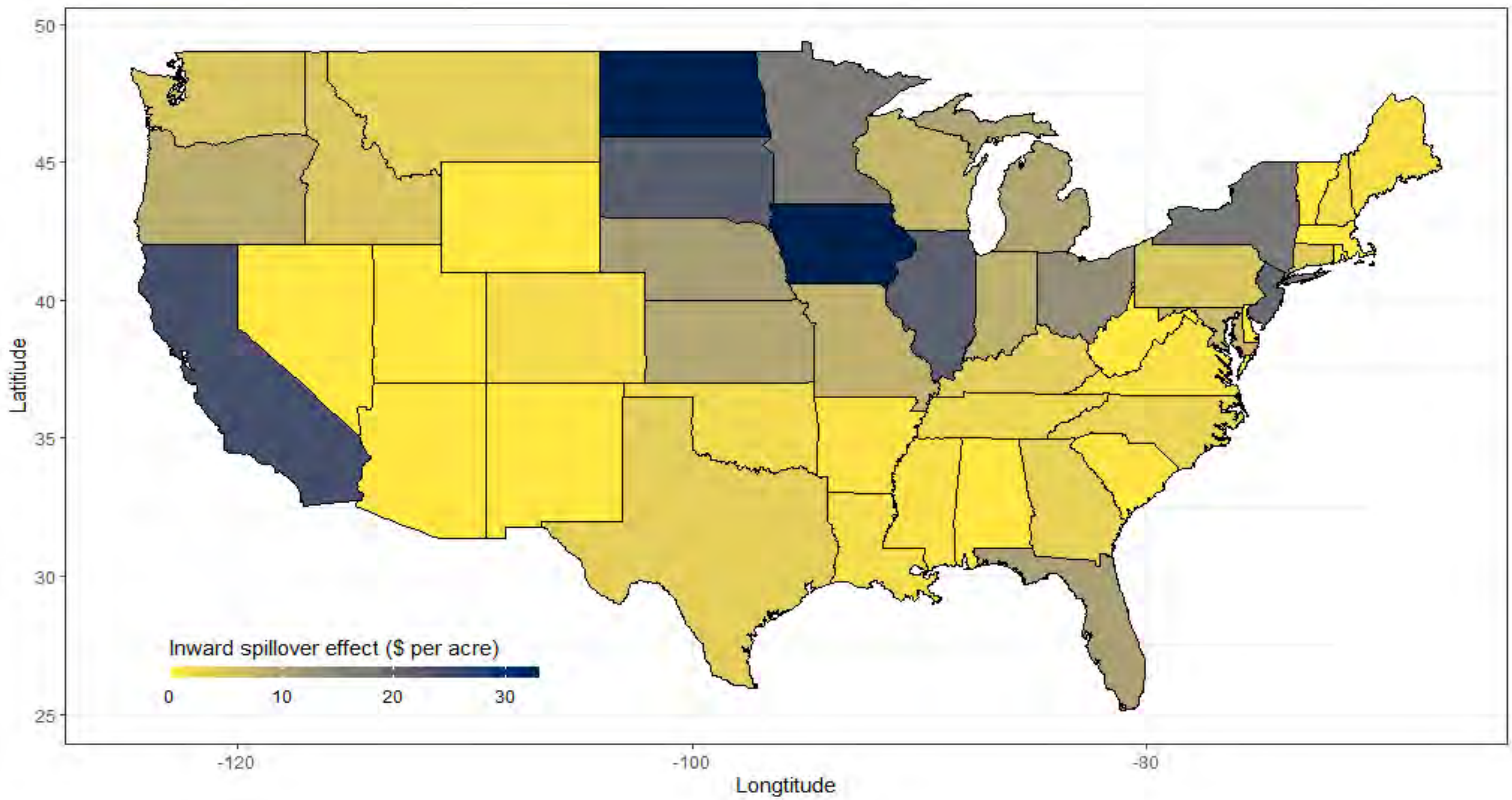
$$\partial \mathrm{y_i}/\partial \mathrm{DTG_i} = \theta + \beta \times \sum_j \partial \widehat{\mathrm{X}}_{\mathrm{ij}}/\partial \mathrm{DTG_i} \quad \text{and} \quad \partial \mathrm{y_i}/\partial \mathrm{DTG_j} = \beta \times \sum_j \partial \widehat{\mathrm{X}}_{\mathrm{ij}}/\partial \mathrm{DTG_j}$$

- 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: $\partial \mathrm{y_i} / \partial \mathrm{DTG_i} = \theta + \beta \times \sum_j \partial \widehat{\mathrm{X}}_{\mathrm{ij}} / \partial \mathrm{DTG_i}$



Average effect on local profit /acre of one extra week of severe drought in the trade partners: $\partial \mathrm{y_i}/\partial \mathrm{DTG_j} = \beta \times \sum_j \partial \widehat{\mathrm{X}}_{\mathrm{ij}}/\partial \mathrm{DTG_j}$



Ricardian approach:
future weather conditions (2038-2070 w.r.t. 1968-2000)

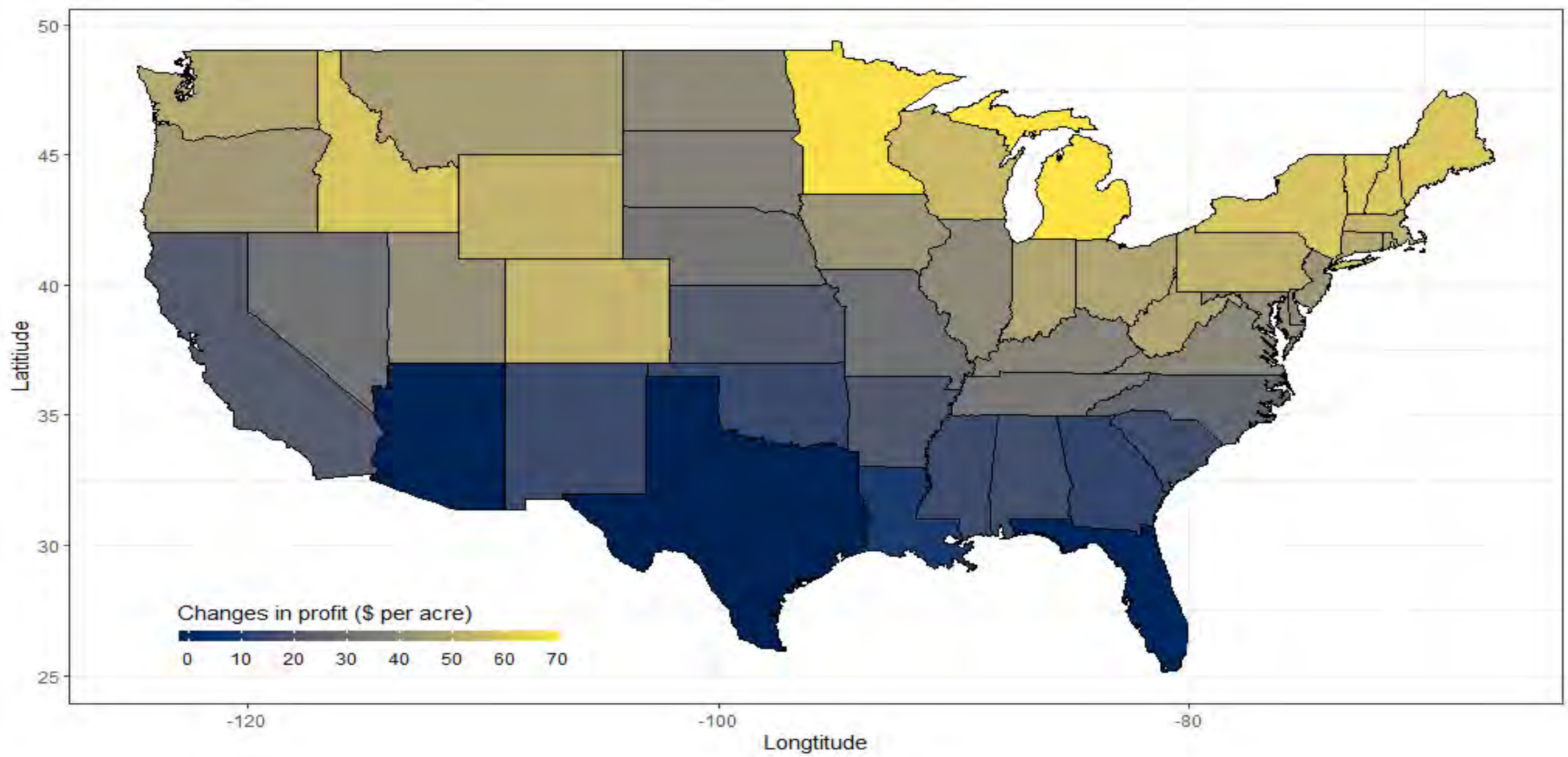
- For temperature and precipitation, we use 4 combinations of RCM-GCM: CRCM-CCSM, CRCM-CGCM, MM5I-CCSM and RCM3-GFDL
- GCMs are: the Community Climate System Model; the Third Generation Coupled Global Climate Model; the Geophysical Fluid Dynamics Laboratory. All based on the 4th IPCC's SRES A2 scenario: 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)

$ 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)

Mitigation effect of interstate trade (average across models)



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

Moore and Lobell 2014, for Europe; Wang et al. 2009, for China). However, several authors have brought to the fore that the international trade of agricultural goods has the capacity to act as a major mechanism for adapting to climate change (Reilly and Hoh-

Pierre Mérel

Professor, UC Davis

Reckoning Climate Change Damages Along an Envelope

Reckoning Climate Change Damages Along an Envelope

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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?"

Estimation strategies

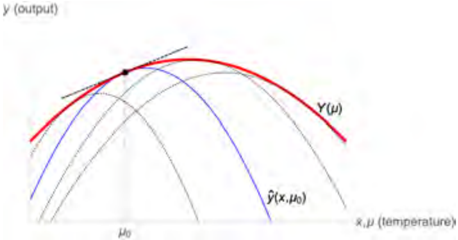
Emerging line of thought:

- 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 *with a purpose*
- ET then implies *tangency* between
  - the (unobserved) value function that allows for adaptation (outer envelope)
  - the (more easily observed) objective function when actions are optimal

marginal climate impact =
marginal weather impact



Theoretical argument

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 $(\mathcal{P}_0) : \max_a y(\mathbb{E} X, a)$

Theoretical argument

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But agents plausibly maximize the *expected outcome*

$(\mathcal{P}_1) : \max_a \mathbb{E}y(X, a)$ instead of $(\mathcal{P}_0) : \max_a y(\mathbb{E}X, a)$

We show that, under $(\mathcal{P}_1)$:

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

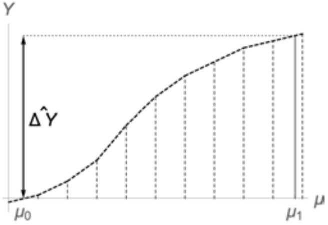
$$y(X, a) = \Gamma(X) + \Psi(a)X + \Phi(a)$$

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, ΔY is the integral of Y' from μ_0 to $\mu_0 + \Delta\mu$

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



Once the weather/climate variables (e.g., temperature) have been chosen, estimation of the long-run response is "model-free"

Illustration using US Agricultural GDP

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 $\mu(i)$:

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

- β_μ is the local marginal effect of weather at μ

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

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

Model (3) adds state-specific weather slopes:

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

- Identification of β_μ 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

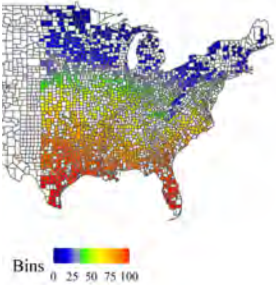
$$\mu_{it} = \frac{\sum_{s=t-30}^{t-1} x_{is}}{30}$$

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

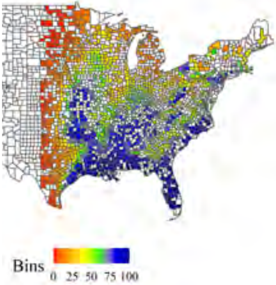
$$\bar{\mu}_i = \frac{\sum_{t=2001}^{2017} \mu_{it}}{17}$$

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

- Each bin includes about 13 counties



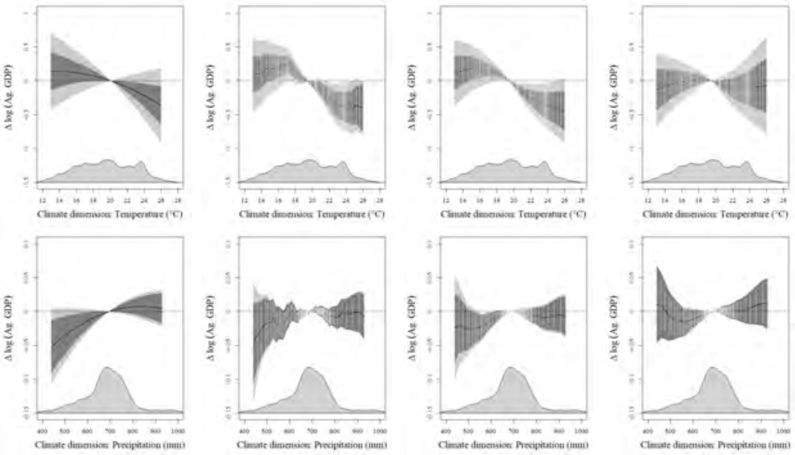
(a) Temperature



(b) Precipitation

Long-run responses to climate

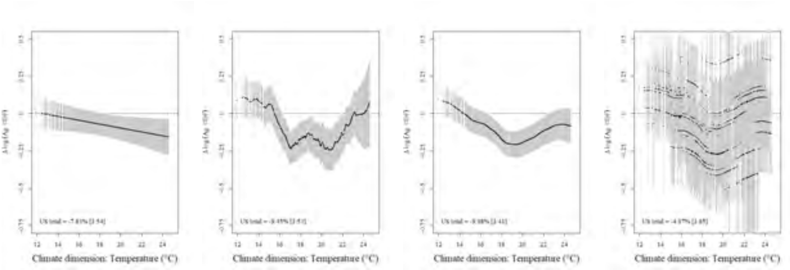
Benchmark: quadratic in temperature and precipitation



(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

Take-home messages

Estimates of weather effects may identify climate impacts if agents:

- follow $(\mathcal{P}_0)$: $\max_a y(\mathbb{E}X, a)$
- follow $(\mathcal{P}_1)$: $\max_a \mathbb{E}y(X, a)$ <u>and</u> cannot alter 2^{nd}-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 $+2^{\circ}$C warming scenario

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Up next – 10:15-11:45am PT

SESSION 6.1

Emerging Research on Financial Adaptations to Climate Impacts

SESSION 6.2

Wading into the Economic Impacts of Climate Change on Water

SESSION 6.3

Equitable Adaptation to Climate-Related Flood Risks: Part 2

CLIMATE ADAPTATION
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