Spatial Correlation, Trade, and Inequality: Evidence from the Global Climate

Jonathan I. Dingel (Chicago Booth)
Kyle C. Meng (UC Santa Barbara)
Solomon M. Hsiang (UC Berkeley)

December 2021

Economic consequences of global phenomona

Global phenomena often produce heterogeneous local impacts

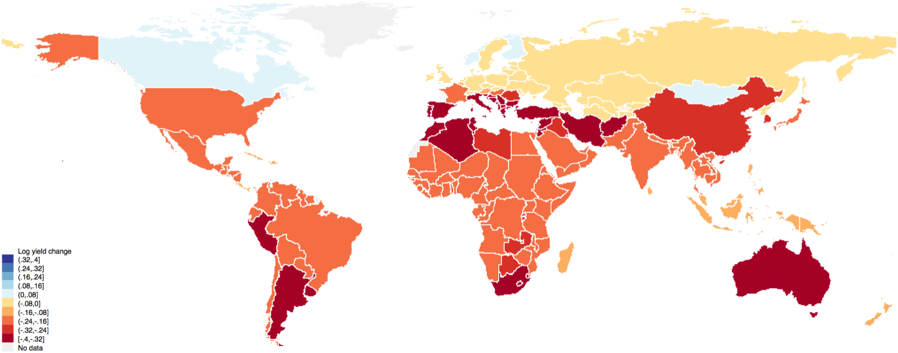
In some cases, heterogeneity exhibits spatial correlation: neighboring locations experience similar impacts

Sometimes called the "first law of geography" (Tobler, 1970)

Examples of global events with spatially correlated outcomes:

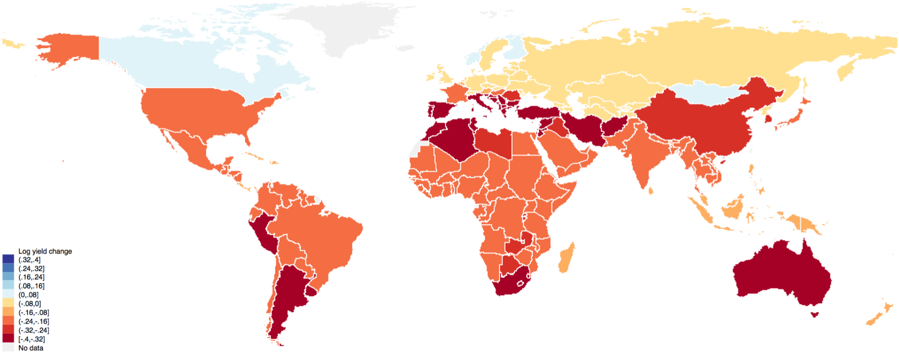
- Great Recession (Piskorski and Seru, 2018)
- Global food price shocks (McGuirk and Burke, 2020)
- Global pandemics (Barro et al., 2020; Dong et al., 2020)

Prime example: anthropogenic climate change



- Spatially correlated footprint of local impacts
- Larger losses in tropics
- Smaller losses (or gains) in temperate latitudes

Prime example: anthropogenic climate change



A full account of global climate impacts requires estimating:

1. local productivity effects (i.e. partial equilibrium)
2. global trade effects (i.e. general equilibrium)

Contrasting approaches to understanding climate change

Quasi-experimental estimates

Relate local temperature to local outcomes, ignoring temperatures elsewhere

Projected global CC impact: sum of each location's impact under isolated warming

What if Kenya warmed by itself, ignoring concurrent warming in Congo, Ethiopia, or Sweden?

Structural models

Use a GE model of global economy to forecast economic outcomes

Typically relies on numerous functional-form assumptions

Our approach

Incorporate spatial linkages in climate-impact projections using quasi-experimental variation without imposing full structure of quantitative trade models

Overview: Paper in 3 parts

1. Theoretically demonstrate that increasing spatial correlation of productivities increases global welfare inequality across a trading network
2. Empirically validate general-equilibrium prediction by examining the last five decades of global agricultural trade driven by a global climatic phenomenon
3. Augment typical quasi-experimental climate-impact projections to include this general-equilibrium effect

Part 1: Theory

In many trade models, a country gains more from trade when partners are

1. more productive, and
2. physically closer

Increased spatial correlation makes neighbors more similar:

- high productivity countries gain more from trade by being near other high productivity countries
- low productivity countries gain less from trade by being near other low productivity countries

Implication:

- Greater spatial correlation of productivities can increase global welfare inequality

Part 2: Empirical validation

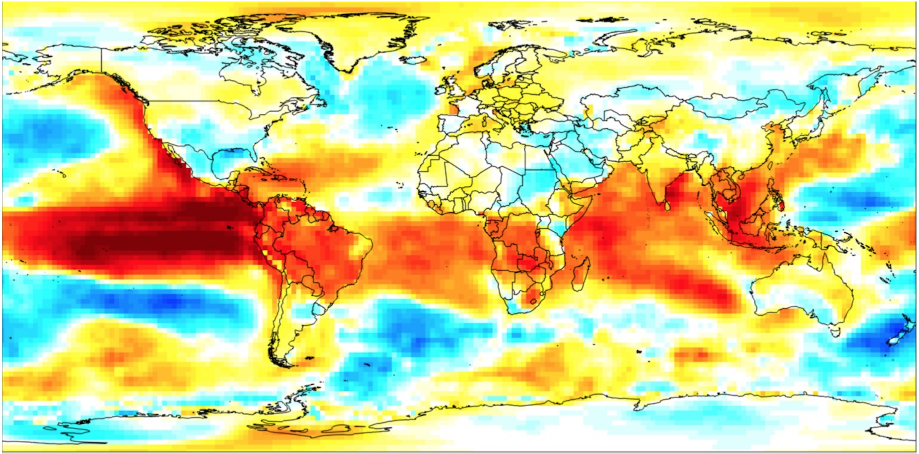
Challenges with identifying a global GE effect

- Prediction about a counterfactual for the entire global economy
- Need exogenous variation affecting spatial structure of productivities at a global scale

Our solution:

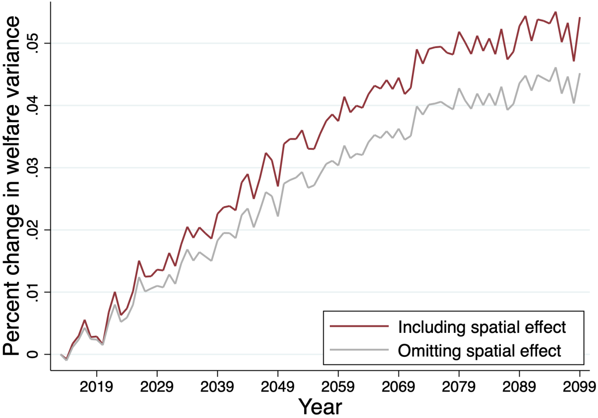
- Global natural experiment: El Niño-Southern Oscillation (ENSO)
- ENSO alters local temperatures in a way that increases global spatial correlation in agricultural productivity, holding mean and variance fixed.

Part 2: Empirical validation



- Over 1961-2013, 1 s.d. increase in spatial correlation of agricultural productivities $\rightarrow$ 2% increase in welfare variance

Part 3: Climate change application



- Incorporate GE mechanism into typical quasi-experimental climate-impact forecast without imposing full structure of trade model
- 20% greater change in global welfare inequality by 2099 under climate change when including changes to spatial correlation in agricultural productivity
- Higher losses in most African countries

Related work

Geography

- Local natural resources associated with local outcomes (Sachs and Warner, 1997; Easterly and Levine, 2003), via productivity (Nordhaus, 2006; Bleakley, 2007), institutions (Nunn and Puga, 2012), investments (Burchfield et al., 2006)

International trade

- We articulate and empirically examine role of spatial correlation using Arkolakis, Costinot and Rodríguez-Clare (2012) sufficient statistic for gains from trade
- Costinot, Donaldson and Smith (2016) examine consequences of predicted shifts in comparative advantage across different crops due to climate change

Inequality under climate change

- Bring reduced-form climate impacts lit. (Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015; Burgess et al., 2014; Houser et al., 2015) conceptually closer to macro/GE approaches (Brock, Engström and Xepapadeas, 2014; Desmet and Rossi-Hansberg, 2015; Krusell and Smith, 2016; Costinot, Donaldson and Smith, 2016)

1. Theoretical framework
2. The El Niño-Southern Oscillation
3. Estimation results
4. Application: Inequality under future climate change
5. Conclusions

Theoretical framework

Welfare variance across a trading network

Welfare = autarky welfare + gains from trade

In a broad class of trade models (Arkolakis, Costinot and Rodríguez-Clare, 2012):

ACR primitives

$$\underbrace{\underbrace{\ln\left(C_i/L_i\right)}_{welfare} = \underbrace{\underbrace{\ln A_i}_{\text{productivity}} + \underbrace{\gamma}_{micro-foundation}}_{\text{autarky welfare}} \underbrace{- \underbrace{\frac{1}{\epsilon}}_{\text{trade elasticity}} \underbrace{\ln \lambda_{ii}}_{\text{domestic share}}}_{\text{gains from trade}}}$$

Global welfare variance across countries:

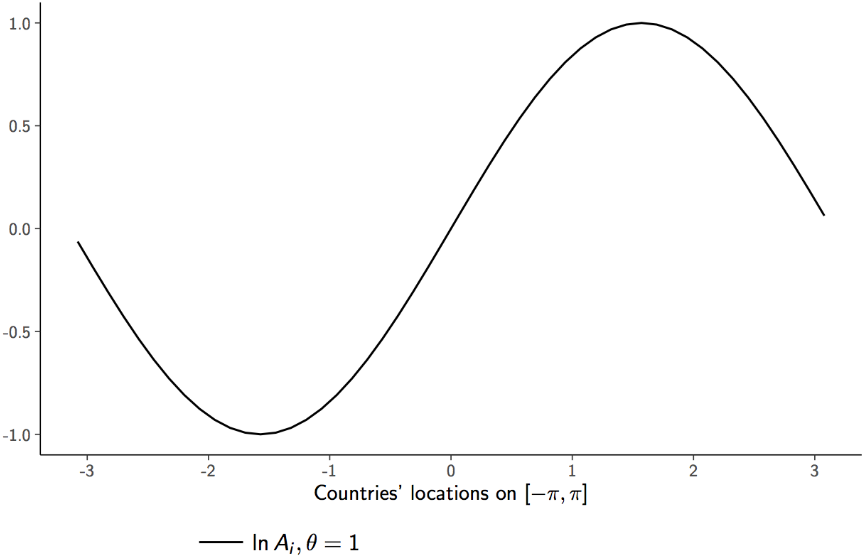
$$var\left(\ln\left(C_i/L_i\right)\right) = var\left(\ln A_i\right) + 2cov\left(\ln A_i, \frac{-1}{\epsilon}\ln \lambda_{ii}\right) + \frac{1}{\epsilon^2} var\left(\ln \lambda_{ii}\right)$$

Spatial correlation and welfare variance

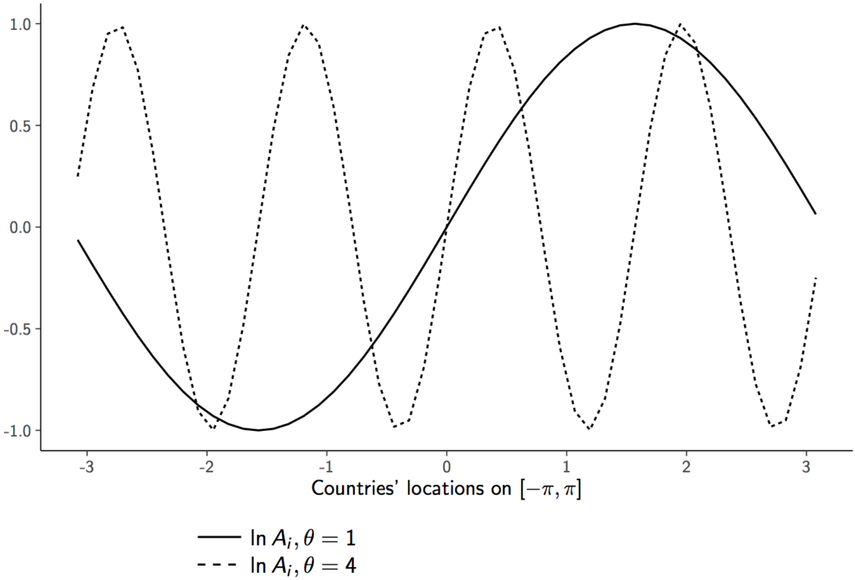
How does spatial correlation affect cov $\left(\ln \mathbf{A_i}, \frac{-1}{\epsilon} \ln \lambda_{\mathbf{ii}}\right)$?

- A country gains more from trade when trading partners are more productive
- Distance-related trade costs $\rightarrow$ larger gains when more productive partners are closer
- Neighbors more similar under greater spatial correlation:
    - high productivity countries gain more from trade by being near other high productivity countries
    - low productivity countries gain less from trade by being near other low productivity countries
- Greater spatial correlation raises inequality by increasing *cov* $\left(\ln A_i, \frac{-1}{\epsilon} \ln \lambda_{ii}\right)$
- Greater spatial correlation reduces *cov* $\left(\ln A_i, \ln \lambda_{ii}\right)$

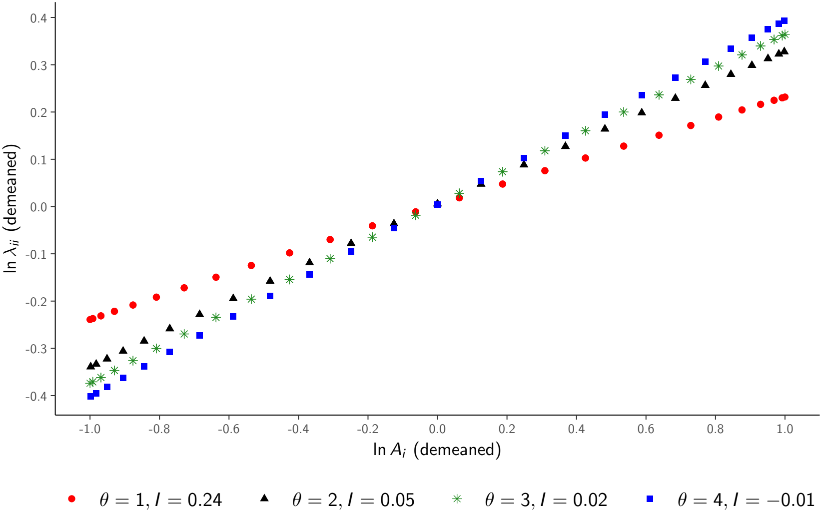
Sine-wave circular economy with uniform countries



Sine-wave circular economy with uniform countries



Sine-wave circular economy with uniform countries



Mean and variance table

From theory to empirics

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \pi_i^I + \pi_t^T + \epsilon_{it}$$

Theoretical extensions and empirical implications

1. Many states, many heterogeneous countries

   Implication: Panel estimator with year and country fixed effects

2. Arbitrary productivity distributions

   Implication: Spatial correlation captured by Moran's I

$$I = \sum_i \sum_{j \neq i} \omega_{ij} \left(x_i - \overline{x} \right) \left(x_j - \overline{x} \right), \quad \omega_{ij} \propto \frac{1}{\text{distance}_{ij}}$$

3. Simulated model with realistic geography

   Implication: Effect is linear in Moran's I

4. Multiple sectors

   Implication: 1-sector effect is upper bound on total wefare effect

From theory to empirics

Remaining identification challenge

- Productivity may still be endogenous to expenditure shares if unobserved:
  1. trade cost shocks affect imported intermediate goods
  2. demand shocks elicit supply responses
- Ideal (impossible) experiment: exogenously reshuffle global productivities to alter its spatial correlation

Solution: a global natural experiment

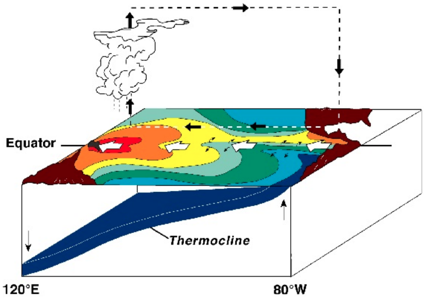
- El Niño-Southern Oscillation (ENSO)

The El Niño-Southern Oscillation (ENSO)

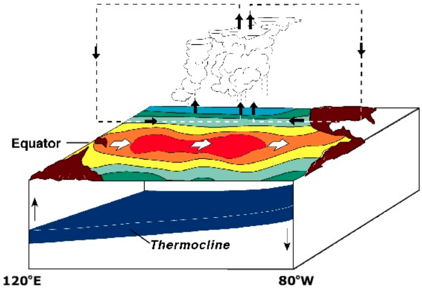
What is ENSO?

Dominant natural year-to-year driver of the global climate

Quasi-periodic (3-7 years) release of heat from the tropical Pacific driven by instabilities in the coupled ocean-atmosphere circulation



La Niña

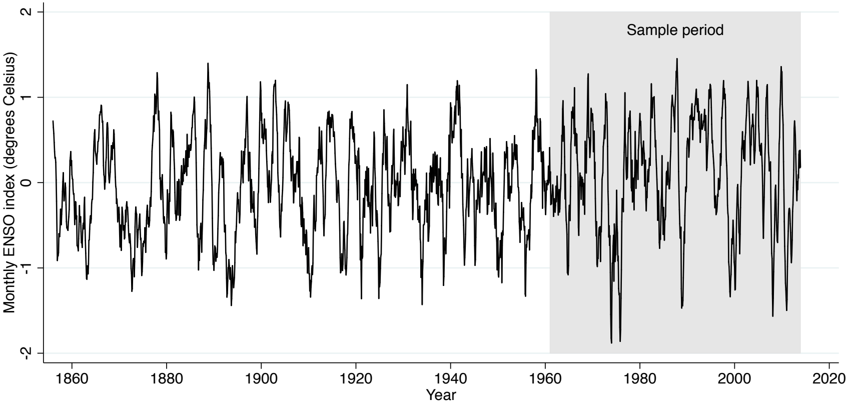


El Niño

ENSO index

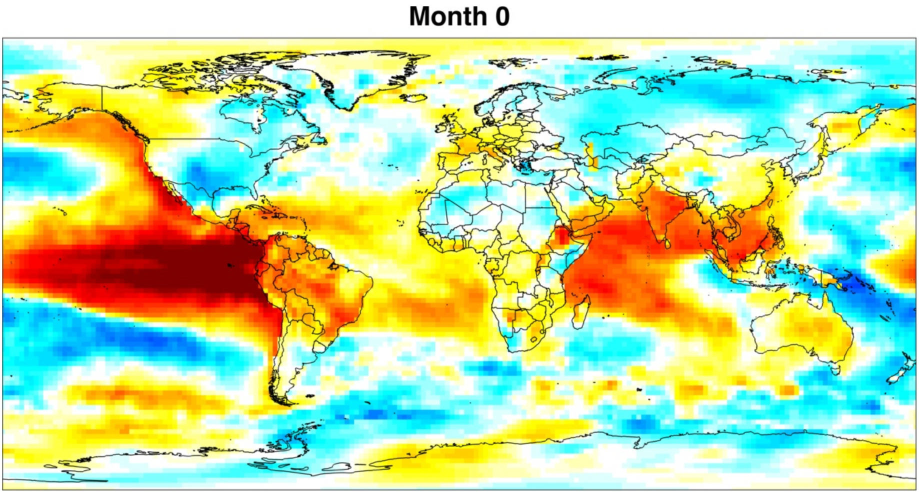
Summarized by avg. sea surface temp. in tropical Pacific Ocean ▸ ENSO index map

Peaks in December ▸ Top 10 ENSO events



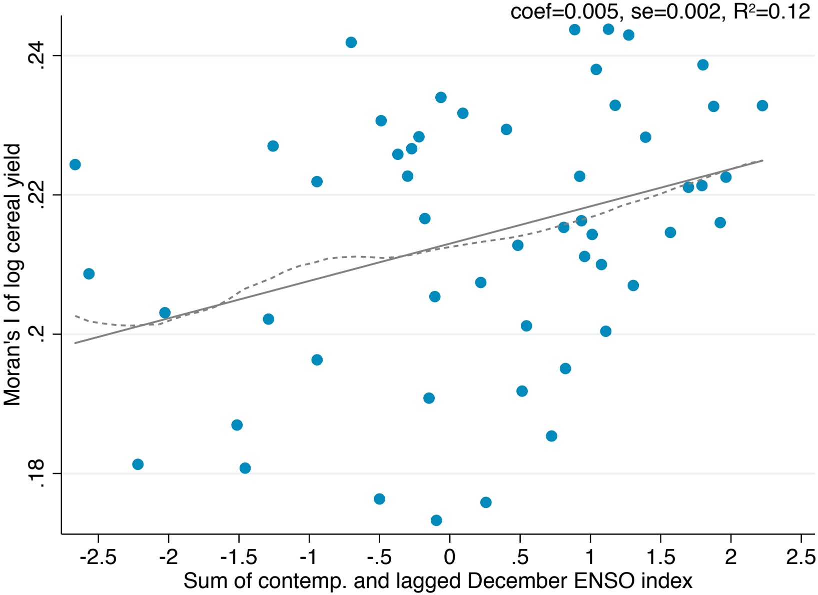
NOTES: Monthly ENSO index during 1856-2013. Shaded area shows 1961-2013 sample period.

Timing of ENSO's local temperature effects



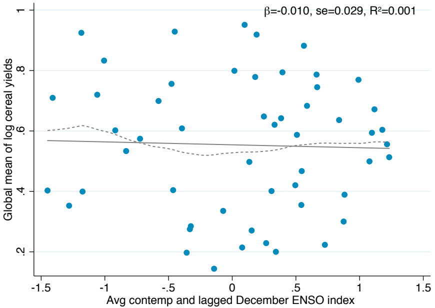
NOTES: Each panel shows pixel-level (0.5° latitude by 0.5° longitude resolution) correlation between the ENSO index in December and pixel-level monthly temperatures for 11 months before (lead) and 12 months after (lag) December. Blue shows areas with negative correlation. Red shows areas with positive correlation.

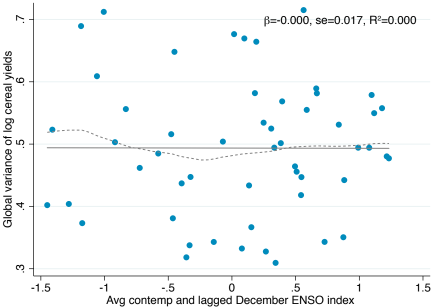
ENSO and Moran's *I* for yields



Temp. scatter
Yield map
Yield table

ENSO and cross-sectional moments of cereal yields





Estimation results

Estimating the effect of spatial correlation

Estimating equation:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \Pi' \mathbb{Z}_{it} + \mu_{it}$$

- Panel over country i (158) and year t (1961-2013)
- λ_{iit}: FAOStat (cereal consumption [output minus export] $\times$ export unit value)
- A_{it}: FAOStat (cereals yield in metric tons per hectare)
- $\mathbb{Z}_{it}$: Country FE, time FE, and i-specific linear trend
- μ_{it}: year clustered
- Gravity fits cereal trade well Gravity results

Prediction: Variance of welfare increases when $\beta_1 < 0$

Endogeneity concern: Need instruments for $\ln A_{it}$ and $\ln A_{it} I_t$

Instrumental-variables strategy

IV approach:

- Drive local yields using country crop area-weighted annual temperature, T_{it}
- Drive global spatial correlation of yields using $ENSO_t$ and $ENSO_{t-1}$

Two first stage equations:

$$\ln A_{it} = \alpha_{11} f(T_{it}) + \alpha_{12} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma_1' \mathbb{Z}_{it} + \upsilon_{1it}$$

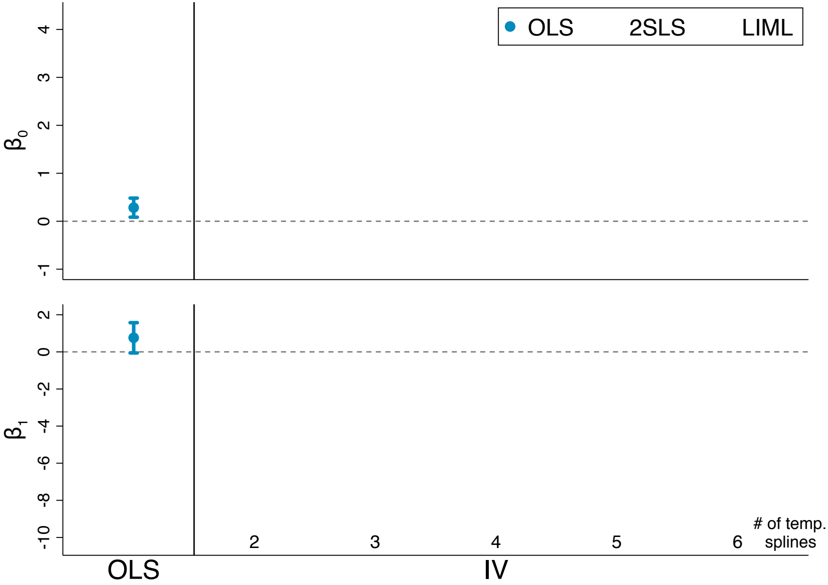
$$\ln A_{it} I_t = \alpha_{21} f(T_{it}) + \alpha_{22} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma_2' \mathbb{Z}_{it} + \upsilon_{2it}$$

- $f()$: restricted cubic spline function (Schlenker & Roberts, '09; Schlenker & Lobell, '10; Welch et al., '10, Moore & Lobell, '10)
- $g()$: quadratic function

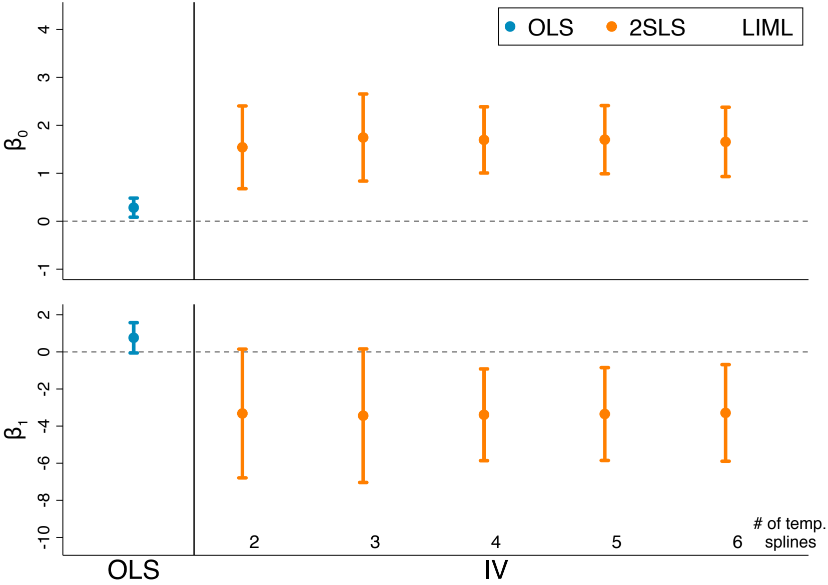
Addressing potential weak-instrument concerns:

1. Compare OLS vs. 2SLS vs. LIML estimates
2. Conduct weak-IV diagnostics
3. Conduct weak-IV robust inference
4. Bekker (1994) standard error adjustment

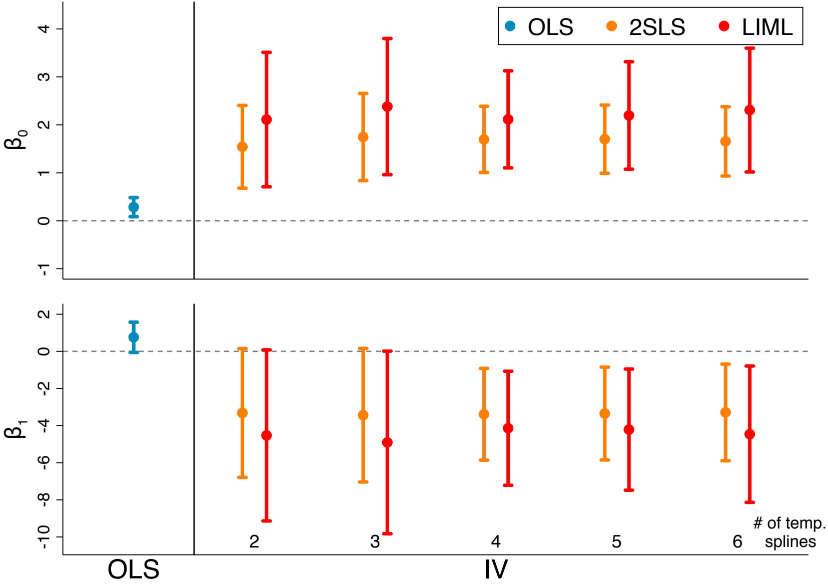
OLS shows no relationship



2SLS: Higher spatial correlation lowers $cov(\ln \lambda_{ii}, \ln A_i)$



LIML: Higher spatial correlation lowers $cov(\ln \lambda_{ii}, \ln A_i)$



First stage coefs. | F-stat | A-R test | Spline selection

Magnitude: 2% increase in global inequality

1 std dev increase relative to historical average Moran's I

Use reduced-form coefficients $\widehat{\beta}_0$, $\widehat{\beta}_1$ and $\epsilon = 8.59$ (Caliendo and Parro, 2015) to calculate pct. change in welfare variance ▸ Welfare calculation

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)
$\ln A_{it}$ (β_0)	2.110**	2.380***	2.114***	2.196***	2.308***
	(0.837)	(0.847)	(0.604)	(0.669)	(0.771)
$\ln A_{it} \times I_t$ (β_1)	-4.530	-4.907	-4.144**	-4.218**	-4.463**
	(2.752)	(2.937)	(1.834)	(1.949)	(2.194)
Pct. change in welfare variance	2.091	2.264	1.914**	1.948*	2.060*
from 1 s.d. increase in I_t	(1.407)	(1.497)	(0.954)	(1.035)	(1.191)
Number of temperature splines in f()	2	3	4	5	6

NOTES: 5452 observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Year-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Other robustness checks

Statistical assumptions

- Randomization inference
- Alternative std errors: clustering and Bekker (1994) LIML adjustment
- Controls for time-varying trade costs
- Sample split by time

Structural interpretation

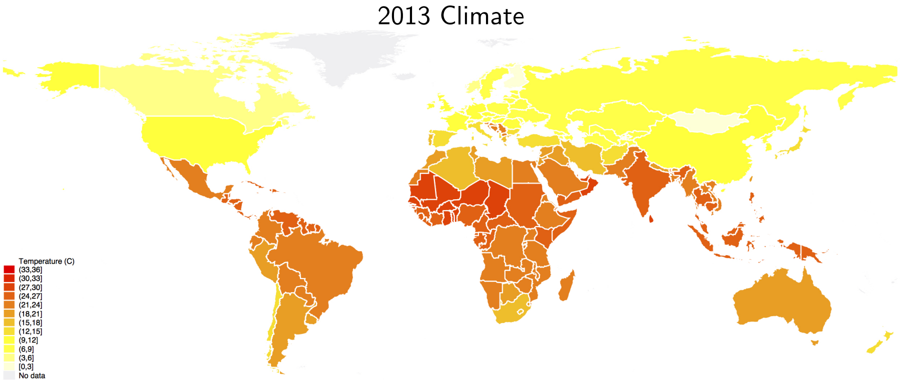
- Exclude large economies
- ENSO anticipation, storage, and other dynamic effects
- Terms of trade

Data construction

- Alternative ENSO and temperature definitions
- Temperature-driven yields
- Domestic expenditure share construction

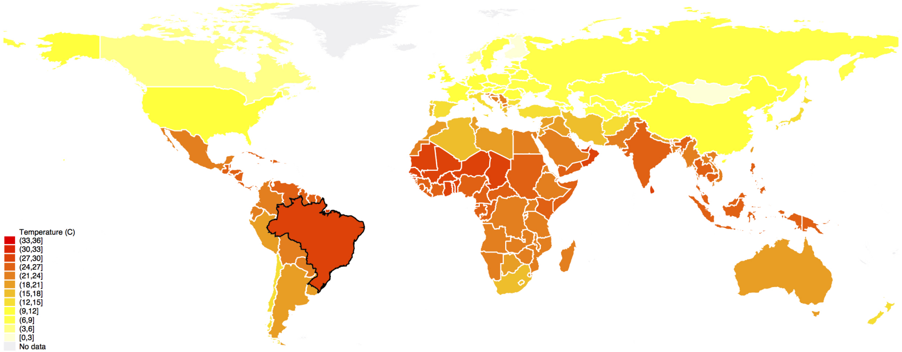
Inequality under future climate change

Climate change projection

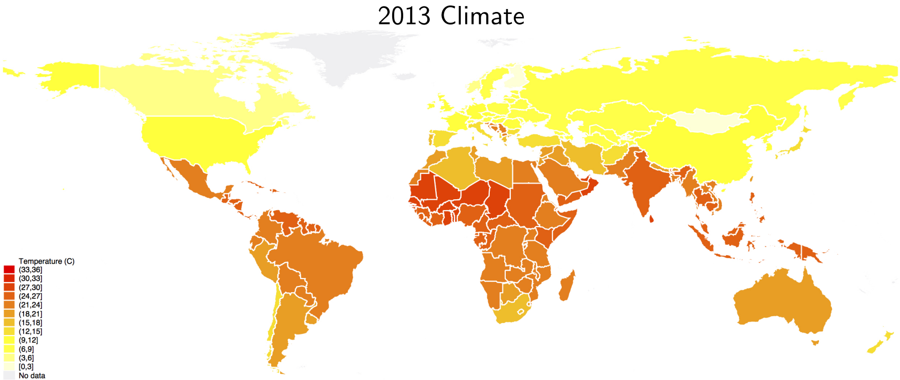


Climate change projection

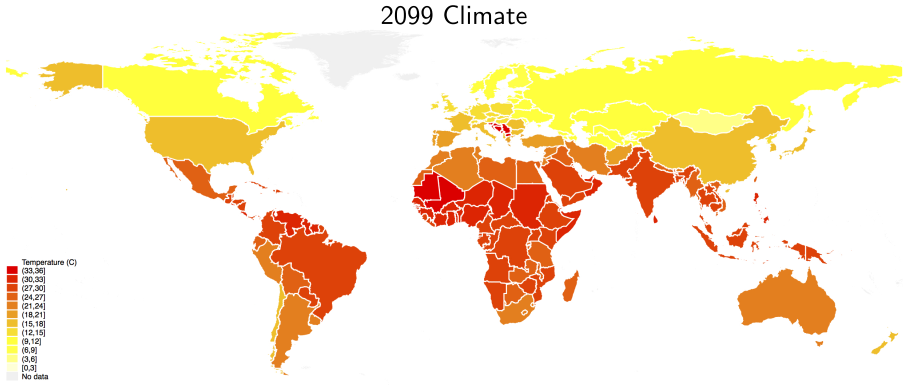
2099 Temperature for Brazil + 2013 Climate



Climate change projection



Climate change projection



Agricultural productivity under climate change

1. Estimate cereal yield response function during period, $t \in [\underline{t}, \bar{t}]$:

$$\ln A_{it} = k(T_{it}) + \Psi' \mathbb{X}_{it} + \nu_{it}$$

   $k()$ a cubic spline; $\mathbb{X}_{it}$ includes country FE, year FE, country quadratic trends

2. Forecast yields to 2099 under RCP 8.5, holding everything else fixed at $\bar{t}$:

$$\widehat{\ln A}_{it} = \widehat{k}(\widehat{T}_{it}) + \widehat{\Psi}' \mathbb{X}_{i\bar{t}} + \widehat{\nu}_{i\bar{t}}$$

3. Obtain welfare with and without change in spatial correlation

$$\widehat{\ln \lambda}^{s}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 \widehat{I}_t) \widehat{\ln A}_{it} + \widehat{\Pi}' \mathbb{Z}_{i\bar{t}} + \widehat{\mu}_{i\bar{t}}$$
$$\widehat{\ln \lambda}^{n}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}}) \widehat{\ln A}_{it} + \widehat{\Pi}' \mathbb{Z}_{i\bar{t}} + \widehat{\mu}_{i\bar{t}}$$

(Usual) caveats:

- Ceteris paribus besides climate-driven agricultural productivity
- No role for expectations
- No other GE effects (i.e. factor reallocation, crop choice)

Estimated log cereal yield temperature relationship

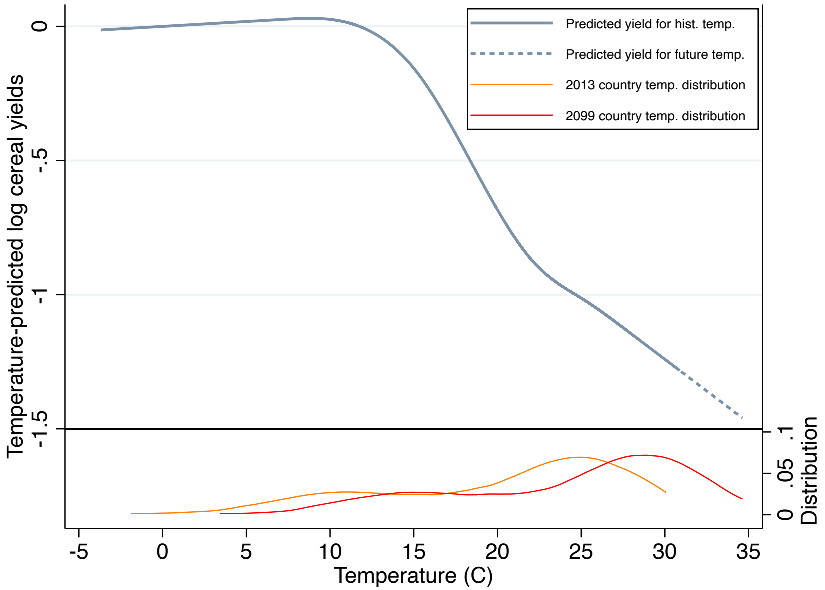
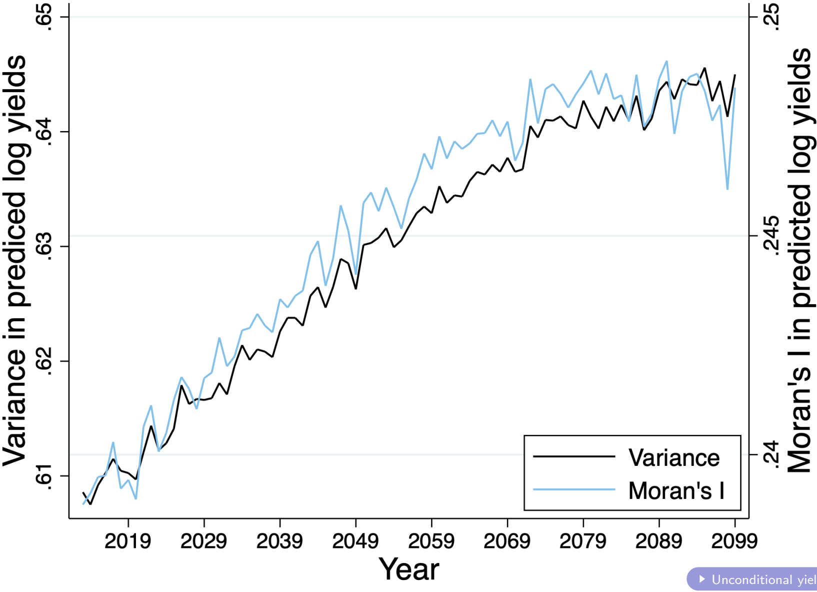


Table Yield map

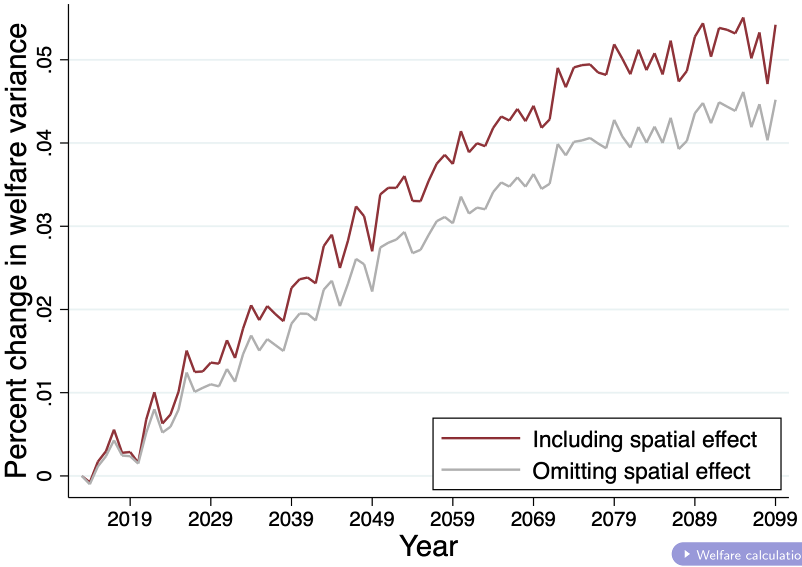
Climate-driven cereal yield variance and spatial correlation



▸ Unconditional yield

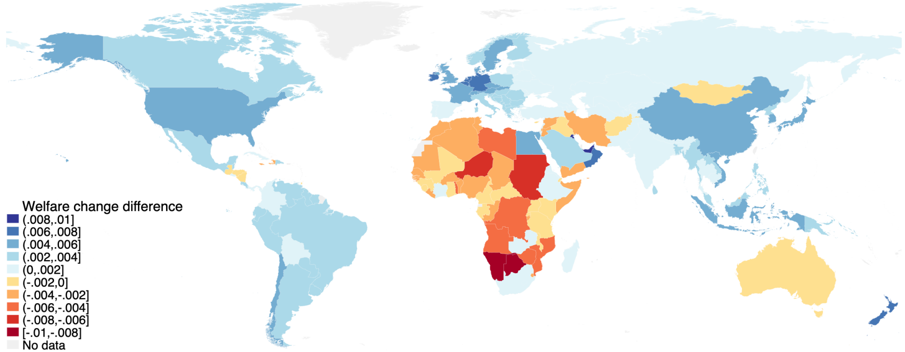
Climate-driven welfare variance

20% larger change in global welfare inequality when including spatial effects

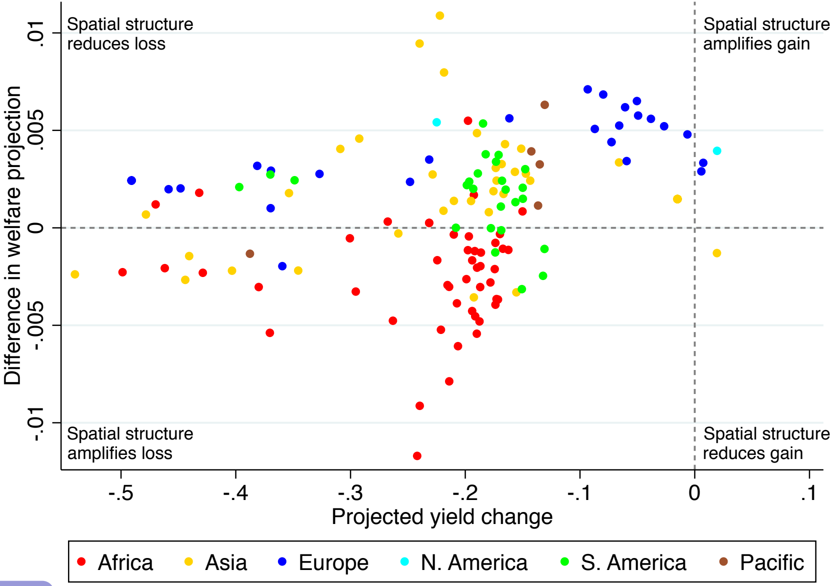


▸ Welfare calculation

Cntry differences in projected welfare due to spatial effects



Cntry differences in projected welfare due to spatial effects



By country

Conclusions

Conclusion

Contributions

- Greater spatial correlation of productivities increases global welfare inequality
- Exploit global climatic phenomenon that drives global spatial correlation of productivities
- Accounting for climate change-driven rise in spatial correlation increases end-of-century global inequality by 20%

Broader implications

- Many determinants of productivity (i.e., demographics, political institutions, natural endowments) exhibit substantial spatial correlation
- Combination of theory and empirics provides framework for quasi-experimental validation of general-equilibrium predictions

Thank you