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

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Economic consequences of global phenomena

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)
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):

\[
\ln \left( \frac{C_i}{L_i} \right) = \ln A_i + \gamma \ln \lambda_{ii} - \frac{1}{\epsilon} \ln \lambda_{ii}
\]

Global welfare variance across countries:

\[
\text{var} \left( \ln \left( \frac{C_i}{L_i} \right) \right) = \text{var} \left( \ln A_i \right) + 2 \text{cov} \left( \ln A_i, \frac{-1}{\epsilon} \ln \lambda_{ii} \right) + \frac{1}{\epsilon^2} \text{var} \left( \ln \lambda_{ii} \right)
\]
Spatial correlation and welfare variance

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

- A country gains more from trade when trading partners are more productive.
- Distance-related trade costs → 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

Countries’ locations on $[-\pi, \pi]$
Sine-wave circular economy with uniform countries

\[
\ln A_i \text{ (demeaned)}
\]

\[
\ln \lambda_{ii} \text{ (demeaned)}
\]

\[
\theta = 1, I = 0.24 \\
\theta = 2, I = 0.05 \\
\theta = 3, I = 0.02 \\
\theta = 4, I = -0.01
\]

Mean and variance table
From theory to empirics

\[ \ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \pi_i^l + \pi_t^T + \epsilon_{it} \]

**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

\[ I = \sum_{i} \sum_{j \neq i} \omega_{ij} (x_i - \bar{x}) (x_j - \bar{x}), \quad \omega_{ij} \propto \frac{1}{\text{distance}_{ij}} \]

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 welfare 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
ENSO index

Summarized by avg. sea surface temp. in tropical Pacific Ocean

Peaks in December

Timing of ENSO’s local temperature effects

Month 0

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

- Coefficient: 0.005, Standard Error: 0.002, \( R^2 = 0.12 \)

Graph showing Moran’s I of log cereal yield against the sum of contemporaneous and lagged December ENSO index.

- Graph indicates a positive correlation between the ENSO index and Moran’s I of log cereal yield.

- The coefficient of determination, \( R^2 \), is 0.12, indicating that 12% of the variation in Moran’s I is explained by the ENSO index.
Global mean of log cereal yields

Avg contemp and lagged December ENSO index

-1.5 -1 -0.5 0 0.5 1 1.5

β=-0.010, se=0.029, R²=0.001

Global variance of log cereal yields

Avg contemp and lagged December ENSO index

-1.5 -1 -0.5 0 0.5 1 1.5

β=-0.000, se=0.017, R²=0.000
Estimation results
Estimating the effect of spatial correlation

Estimating equation:

\[ \ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \Pi' Z_{it} + \mu_{it} \]

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

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:**
\[
\ln A_{it} = \alpha_{11} f(T_{it}) + \alpha_{12} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma'_1 Z_{it} + \nu_{1it}
\]
\[
\ln A_{it} I_t = \alpha_{21} f(T_{it}) + \alpha_{22} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma'_2 Z_{it} + \nu_{2it}
\]

- $f()$: 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 $cov(\ln \lambda_{ii}, \ln A_i)$

The diagram shows the estimates of $\beta_0$ and $\beta_1$ for OLS and 2SLS at different numbers of temporal splines. The legend indicates the methods used: OLS, 2SLS, and LIML. The y-axis represents the estimates, while the x-axis shows the number of temporal splines ranging from 2 to 6.
LIML: Higher spatial correlation lowers $\text{cov}(\ln \lambda_{ii}, \ln A_i)$
**Magnitude: 2% increase in global inequality**

1 std dev increase relative to historical average Moran’s $I$

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

Outcome is log domestic share of expenditure

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<tr>
<td>$\ln A_{it} (\beta_0)$</td>
<td>2.110**</td>
<td>2.380***</td>
<td>2.114***</td>
<td>2.196***</td>
<td>2.308***</td>
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<tr>
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<td>(0.837)</td>
<td>(0.847)</td>
<td>(0.604)</td>
<td>(0.669)</td>
<td>(0.771)</td>
</tr>
<tr>
<td>$\ln A_{it} \times I_t (\beta_1)$</td>
<td>-4.530</td>
<td>-4.907</td>
<td>-4.144**</td>
<td>-4.218**</td>
<td>-4.463**</td>
</tr>
<tr>
<td></td>
<td>(2.752)</td>
<td>(2.937)</td>
<td>(1.834)</td>
<td>(1.949)</td>
<td>(2.194)</td>
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Pct. change in welfare variance from 1 s.d. increase in $I_t$

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<tr>
<td></td>
<td>2.091</td>
<td>2.264</td>
<td>1.914**</td>
<td>1.948*</td>
<td>2.060*</td>
</tr>
<tr>
<td></td>
<td>(1.407)</td>
<td>(1.497)</td>
<td>(0.954)</td>
<td>(1.035)</td>
<td>(1.191)</td>
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Number of temperature splines in $f()$

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<tr>
<td>Notes</td>
<td>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&lt;0.01, ** p&lt;0.05, * p&lt;0.1.</td>
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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
Agricultural productivity under climate change

1. Estimate cereal yield response function during period, $t \in [t, \bar{t}]$:
   \[
   \ln A_{it} = k(T_{it}) + \psi'\bar{X}_{it} + \nu_{it}
   \]
   $k()$ a cubic spline; $\bar{X}_{it}$ includes country FE, year FE, country quadratic trends

2. Forecast yields to 2099 under RCP 8.5, holding everything else fixed at $\bar{t}$:
   \[
   \hat{\ln} A_{it} = \hat{k}(\hat{T}_{it}) + \hat{\psi}'\hat{\bar{X}}_{i\bar{t}} + \hat{\nu}_{i\bar{t}}
   \]

3. Obtain welfare with and without change in spatial correlation
   \[
   \hat{\ln} \lambda_{iit} = (\hat{\beta}_0 + \hat{\beta}_1 I_t)\hat{\ln} A_{it} + \hat{\Pi}'\hat{Z}_{i\bar{t}} + \hat{\mu}_{i\bar{t}}
   \]
   \[
   \hat{\ln} \lambda_{iit}^n = (\hat{\beta}_0 + \hat{\beta}_1 I_{\bar{t}})\hat{\ln} A_{it} + \hat{\Pi}'\hat{Z}_{i\bar{t}} + \hat{\mu}_{i\bar{t}}
   \]

(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

The graph illustrates the relationship between temperature (C) and estimated log cereal yields. It shows predicted yields for historical and future temperatures, along with the 2013 and 2099 country temperature distributions.
Climate-driven cereal yield variance and spatial correlation

Variance in predicted log yields vs Moran's I in predicted log yields over years 2019 to 2099.
Climate-driven welfare variance

20% larger change in global welfare inequality when including spatial effects
Country differences in projected welfare due to spatial effects
Cntry differences in projected welfare due to spatial effects

Spatial structure reduces loss
Spatial structure amplifies loss
Spatial structure reduces gain
Spatial structure amplifies gain

Projected yield change

-0.5 -0.4 -0.3 -0.2 -0.1 0 0.1

Difference in welfare projection

-0.01 -0.005 0 0.005 0.01

By country

- Africa
- Asia
- Europe
- N. America
- S. America
- Pacific
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