The Spatial Structure of Productivity, Trade, and Inequality:
Evidence from the Global Climate*

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Abstract

This paper shows that welfare inequality in a trading network is greater when productivities are rearranged such that neighboring locations are more similar. An increase in the spatial correlation of productivities amplifies cross-country welfare dispersion by increasing the correlation between productivity and the gains from trade. To empirically examine this prediction, we study how global agricultural trade responds to exogenous changes in the spatial correlation of agricultural productivity driven by a naturally occurring global climatic phenomenon. As predicted, higher spatial correlation in cereal yields increases the correlation between productivity and the gains from trade. In a forecasting application, climate-change projections for 2099 that incorporate this general-equilibrium effect exhibit substantially greater global welfare inequality, with higher welfare losses across most of Africa.

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1 Introduction

Natural endowments shape economic activity. Past research has linked local economic outcomes to local endowments. However, natural endowments are rarely confined to specific economic or political jurisdictions. Mineral deposits cross national borders, coastlines stretch across continents, and climate zones encompass much of a hemisphere. When locations trade with each other, local economic outcomes depend on both local economic conditions and conditions elsewhere. This paper addresses how the spatial structure of endowments influences the distribution of local economic outcomes. In particular, we show that when productivity levels are rearranged so that neighboring locations have more similar total factor productivities, this greater spatial correlation of productivities increases global dispersion of welfare across locations.

We theoretically demonstrate this mechanism in a standard model of international trade with distance-related trade costs. When a country’s neighbors have higher total factor productivity, it enjoys larger gains from trade. Greater spatial correlation of productivities increases welfare inequality by increasing the correlation between a country’s productivity and its gains from trade. When endowments are spatially uncorrelated, high- and low-productivity locations are evenly distributed across space; so too are the gains from trade, as all locations are similarly near both more and less productive trading partners. Conversely, when endowments are spatially correlated, there are clusters of high- and low-productivity locations: high-productivity locations gain more from trade because they are near high-productivity trading partners, while low-productivity locations gain less from trade because they are surrounded by similarly low-productivity locations. Thus, simply rearranging productivities such that they have higher spatial correlation increases inequality of welfare throughout the trading system.

To empirically investigate this general-equilibrium prediction, we study a natural experiment over the course of a half century of global agricultural trade. Causal inference is challenging when the prediction of interest concerns a system-wide feature of a trading network. In our context, we cannot experimentally rearrange the planet’s natural endowments. Our solution is to exploit an annual climatic phenomenon that approximates the ideal experiment in the agricultural sector by exogenously altering the spatial correlation of agricultural productivities. In particular, historical annual variation in the El Niño-Southern Oscillation (ENSO) abruptly causes a spatial reshuffling of agricultural productivity across the planet, creating large, spatially contiguous regions with similar productivities. We use a sufficient-statistics approach to infer the gains from trade from observed expenditure shares (Arkolakis, Costinot and Rodríguez-Clare, 2012). As predicted, we find that greater spatial correlation of productivity increases the correlation between productivity and the gains from trade. A one-standard-deviation increase in the spatial correlation of agricultural productivities increases the dispersion of welfare attributable to agricultural consumption by 2%.

We show how to incorporate this general-equilibrium mechanism when forecasting the economic impacts of anthropogenic climate change. Climate change is expected to induce a large spatial restructur-
try. A full account of climate change’s economic impacts must incorporate both local productivity changes and how the new spatial structure of productivities alters patterns of economic exchange in general equilibrium. We show that including the change in the spatial structure of productivities has an important consequence for our forecast of global inequality. Specifically, climate impact projections that incorporate the projected change in the spatial correlation of agricultural productivity due to climate change predict a 19% higher increase in welfare inequality from agricultural consumption by the end of the twenty-first century. Projections that omit this general-equilibrium effect considerably understate the climate-driven welfare losses for most countries in Africa. More generally, this general-equilibrium mechanism can be applied to studying settings in which there is a change in the spatial correlation of productivities following the relocation of existing endowments (e.g., migrating wildlife stocks), the discovery of new uses for them (e.g., solar and wind resources), or the discovery of new endowments (e.g., fossil fuel deposits).

This paper relates to the ongoing, centuries-old dialogue regarding the possible contribution that environmental and geographic endowments may have in determining the long-run well-being of societies (Sachs and Warner, 1997; Easterly and Levine, 2003). Persistent correlations between geographic endowments and economic outcomes are often remarkable (Hornbeck, 2012), with prior work articulating numerous potential channels of influence, such as differing availability of local inputs leading to differing local productivities (Nordhaus, 2006; Bleakley, 2007), as well as differing local conditions producing differing local institutions (Numm and Puga, 2012) or differing patterns of local investment (Burchfield et al., 2006). Our analysis proceeds to explore the influence of non-local geographic endowments, occurring at both neighboring and distant locations, in the determination of local outcomes—an effect that depends critically on the spatial relationship between local and non-local endowments. In short, we focus on the general-equilibrium role of geography.

Our paper thus contributes to a large literature in international trade and economic geography studying local economic consequences of the geographic distribution of economic activity. Prior research has demonstrated that better market access, which is the sum of other locations’ economic activity discounted by bilateral trade costs, is associated with higher per capita income and higher land values (Head and Mayer, 2004; Redding and Venables, 2004; Allen and Arkolakis, 2014; Donaldson and Hornbeck, 2016). These studies infer these benefits from observed changes in bilateral trade costs or cross-sectional variation in access to endogenous economic activity. Prior examinations of heterogeneity in the gains from trade have overwhelmingly focused on the role of country size rather than geography (e.g., Costinot and Rodríguez-Clare 2014). By contrast, we exploit exogenous variation in the global distribution of agricultural productivities to study how the distribution of welfare outcomes depends on the spatial arrangement of economic primitives.

The most closely related study of global agricultural trade is Costinot, Donaldson and Smith (2016), who study the consequences of climate change using a model of international trade and an agronomic productivity forecast. While we focus on the spatial correlation of absolute advantage, they focus on changes in comparative advantage and find that within-country crop switching substantially reduces predicted output and welfare losses. Since their theoretical framework in-
corporates a standard gravity model of trade flows, their results implicitly incorporate the spatial structure of productivity in the agronomic forecast. We contribute to the understanding of our mechanism by empirically examining the role of spatial correlation using historical variation in agricultural productivities.

Finally, this paper speaks to the growing empirical literature examining how anthropogenic climate change may affect inequality. Prior research employing estimates from historical local temperature variation has forecast considerable dispersion in various economic outcomes under projected climate change, both across countries (Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015) and within countries (Burgess et al., 2014; Houser et al., 2015). This paper shows that climate impact projections that omit general-equilibrium effects due to climate-driven changes in the spatial structure of productivities may understate future inequality. Thus, our paper brings the reduced-form climate-impacts literature conceptually closer to recent macroeconomic analyses exploring the spatial distribution of economic activity under climate change (Brock, Engström and Xepapadeas, 2014; Desmet and Rossi-Hansberg, 2015; Krusell and Smith, 2016).

The rest of the paper is structured as follows: Section 2 provides our theoretical framework and prediction about the spatial correlation of productivity. Section 3 introduces the El Niño-Southern Oscillation and shows how it affects the spatial correlation of agricultural productivity across the world. Section 4 uses ENSO-driven variation in agricultural productivity to empirically validate our prediction. Section 5 considers implications for projecting the global impacts of anthropogenic climate change. Section 6 concludes.

2 Theoretical framework

This section introduces our theoretical framework that shows how the spatial correlation of productivities affects welfare inequality and guides our empirical investigation of this prediction.

In any trade equilibrium, a country’s welfare can be stated as the sum of its welfare under autarky and its gains from trade. A country’s welfare under autarky depends only on its own productivity. Its gains from trade depend on the entire distribution of productivities across the trading network. The variance of welfare across countries is the variance of this sum. It therefore depends on not only the variances of productivity and the gains from trade but also the covariance between these two components.

We investigate how the spatial correlation of productivities influences the covariance between a country’s productivity and its gains from trade. This requires an observable outcome that identifies the gains from trade. Across a broad class of models, a country’s gains from trade are revealed by the share of its expenditure devoted to its own output. The less a country spends on its own output, the larger its gains from trade. In autarky, all its expenditure is on its own output. In the trade equilibrium, this expenditure share, when combined with the “trade elasticity” governing how consumers substitute across consumption sources, summarizes the welfare gain from exchange with other locations (Arkolakis, Costinot and Rodríguez-Clare, 2012).
Section 2.1 establishes that within this class of trade models our object of interest is the covariance between a country’s productivity and its domestic share of expenditure. Section 2.2 illustrates how this covariance depends on the spatial correlation of the productivity distribution and shows how to identify this \textit{ceteris paribus} prediction in empirical settings. Section 2.3 describes conditions under which examining one sector in isolation is informative about welfare dispersion in a multi-sector world. Details and derivations are available in Appendix A.

2.1 Sufficient statistics for welfare dispersion

We consider a general economic environment within the class of models characterized by Arkolakis, Costinot and Rodríguez-Clare (2012), in which the gains from trade can be inferred from the domestic share of expenditure. We assume perfect competition in the main text, while Appendix A.1 covers the case of monopolistic competition. The world economy is comprised of \( j = 1, \ldots, N \) countries.

\textbf{Preferences}. Individuals in country \( j \) have preferences with a constant elasticity of substitution \( \sigma > 1 \) over goods indexed by \( \omega \). The accompanying price index is

\[
P_j = \left( \int \omega p_j(\omega)^{1-\sigma} d\omega \right)^{1/(1-\sigma)}.
\]

\textbf{Production}. There is one factor of production, and each country \( j \) inelastically supplies \( L_j \) units of that factor, which earns wage \( w_j \). A country’s income is therefore \( Y_j = w_j L_j \). The production technology exhibits constant returns to scale and is employed by perfectly competitive firms. The cost of producing in country \( j \) depends on productivity \( A_j \). This parameter’s microeconomic meaning is model-specific: \( A_j \) governs the cost of producing \( j \)’s good in the Armington model and the location parameter of \( j \)’s cost distribution for a continuum of goods in the Eaton and Kortum (2002) model.

\textbf{Trade costs}. There are iceberg trade costs, such that selling one unit of a good to \( j \) from \( i \) requires \( \tau_{ij} \geq 1 \) units, with \( \tau_{ii} = 1 \). By the no-arbitrage condition, \( p_j(\omega) \leq \tau_{ij} p_i(\omega) \).

\textbf{Gravity equation}. Denote sales from \( i \) to \( j \) by \( X_{ij} \) and \( j \)’s total expenditure by \( X_j \equiv \sum_{i=1}^{N} X_{ij} \). The share of expenditure by \( j \) on goods from \( i \) takes the form of a gravity equation:

\[
\lambda_{ij} = \frac{X_{ij}}{X_j} = \frac{\chi_i \left( \tau_{ij} w_i \right)^{-\epsilon}}{\sum_{l=1}^{N} \chi_l \left( \tau_{lj} w_l \right)^{-\epsilon}} = \frac{\chi_i \left( \tau_{ij} w_i \right)^{-\epsilon}}{\Phi_j},
\]

where \( \chi_i \) is a function of \( A_i \) and other structural parameters that are not trade costs, \( \epsilon \) is the “trade elasticity”, and \( \Phi_j \equiv \sum_{l=1}^{N} \chi_l \left( \tau_{lj} w_l \right)^{-\epsilon} \) is the “inward multilateral resistance” term (Head and Mayer, 2014). \( \Phi_j \) is a (decreasing) transformation of \( j \)’s price index that summarizes consumers’ access to goods from every source.

\textbf{Equilibrium}. In equilibrium, labor-market clearing, goods-market clearing, and budget constraints are satisfied such that total income \( Y_i = w_i L_i \) equals total expenditure \( X_i \). Thus, an
equilibrium is a set of incomes \( \{Y_i\}_{i=1}^N \) such that

\[
Y_i = \sum_{j=1}^N \lambda_{ij} Y_j.
\]

In this environment, the results of Arkolakis, Costinot and Rodríguez-Clare (2012) imply that real consumption per capita is

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

where \( \gamma \) is a constant determined by structural parameters that are not productivity. The former term, \( \ln A_i + \gamma \), is per capita welfare in autarky. In the absence of trade, a country’s welfare is independent of other countries’ conditions and depends only on its own productivity. The latter term, \(-\frac{1}{\epsilon} \ln \lambda_{ii}\), is a sufficient statistic for the gains from trade relative to autarky. It is a country’s expenditure share on its own goods, mediated by the trade elasticity \( \epsilon \) that governs how bilateral expenditures respond to changes in bilateral trade costs. With this standard equilibrium expression for welfare in hand, we can consider how dispersion in \( \ln (C/L) \) across countries depends on the spatial distribution of productivities.

From equation (1), variance in welfare across countries is governed by the variance of productivity, the covariance of productivities and gains from trade, and the variance of those gains.

\[
\text{var} (\ln (C_i/L_i)) = \text{var} (\ln A_i) + 2 \text{cov} \left( \ln A_i, \frac{1}{\epsilon} \ln \lambda_{ii} \right) + \text{var} \left( \frac{1}{\epsilon} \ln \lambda_{ii} \right)
\]

(2)

To examine the role of spatial correlation, consider two productivity distributions – a correlated state \( c \) and an uncorrelated state \( u \) – in which the unconditional variance in productivities is identical, \( \text{var}(\ln A^c_i) = \text{var}(\ln A^u_i) \). Under this assumption, the difference in welfare dispersion between the correlated and uncorrelated states is

\[
\text{var} (\ln (C^c_i/L_i)) - \text{var} (\ln (C^u_i/L_i)) = -\frac{2}{\epsilon} \left[ \text{cov} (\ln A^c_i, \ln \lambda^c_{ii}) - \text{cov} (\ln A^u_i, \ln \lambda^u_{ii}) \right] + \frac{1}{\epsilon^2} \left[ \text{var} (\ln \lambda^c_{ii}) - \text{var} (\ln \lambda^u_{ii}) \right].
\]

(3)

The latter term should make only a second-order contribution to the difference in welfare dispersion, since \( \frac{1}{\epsilon^2} \) is an order of magnitude smaller than \( \frac{2}{\epsilon} \) for empirically relevant values of the trade elasticity.\(^2\)

\(^{2}\) Typical estimates of the aggregate trade elasticity are between 4 and 8. Caliendo and Parro (2015) estimate that the trade elasticity for agricultural goods is between 8 and 16. Provided that \( \text{var} (\ln \lambda^c_{ii}) - \text{var} (\ln \lambda^u_{ii}) \) is the same order of magnitude or smaller than \( \text{cov} (\ln A^c_i, \ln \lambda^c_{ii}) - \text{cov} (\ln A^u_i, \ln \lambda^u_{ii}) \), this means that the second term on the right side of equation (3) is an order of magnitude smaller than the first term. Appendix A.1.3 shows that, if trade costs are symmetric (\( \tau_{ij} = \tau_{ji} \)) and countries equal sized (\( L_i = L \ \forall i \)), \( \text{var} (\ln \lambda^c_{ii}) - \text{var} (\ln \lambda^u_{ii}) = \frac{1}{N+1} \left[ \text{cov} (\ln A^c_i, \ln \lambda^c_{ii}) - \text{cov} (\ln A^u_i, \ln \lambda^u_{ii}) \right] + \frac{1+2\epsilon}{\epsilon^2} \left[ \text{cov} (\ln \Phi_i, \ln \lambda^c_{ii}) - \text{cov} (\ln \Phi_i, \ln \lambda^u_{ii}) \right] \). Heuristically, the latter term is of smaller magnitude, since \( \Phi_i \) is a price-index term that is a weighted sum of all other countries’ prices. Thus, \( \text{var} (\ln \lambda^c_{ii}) - \text{var} (\ln \lambda^u_{ii}) \) is the same order of magnitude as \( \text{cov} (\ln A^c_i, \ln \lambda^c_{ii}) - \text{cov} (\ln A^u_i, \ln \lambda^u_{ii}) \).
The first-order difference in welfare dispersion is governed by the covariance of productivities and domestic shares of expenditure. All else equal, this covariance will typically be positive: since a more productive country sells more to every consumer, a more productive country purchases more from itself.

Our concern here, however, is how this covariance changes with the degree of spatial correlation in productivities. We will estimate this relationship empirically, but we first illustrate why we expect that $\text{cov}(\ln A^c_i, \ln \lambda^c_{ii}) < \text{cov}(\ln A^u_i, \ln \lambda^u_{ii})$ and thus that $\text{var}(\ln (C^c_i/L_i)) > \text{var}(\ln (C^u_i/L_i))$.

### 2.2 Spatial correlation and the covariance of productivity and gains from trade

This section illustrates how the spatial correlation of productivity influences the variance of welfare by shaping the covariance of productivity and gains from trade. The key is that bilateral trade costs increase with the physical distance between trading partners. Thus, when proximate countries have more similar productivity levels, more productive countries tend to enjoy greater gains from trade because their nearby trading partners are also more productive. Conversely, less productive countries experience lower gains from trade when productivity is more spatially correlated. To demonstrate this mechanism more formally, we start by examining the role of the spatial correlation of productivity in two settings in which countries are perfectly symmetric except for productivity differences. These stylized examples allows us to clearly illustrate our economic mechanism in isolation. We then examine how to identify this *ceteris paribus* prediction in asymmetric environments in which countries differ by other, potentially confounding, determinants of equilibrium trade flows. These more realistic examples inform how we empirically investigate our prediction.

#### 2.2.1 Stylized example 1: Four-country case

We start with the simplest possible environment in which one can demonstrate our result. The world is comprised of $N = 4$ countries of equal size, $L_i = L$ for $i = 1, \ldots, 4$. The four countries are evenly spaced on a symmetric geography such that each country is “near” two neighboring countries and farther from the remaining country. Thus, the trade cost matrix is

\[
\tau \equiv \begin{bmatrix}
1 & d_1 & d_2 & d_1 \\
d_1 & 1 & d_1 & d_2 \\
d_2 & d_1 & 1 & d_1 \\
d_1 & d_2 & d_1 & 1
\end{bmatrix}, \quad 1 < d_1 < d_2 < d_1^2
\]

(4)

where the trade costs $d_2 > d_1$, a mnemonic for distance, obey the triangle inequality: $d_2 < d_1^2$.

For these four countries, consider a mirror-image productivity distribution in which two countries have high productivity and the other two countries have low productivity. Without loss of generality, normalize the lower productivity to one and denote the higher productivity level by $\tilde{a} > 1$. For this symmetric geography with four countries, these productivities might alternate – high, low, high, low – or the world may be divided into a high-productivity region and a low-
productivity region. These two spatial arrangements are depicted in Figure 1. What are the consequences for trade and welfare?

Proposition 1 shows that the “regional” arrangement of productivities exhibits greater spatial correlation, as measured by Moran’s $I$. As a result, the covariance of productivity and the domestic share of expenditure is lower when productivities are distributed this way. That makes the variance of welfare across countries greater. The mean of welfare across countries is lower. The proof of Proposition 1 appears in Appendix A.2.1.

**Proposition 1** (Four-country case). Consider an economy in which $N = 4$, $L_i = L \forall i$, $\epsilon \geq 1$, and trade costs $\tau_{ij}$ are given by condition (4). Comparing the productivity distributions $A^c = (\tilde{a}, \tilde{a}, 1, 1)$ and $A^u = (\tilde{a}, 1, \tilde{a}, 1)$, where $\tilde{a} > 1$,

- $A^c$ is more spatially correlated than $A^u$ in the sense that the value of Moran’s $I$ for $\ln A^c$ is greater for any spatial weight matrix that is a one-to-one mapping between $\omega_{ij}$ and $\tau_{ij}$ and assigns a higher weight to the pairs with $\tau_{ij} = d_1$ than pairs with $\tau_{ij} = d_2$.

- Equilibrium income inequality, given by $Y_1/Y_4$, is greater for the more spatially correlated productivity distribution, $A^c$. Equivalently, the more productive economies’ equilibrium double-factoral terms of trade are greater for the more spatially correlated productivity distribution.

- The covariance of productivity and the domestic share of expenditure is lower for the more spatially correlated productivity distribution: $\text{cov}(\ln A^c_i, \ln \lambda^c_{ii}) < \text{cov}(\ln A^u_i, \ln \lambda^u_{ii})$.

- The variance of welfare across counties is greater for the more spatially correlated productivity distribution: $\text{var}(\ln(C^c_i/L)) > \text{var}(\ln(C^u_i/L))$.

- The mean of welfare across countries is lower for the more spatially correlated productivity distribution: $\mathbb{E}(\ln(C^c_i/L)) < \mathbb{E}(\ln(C^u_i/L))$.

---

3 Moran’s $I$ is a commonly used measure of global spatial correlation that can be computed for any geography endowed with a distance metric. Formally, Moran’s $I$ for $\ln A_{it}$ in year $t$ is

$$I_t = \frac{\sum_i \sum_{j \neq i} \omega_{ij} (\ln A_{it} - \ln A_i) (\ln A_{jt} - \ln A_j)}{\sum_i (\ln A_{it} - \ln A_i)^2},$$

where $\omega_{ij}$ is a spatial weight and $\ln A_i$ is the cross-sectional average in year $t$. 

7
This four-country case establishes our prediction linking the spatial correlation of productivity to welfare inequality. Next, we illustrate this logic in a setting with an arbitrary number of countries that are perfectly symmetric except for productivity differences.

2.2.2 Stylized example 2: Circular geography with productivity sine wave

Our second stylized environment has productivity follow a sine wave over a one-dimensional space. There are \( N \) locations evenly spaced on the unit circle. These locations have equal population sizes, \( L_i = 1 \) \( \forall i \). Trade costs depend only on distance: the log trade cost between two locations is proportionate to the log distance between them. The trade elasticity is \( \epsilon = 1 \). Productivity \( \ln A_i \) follows a sine-wave distribution, with an integer frequency of \( \theta \) over the circle’s circumference. This functional form has two convenient properties. First, the spatial correlation of productivity is governed by the frequency \( \theta \): lower frequencies exhibit greater spatial correlation. Second, the mean, variance, skewness, and kurtosis of the productivity distribution are independent of the frequency. Thus, we can explore the effect of spatial correlation by varying \( \theta \) alone.\(^4\)

![Figure 2: Circular geography with productivity sine wave](image)

Notes: This figure depicts an economy with a circular geography and a productivity distribution that follows a sine wave with frequency \( \theta \). There are \( N = 50 \) locations evenly spaced on the unit circle. Bilateral log trade costs are proportionate to the log length of the arc between two points on the circle. The (demeaned) distributions of productivities, equilibrium domestic shares of expenditure, and welfare are depicted for the cases of \( \theta = 1 \) and \( \theta = 4 \). See Appendix A.2.2 for parameterization details.

Figure 2 depicts the spatial distributions of productivities (\( \ln A_i \)), domestic shares of expenditure (\( \ln \lambda_{ii} \)), and welfare (\( \ln C_i \)) in this circular economy for the cases in which the sine wave has

\(^4\) Details of the parameters underlying Figure 2 are in Appendix A.2. By Theorem 1 of Allen, Arkolakis and Takahashi (2017), the equilibrium solution depicted for each parameter value is unique.
Figure 3: Circular geography with productivity sine wave: $cov(ln \lambda_{ii}, ln A_i)$

NOTES: This figure depicts the $ln \lambda_{ii} - ln A_i$ relationship for an economy with a circular geography and a productivity distribution that follows a sine wave with frequency $\theta$. Geographic locations and trade costs as in Figure 2. See Appendix A.2 for parameterization details.

frequencies of $\theta = 1$ and $\theta = 4$. It is clear that the spatial correlation of productivity is greater in the $\theta = 1$ case, as location “zero” divides the circle into two contiguous regions with above-average and below-average productivity. In the $\theta = 4$ case, lower spatial correlation means that locations of opposing productivity are more closely situated. In the case of higher spatial correlation, $\theta = 1$, the equilibrium domestic share of expenditure series less closely follows the productivity series, as evident by the larger vertical gap between them. Thus, the smaller amplitude of the $ln \lambda_{ii}$ series when productivity is more spatially correlated is accompanied by a lower value of $cov(ln A_i, ln \lambda_{ii})$. As a result, the amplitude of the welfare series is greater in the $\theta = 1$ case. Welfare dispersion is higher when productivity is more spatially correlated.\footnote{In this particular parameterization, average welfare is slightly lower when productivity is more spatially correlated. See Table A.1 for details.}

Figure 3 depicts the expenditure-productivity relationship in our sine-wave example for more values of the sine-wave frequency, $\theta$. The scatter plot reveals an almost perfectly linear relationship between $ln \lambda_{ii}$ and $ln A_i$. The slope of this relationship, which is proportionate to $cov(ln A_i, ln \lambda_{ii})$, systematically varies with the frequency of the sine wave.\footnote{This pattern is exhibited for many parameter values in our numerical simulations. We have yet to prove this result analytically.} At lower frequencies, when the productivities are more spatially correlated, a location’s domestic share of expenditure is less responsive to its own productivity level.
2.2.3 Asymmetric environments

Our stylized, many-country example in Section 2.2.2 demonstrates the consequence of spatial correlation of productivity for global welfare inequality in an ideal environment that holds fixed all other economic elements. Compared to such an environment, any empirical setting is more complicated because (1) there are other determinants of equilibrium trade flows, (2) productivities do not follow a sine wave, and (3) countries are not evenly spaced on a circular geography. In this section, we discuss how to identify our ceteris paribus prediction about the impact of spatial correlation when such asymmetries are present.

Economic characteristics other than productivity that influence domestic shares of expenditure complicate bivariate plots like Figure 3. A simple example is heterogeneity in country size $L_i$: all else equal, larger economies have a larger domestic share of expenditure. Variation in size orthogonal to productivity simply adds noise to the bivariate plot. However, variation in size correlated with productivity also introduces omitted variable bias. This can be empirically addressed by examining the covariance of the domestic share of expenditure and productivity conditional on size. More generally, any time-invariant country characteristics that influence the domestic share of expenditure and might be correlated with productivity can be absorbed by country fixed effects.

We illustrate this in Figure 4, which depicts the relationship between $\ln \lambda_{ii}$ and $\ln A_i$ in an environment that features, like the previous section, a circular geography and sine-wave productivity, and, unlike the previous section, heterogeneous country sizes. In particular, country size $\ln L_i$ is positively correlated with productivity $\ln A_i$ in the $\theta = 1$ state. The left panel depicts the covariance of $\ln \lambda_{ii}$ and $\ln A_i$ for the frequencies $\theta = 1$ and $\theta = 4$. The right panel depicts these covariances conditional on country fixed effects. While our ceteris paribus prediction is not evident in the left panel due to omitted variable bias, the right panel shows that the covariance of $\ln \lambda_{ii}$ and $\ln A_i$ is lower when $\theta$ is lower, controlling for heterogeneous sizes.

Since actual productivity does not exhibit a sine-wave distribution, we cannot conduct our empirical examination in terms of the frequency $\theta$. Instead, we employ Moran’s $I$, a standard measure of global spatial correlation for any characteristic arbitrarily distributed over a geography endowed with a distance metric. To illustrate our prediction with this more general measure, consider again the circular geography with equal-sized countries. We generate random productivity distributions that differ only in their spatial correlation as measured by Moran’s $I$.\footnote{See Appendix A.2 for details.} Figure 5 plots the expenditure-productivity relationship against Moran’s $I$ for three productivity draws with different levels of spatial correlation. There is a clear negative relationship: as Moran’s $I$ increases, the equilibrium domestic share of expenditure is less responsive to domestic productivity.

Employing Moran’s $I$ to measure spatial correlation and introducing country fixed effects are also jointly sufficient to address the fact that countries are not evenly spaced on a circular geography. As mentioned above, the Moran’s $I$ statistic can be computed for any geography endowed with a distance metric. In asymmetric geographies, some countries are more “remote” from economic activity, regardless of the distribution of productivities. All else equal, remote countries exhibit a
Figure 4: Circular geography with heterogeneous sizes and productivity sine wave

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

Unconditional relationship

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

\[ \theta = 1 \quad \theta = 4 \]

Relationship conditional on fixed effects

Notes: This figure depicts the $\lambda_{ii}-A_i$ relationship for an economy with a circular geography and a productivity distribution that follows a sine wave with frequency $\theta$. Geographic locations and trade costs as in Figure 2. Country sizes $L_i$ are positively correlated with $A_i$ in the $\theta = 1$ state. See Appendix A.2 for parameterization details.

Figure 5: Circular geography with equal-sized countries and arbitrary productivities

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

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

\[ I = 0.00 \quad I = 0.10 \quad I = 0.20 \]

Notes: This figure depicts the $\lambda_{ii}-A_i$ relationship for an economy with a circular geography and three selected randomly generated productivity distributions. Geography, equal-sized locations, and trade costs as in Figure 2. See Appendix A.2 for parameterization details.

higher domestic share of expenditure. This variation is absorbed by country fixed effects.

Figure 6 plots the expenditure-productivity relationship against Moran’s $I$ for an economy with randomly located countries on a two-dimensional space and random assignments of productivity
levels that differ only in their spatial correlation. The vertical axis is the coefficient from a linear regression of the domestic share of expenditure on own productivity,

\[
\ln \lambda_{iit} = \beta_t \ln A_{it} + \pi_t^I + \pi_t^T + \epsilon_{it},
\]

(5)

for country \(i\) at “time” \(t\), where each \(t\) denotes an equilibrium associated with a different productivity distribution. The country fixed effects \(\pi_t^I\) control for differences in countries’ time-invariant determinants of the domestic share of expenditure, such as remoteness. The “year” fixed effects \(\pi_t^T\) control for differences in the average domestic shares of expenditure across different spatial distributions of productivity. The year-specific (distribution-specific) slope coefficient \(\beta_t\) captures the resulting expenditure-productivity relationship for each spatial distribution. There is a clear negative relationship between the responsiveness of domestic share of expenditure to own productivity and the spatial correlation of productivities. While the relationship is not literally monotonic, the elasticity of \(\lambda_{iit}\) with respect to \(A_{it}\) is systematically lower at higher levels of Moran’s \(I\). This generalizes the patterns in our stylized, one-dimensional case to more realistic geographies.

Figure 6: Random-geography economy

Notes: This figure depicts how \(\text{cov}(\ln \lambda_{iit}, \ln A_{i})\) varies with the spatial correlation of productivity, as measured by Moran’s \(I\), over a randomly generated geography. We vary the spatial distribution of productivity while holding the first and second moments fixed. The elasticity of \(\lambda_{iit}\) with respect to \(A_{it}\) is \(\hat{\beta}_t\) estimated from \(\ln \lambda_{iit} = \beta_t \ln A_{it} + \pi_t^I + \pi_t^T + \epsilon_{it}\), as described in the text. See Appendix A.2 for parameterization details.

---

8 We generate a two-dimensional geography by randomly drawing \(N\) locations’ coordinates from a normal distribution. The bilateral log trade costs between these \(N\) locations are proportionate to the log straight-line distances between them. We fix the first, second, and higher-order moments of the productivity distribution while varying its spatial correlation. Appendix A.2 details our procedure generating the geography and productivity distributions.
2.3 Multiple-sector case

Our empirical investigation exploits exogenous variation in the spatial distribution of productivities in the agricultural sector, which constitutes a small share of global trade. What happens in an economy with multiple sectors? Appendix A.3 shows that our prediction linking the spatial correlation of productivity and the productivity-expenditure relationship holds for each sector in a multi-sector gravity model of trade. When consumers have Cobb-Douglas preferences over sectors and CES preferences over varieties within sectors, there are multi-sector analogues of equations (1), (2), and (3) that sum over sectors using their expenditure shares. Thus, the previous section’s predictions about trade in one sector can be empirically investigated in a multi-sector world.

Figure 7: Two-sector sine-wave economy: $cov(\ln \lambda_{i1}, \ln A_{i1})$

Notes: This figure depicts the $\lambda_{i1s}$–$A_{i1s}$ relationship for $s = 1$ in a two-sector economy in which sectoral productivity follows a sine wave with frequency $\theta_s$. The two series depicted are frequencies $\theta_1 = 1$ and $\theta_1 = 4$ for the first sector. The second sector has frequency $\theta_2 = 10$ in both cases. The two sectors have identical trade costs $\tau_{ij}$, expenditure shares $\alpha_{i1} = \alpha_{i2} = \frac{1}{2}$, and trade elasticities $\epsilon_1 = \epsilon_2$. The two lines are the line of best fit for each series. When productivity is more spatially correlated (when $\theta_1$ is lower), $cov(\ln \lambda_{i1}, \ln A_{i1})$ is lower. See Table A.2 in Appendix A.2 for details of this example.

Compared to a one-sector model, the opportunity to produce non-agricultural goods is an additional margin of adjustment that may dampen the magnitude of the welfare consequence of a given agricultural productivity shock. If agricultural and non-agricultural activities were positively correlated, there would be little scope for adjustment. To illustrate the case in which these productivities are orthogonal, Figure 7 presents a multi-sector analogue of Figure 3 for an economy with two symmetric sectors that differ only in their sine-wave frequency. The idiosyncratic, orthogonal variation in the second sector’s productivity adds noise to the relationship between the

---

9 Appendix A.3 shows that a multi-sector model with perfectly correlated productivities, proportionate bilateral trade costs, and equal trade elasticities delivers a welfare-difference expression exactly proportionate to the single-sector expression in equation (3).
domestic share of agricultural expenditure and agricultural productivity, but it does not change
the comparative static of interest. When the first sector’s productivity is more spatially correlated,
the covariance of its log productivity and log domestic share of expenditure is smaller. This raises
dispersion in welfare relative to the case in which the first sector’s productivity is less spatially
correlated.

3 The El Niño-Southern Oscillation

Does greater spatial correlation of productivities in fact increase the covariance between produc-
tivity and the gains from trade? In an ideal experiment, a researcher could test our prediction by
manipulating productivities around the world in a way that alters the global spatial correlation
of productivities without changing the global mean or variance of productivities. Such an exper-
iment is obviously not possible with international trade. However, we are able to approximate
this idealized setting by exploiting a global climatic phenomenon known as the El Niño-Southern
Oscillation (ENSO). This section first summarizes the basic physics of ENSO and then empirically
demonstrates that it drives annual changes in the global spatial correlation of cereal productivity.

3.1 Background

The El Niño-Southern Oscillation is a naturally occurring climatic phenomenon characterized by
mutually reinforcing circulation patterns between the atmosphere and the tropical Pacific ocean.
While ENSO originates in the tropical Pacific, it is a major determinant of weather conditions
around the world. Indeed, at an annual frequency, ENSO is often recovered as the first principal
component of various local atmospheric or oceanographic variables across the planet (Sarachik and
Cane, 2010).

ENSO is often colloquially described as consisting of one neutral state and two extreme states.
Oscillations across the two extreme states occur over a quasi-periodicity of 3-7 years. These con-
ditions are broadly characterized by the amount of heat that is released from the tropical Pacific
ocean into the atmosphere (Cane and Zebiak, 1985). In typical, “ENSO neutral” years, normal
circulation patterns pushing westward hold a pool of warm water against Indonesia and other land
masses in the South Pacific. An extreme “El Niño” state occurs when this circulation pattern
weakens such that this pool of warm water spills eastward across a large area of the equatorial
Pacific Ocean. With warm water exposed to the atmosphere over a greater area, El Niño releases
more ocean heat into the atmosphere over a relatively short period. The opposite occurs during
the “La Niña” state. Under La Niña, circulation patterns strengthen such that the same volume
of warm water is pushed more firmly against the Indonesian landmass reducing sea-surface contact
with the atmosphere and thus reducing heat released from the ocean.

These distinct states are useful for broadly characterizing the ENSO phenomenon. However,
in reality there is a continuum of ENSO conditions, with the amount of heat released into the
tropical atmosphere each year typically somewhere in between La Niña and El Niño extremes. We
henceforth refer to a positive ENSO event when conditions falls in between neutral and El Niño states. Similarly, a negative ENSO event occurs when conditions are between neutral and La Niña states.

ENSO conditions in the tropical Pacific affect the spatial pattern of weather conditions across the planet due to how heat travels when it is released in the tropics. Because there is almost no Coriolis effect near the equator (a result of the simple facts that the Earth is round and spins), atmospheric signals propagate rapidly throughout the tropics. During a positive ENSO event, the warm air initially released above the tropical Pacific Ocean is propagated throughout the tropics by a transport mechanism in the atmosphere known as an equatorial Kelvin wave that sweeps across the globe, altering weather conditions almost simultaneously throughout the tropics (Chiang and Sobel, 2002).10 For this reason, it is often said that the tropical atmosphere is “teleconnected” through ENSO, as atmospheric conditions in locations distant from each other are linked through this mechanism. Because the equatorial Kelvin wave that connects local weather around the equator is constrained primarily to the tropics, where the Coriolis effect is weak, the warming that prevails during a positive ENSO event does not generally extend to higher latitudes. Instead, higher-latitude locations become slightly cooler on average because of changes to the circulation of the atmosphere.

As shown below, this physical mechanism causes ENSO to have spatially broad effects on temperatures around the planet. During a positive ENSO event, temperature conditions around the world are reorganized such that there is a spatially contiguous area of relatively warm temperature across the tropics and subtropics while almost simultaneously there is a spatially contiguous area of relatively cooler temperatures in higher-latitude locations. The opposite occurs during negative ENSO events. Less heat is released into the atmosphere and temperatures across the globe are less organized spatially.11

ENSO conditions are typically summarized by the average sea-surface temperature over a fixed area in the tropical Pacific. In our main analysis, we employ the widely used NINO4 index, a statistic defined as average ocean temperature (in degrees Celsius) over a rectangular area bounded by 5°S - 5°N, 160°E - 150°W (see Figure E.1). Henceforth, we refer to the NINO4 index simply as the ENSO index. As shown later, choice of this particular ENSO measure is inessential for our results.

Figure 8 plots the monthly ENSO index for 1856-2013, which extends further back than our sample period of 1961-2013. Observe that the index fluctuates between positive and negative ENSO values and appears stationary during this period. There are two important features of ENSO relevant for our empirical application: (i) the monthly timing of a typical ENSO event and (ii) how an ENSO event influences local temperatures around the planet both spatially and temporally.

10 This tropical phenomenon is described in Hsiang and Meng (2015). For a complete scientific treatment of ENSO physics, we refer interested readers to Sarachik and Cane (2010).
11 ENSO also influences other weather variables, such as precipitation and humidity, around the world. However, those effects generally exhibit smaller spatial scales. For example, during positive ENSO events there is typically flooding over the Pacific coast of South America while the Atlantic coast of South America primarily experiences drought conditions (Ropelewski and Halpert, 1987).
The timing of ENSO events, due to its tropical origins, is phase-shifted relative to the calendar year. An ENSO event generally begins during April-May of a given year and lasts until the following April-May, an interval known as the “tropical year.” To illustrate the within-year evolution of ENSO events, Figure E.2 isolates the 10 most positive ENSO events during our 1961-2013 sample period and plots the monthly ENSO index 12 months before and after a given December. For each ENSO event, the ENSO index begins rising around April-May of a given year and fully dissipates by June of the following year. Because the ENSO index typically peaks in December, the cleanest annual measure of any ENSO event is simply the December ENSO index. In all following empirical analyses, we use December values as our annualized measure of ENSO.

There is a spatially and temporally distinct manner in which a typical ENSO event affects local temperatures around the planet. Figure 9 displays the canonical structure of warming that occurs when the ENSO index increases, month by month. Each map displays the time-series correlation of monthly temperatures for each pixel during the specified month and ENSO in month zero, defined as December. Yellow, orange, and red colors indicate locations that warm as the ENSO index increases; blues indicate locations that cool. In May before a December ENSO event (month -7), the east equatorial Pacific begins to warm. Regions throughout the tropics, both over land and the oceans, continue to warm for the next several months, peaking in the east Pacific in December (month 0) and over the rest of the tropics in March and April (months +3 and +4). This warming then dissipates across the tropics with little visible effect more than a year after the December peak. Higher latitudes experience some cooling through these months, though the effect is weaker. Figure 9 shows that the local impacts on temperatures around the planet from a single ENSO event straddles two calendar years. When using socio-economic data that is indexed by calendar years, this implies that one must examine how outcomes in a given year are influenced by both ENSO in that year and by ENSO in the previous year.
Figure 9: Lead and lag local temperature correlation with December ENSO

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.
3.2 ENSO and the spatial correlation of cereal productivity

The spatial and temporal patterns shown in Figure 9 suggest that ENSO could drive global spatial correlation in cereal yields, a productivity measure that is both directly observed at the country level with near global data coverage and has previously been documented to be sensitive to local temperature conditions (Schlenker and Roberts, 2009; Hsiang and Meng, 2015).\(^\text{12}\) To demonstrate this at an annual time scale, for which productivity and trade data is available, Figure 10 shows the country-level linear coefficients due to a 1-degree increase in the sum of contemporaneous and lagged December ENSO indices on crop-area weighted annual temperature (top panel) and log cereal yields (bottom panel). ENSO fluctuations generate a clear spatial pattern in country-level temperatures and cereal productivity. Consistent with the tropical climatic dynamics discussed above, increases in the ENSO index tend to raise temperatures and lower cereal productivities in countries closer to the equator and lower temperatures and raise cereal productivities in countries farther from the equator.

Figure 10 suggests that ENSO could drive global spatial correlation in cereal yields, but it does not quantify the relationship. To calculate spatial correlation within each year, we turn to a standard measure, Moran’s I. In particular, we construct an annual Moran’s I statistic for both country-level temperature and log cereal yields.\(^\text{13}\)

Figure 11 shows a relationship between ENSO and the global spatial correlation in temperature (left panel) and cereal productivity (right panel). To characterize the ENSO phenomenon in terms of a scalar, we simplify the timing issues discussed above by plotting the sum of December ENSO indices in years \(t\) and \(t-1\) on the horizontal axis and Moran’s I in year \(t\) on the vertical axis. An increase in the ENSO index raises both the global spatial correlation in temperature and log cereal productivity. ENSO, in this simple bivariate model, explains 11% and 12% of annual variation in the global spatial correlations of temperature and cereal productivity, respectively.

To relax the timing simplification of Figure 11, Table 1 presents regressions of the annual Moran’s I statistic for log cereal yields on flexible polynomial functions of December ENSO in year \(t\) and \(t-1\). All models include a linear time trend and standard errors robust to serial correlation and heteroskedasticity. In column 1, we include only linear contemporaneous and lagged ENSO terms. Column 2 augments column 1 by further including a linear interaction term and quadratic contemporaneous and lagged ENSO terms. Column 3 estimates the linear and quadratic effects for the sum of contemporaneous and lagged ENSO. This is a more parsimonious but restrictive version of column 2 by requiring a single coefficient for \(ENSO_t\) and \(ENSO_{t-1}\) and a single coefficient for \(ENSO_t \times ENSO_{t-1}\), \(ENSO_t^2\), and \(ENSO_{t-1}^2\). Two results are evident. First, both contemporaneous and lagged ENSO affects the spatial correlation of cereal productivity but only after controlling for higher order terms, as shown in column 2. Second, compared with the model

---

\(^{12}\) We compute yields for the top eight globally produced cereals: barley, maize, millet, oats, rice, rye, sorghum, and wheat.

\(^{13}\) Proposition 1 is true for any spatial weight matrix that assigns greater weight to pairs of countries with lower trade costs. In our empirical applications, we use spatial weights \(\omega_{ij} = 1/(d_{ij} + 1)\), where \(d_{ij}\) is the great-circle distance between the two countries’ area-weighted centroids.
Figure 10: ENSO’s effects on temperatures and cereal yields

Notes: Map shows the linear coefficient on the sum of contemporaneous and lagged ENSO for crop area-weighted temperature (top panel) and log cereal yields (bottom panel) for each country. Each country-specific time series model includes a constant and a linear time trend.

Figure 11: Moran’s $I$ for temperatures and cereal yields and ENSO

Notes: Left (right) panel shows the relationship between Moran’s $I$ of crop-weighted country-level temperature (log cereal yields) in year $t$ and the sum of contemporaneous and lagged December ENSO. Linear fit shown as solid line. Local polynomial fit shown as dashed line.
in column 2, column 3 produces a stronger fit, as summarized by a lower Bayesian Information
Criterion (BIC) value. As a consequence, all empirics in Section 4 will use the functional form
in column 3 to model the relationship between ENSO and the global spatial correlation of cereal
productivity as it strikes a balance between allowing nonlinearity while limiting overfitting.

Finally, consistent with our thought experiment in Section 2.1, ENSO appears to affect neither
the global mean nor the variance of cereal productivity, as shown by the left and right panels of
Figure 12, respectively.

<table>
<thead>
<tr>
<th>Table 1: Moran’s I in cereal productivity and ENSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome is Moran-I in log cereal yields</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$ENSO_t$</td>
</tr>
<tr>
<td></td>
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<td></td>
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<tr>
<td>$ENSO_{t-1}$</td>
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<tr>
<td>$(ENSO_t + ENSO_{t-1})$</td>
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</tr>
<tr>
<td>$(ENSO_t + ENSO_{t-1})^2$</td>
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<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td>BIC</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Notes: Time-series regressions of Moran’s I in log cereal yields on nonlinear functions of contemporaneous and lagged December ENSO. All models include a linear time trend. Serial correlation and heteroskedasticity-robust Newey-West standard errors with optimal bandwidth in parentheses (Newey and West, 1987); p-values in brackets.

4 Empirical results

The theoretical results in Section 2 suggest that the covariance between agricultural productivity, $\ln A_i$, and the domestic share of expenditure, $\ln \lambda_{ii}$, should be lower when the spatial correlation of productivity across the entire trading network increases. This section examines this relationship
empirically using exogenous ENSO-driven changes in the global spatial correlation of productivity. We first describe our estimation strategy, then report our main finding and subject it to a series of robustness checks. Appendix B details our data sources and how we construct country-year-level measures of $\ln \lambda_{it}$ and $\ln A_{it}$ from output and trade data for eight major cereals.

### 4.1 Estimation strategy

We empirically estimate a variant of equation (5), used in Section 2.2.3 to theoretically demonstrate our prediction under the most realistic set of modeling assumptions. Specifically, for country $i$ in year $t$, we consider the following regression equation:

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

(6)

where $\lambda_{it}$ is country $i$’s agricultural domestic share of expenditure in year $t$, $A_{it}$ is its cereal yield, and $I_t$ is the Moran’s $I$ statistic capturing the spatial correlation of $\ln A_{it}$ for all countries in year $t$. $Z_{it}$ is a vector of semi-parametric controls. In Section 2.2.3, we discussed how time-invariant country characteristics such as size and remoteness could potentially generate omitted variable bias. We also noted that the average domestic share of expenditure may differ across equilibria. We empirically address these issues by including country and year fixed effects in $Z_{it}$. In addition, $Z_{it}$ includes country-specific time trends. $\mu_{it}$ is an error term.

$\beta_0$ and $\beta_1$ are our two reduced-form parameters of interest. $\beta_0$ captures the relationship between a country’s gains from trade and productivity when productivity is spatially uncorrelated (when Moran’s $I$ is zero). $\beta_1$ captures the degree to which the global spatial correlation of productivities mediates this relationship between gains from trade and productivity.

$\hat{\beta}_1$ connects the spatial correlation of productivity to the global variance of welfare. $\hat{\beta}_1 < 0$
means that greater spatial correlation lowers the covariance of productivity and the domestic share of expenditure. Provided that the trade elasticity $\epsilon$ is unaltered by ENSO-driven variation in the spatial correlation of productivity, this implies a lower covariance of productivity $\ln A_i$ and the sufficient statistic for the gains from trade, $\frac{1}{\epsilon} \ln \lambda_{ii}$. Greater spatial correlation of agricultural productivity causes more productive countries to experience greater gains from trade and less productive countries to experience lower gains from trade. Thus, all else equal, an increase in the spatial correlation of productivities increases global welfare dispersion.

OLS estimation of equation (6) may be problematic if expenditure shares and productivity are simultaneously determined or if there are omitted determinants of expenditure shares that are correlated with productivity, even after conditioning on $Z_{it}$. For example, demand shocks could affect expenditure shares and elicit supply responses that change average yields. Similarly, if domestic cereal production employs imported intermediate goods, then unobserved trade-cost shocks could jointly affect domestic cereal yields and the domestic share of expenditure.

To address these potential sources of bias, we employ an instrumental-variables (IV) strategy that exploits plausibly exogenous variation in local yields and the global spatial correlation of yields. To drive local yields, we use country-level crop-area-weighted annual temperature, $T_{it}$. Following the ENSO discussion in Section 3.1, global spatial correlation of yields is driven by contemporaneous and lagged ENSO.

Our second-stage equation (6) has two endogenous variables, $\ln A_{it}$ and $\ln A_{it}I_t$. We instrument for them using the following first-stage equations:

$$\ln A_{it} = \alpha'_{11} f(T_{it}) + \alpha'_{12} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma'_1 Z_{it} + \nu_{1it} \tag{7}$$

$$\ln A_{it}I_t = \alpha'_{21} f(T_{it}) + \alpha'_{22} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma'_2 Z_{it} + \nu_{2it} \tag{8}$$

where the vector of semi-parametric controls, $Z_{it}$, includes the same variables as our second-stage equation (6). $\alpha'_{11}$, $\alpha'_{12}$, $\alpha'_{21}$, and $\alpha'_{22}$ each represent a vector of first-stage coefficients. $f()$ captures the relationship between local temperature and yield; nonlinearity in $f()$ is well documented around the world (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Welch et al., 2010; Moore and Lobell, 2015). In particular, $f()$ is modeled as a restricted cubic spline of local temperature; the choice of the number of splines is detailed below. $g()$ captures the relationship between ENSO and the global spatial correlation of yields. Following the model selection results in Table 1, $g()$ is modeled as linear and quadratic terms of $(ENSO_t + ENSO_{t-1})$. $\nu_{1it}$ and $\nu_{2it}$ are error terms.

Nonlinear functional forms for $f()$ and $g()$ are necessary to capture nonlinearities in our first-stage equations, but this means that we have more than two instruments for the two endogenous variables. Two-stage least squares (2SLS) estimation in such over-identified IV settings can exacerbate issues with biased point estimates and incorrectly sized inference. These issues worsen if the many instruments are also weak (Bound, Jaeger and Baker, 1995).

We address this concern using several weak-instrument diagnostics. First, we employ the limited information maximum likelihood (LIML) IV estimator, which is approximately median-unbiased for
over-identified models (Mariano, 2001). Second, we conduct tests to detect weak instruments in our LIML estimator. Third, we conduct inference that is robust to the presence of weak instruments.

4.2 Main results

To begin, consider OLS estimates of $\beta_0$ and $\beta_1$ from equation (6), as shown in column 1 of Table 2. The estimate of $\beta_0$ is statistically precise and positive, but the OLS estimate of $\beta_1$ is noisy and in fact positive.

Columns 2 through 6 of Table 2 report IV estimates that address the potential bias of OLS estimates. Across columns, the number of spline terms in the temperature function $f()$ varies. Column 2 has 2 spline terms, the minimum needed to capture nonlinearity in $f()$. Each subsequent column adds an additional spline term in $f()$. Because all models include a quadratic function of sum of contemporaneous and lagged ENSO term, this corresponds to 6, 9, 12, 15, and 18 instruments used jointly across the first-stage equations (7) and (8). Panel A shows 2SLS estimates, while panel B shows LIML estimates. Because ENSO varies only in the time dimension, we cluster standard errors by year to allow arbitrary forms of spatial correlation and heteroskedasticity across countries within a given year. In robustness checks, we consider other error structures, including the Bekker (1994) adjustment that accounts for LIML standard errors being too small in the presence of many weak instruments.

We first discuss our weak-instrument diagnostics. Across 2SLS estimates in columns 2 to 6 of panel A, we consistently find similar point estimates for $\hat{\beta}_0 > 0$ and $\hat{\beta}_1 < 0$. 2SLS estimates for both parameters are also statistically different from OLS estimates, suggesting that 2SLS estimates do not exhibit the same bias as OLS and thus are not the result of completely uninformative instruments. However, in over-identified IV settings, 2SLS estimates are still biased and incorrectly sized. This is evident as the Cragg-Donald joint F-statistic for both first-stage regressions across columns 2 to 6 is well below the Stock-Yogo critical values for 10% maximal 2SLS bias and size (Cragg and Donald, 1993; Stock and Yogo, 2005).

To address these issues, columns 2 to 6 of panel B present LIML estimates. Again, we consistently find similar point estimates for $\hat{\beta}_0 > 0$ and $\hat{\beta}_1 < 0$. The LIML estimates are even farther away from the OLS estimates than the 2SLS estimates, suggesting that the LIML estimator mitigates bias in our 2SLS estimates.

LIML is an approximately median-unbiased estimator in over-identified settings, but standard errors may still be incorrectly sized in the presence of weak instruments. We show two tests to

---

14 2 to 6 spline terms correspond to 3 to 7 knots. Knots are placed between equally spaced percentiles of the temperature empirical distribution according to Harrell (2001).

15 Columns 1-5 of Table F.1 show first-stage statistics for $\alpha'_1$ and $\alpha'_2$ from equation (7) and $\alpha''_1$ and $\alpha''_2$ from equation (8), corresponding to the IV specifications shown in columns 2-6 of Table 2. They show p-values from F-tests examining the joint significance of elements in each vector of first-stage coefficients. As expected, uninteracted local temperature is consistently a strong predictor of local cereal yields in first-stage equation (7). For the interaction between local yields and the global spatial correlation of yields in first-stage equation (8), both uninteracted local temperature (i.e. 0th order ENSO) and local temperature interacted with ENSO (i.e. 1st and 2nd order ENSO) are strong predictors.
Table 2: Domestic share of expenditure and spatial correlation of productivity

<table>
<thead>
<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: 2SLS estimates</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\ln A_{it} (\beta_0))</td>
<td>0.284</td>
<td>1.541</td>
<td>1.746</td>
<td>1.696</td>
<td>1.701</td>
<td>1.654</td>
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<td>(0.119)</td>
<td>(0.515)</td>
<td>(0.542)</td>
<td>(0.412)</td>
<td>(0.425)</td>
<td>(0.431)</td>
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</tr>
<tr>
<td>(\ln A_{it} \times I_t (\beta_1))</td>
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<td>-3.440</td>
<td>-3.391</td>
<td>-3.350</td>
<td>-3.290</td>
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<td>(0.487)</td>
<td>(2.071)</td>
<td>(2.148)</td>
<td>(1.476)</td>
<td>(1.493)</td>
<td>(1.555)</td>
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</tr>
<tr>
<td>Pct. change in welfare variance</td>
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<td>1.591</td>
<td>1.568</td>
<td>1.549</td>
<td>1.521</td>
</tr>
<tr>
<td>from 1 s.d. increase in (I_t)</td>
<td>(0.226)</td>
<td>(0.976)</td>
<td>(1.023)</td>
<td>(0.716)</td>
<td>(0.728)</td>
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<td><strong>Panel B: LIML estimates</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
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<td>2.114</td>
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<td>(0.487)</td>
<td>(2.752)</td>
<td>(2.937)</td>
<td>(1.834)</td>
<td>(1.949)</td>
<td>(2.194)</td>
<td></td>
</tr>
<tr>
<td>Pct. change in welfare variance</td>
<td>-0.353</td>
<td>2.091</td>
<td>2.264</td>
<td>1.914</td>
<td>1.948</td>
<td>2.060</td>
</tr>
<tr>
<td>from 1 s.d. increase in (I_t)</td>
<td>(0.226)</td>
<td>(1.407)</td>
<td>(1.497)</td>
<td>(0.954)</td>
<td>(1.035)</td>
<td>(1.191)</td>
</tr>
</tbody>
</table>

Number of temperature splines in \(f()\) 2 3 4 5 6
ENSO polynomial order in \(g()\) 2 2 2 2 2
Number of instruments 6 9 12 15 18
Cragg-Donald F-stat 7.052 5.832 5.174 4.324 3.801
Stock-Yogo crit. value: 10% max 2SLS bias 9.480 10.430 10.780 10.930 11.000
Stock-Yogo crit. value: 10% max 2SLS size 21.680 27.510 32.880 38.080 43.220
Kleibergen-Paap F-stat 6.100 5.664 3.963 3.332 3.069
Anderson-Rubin weak-id robust joint p-value 0.000 0.000 0.000 0.000 0.000
BIC for first stage equations -30933.68 -30917.40 -31134.01 -31120.19 -31091.75
Observations 5452 5452 5452 5452 5452

Notes: Estimates of \(\beta_0\) and \(\beta_1\) from equation (6). Column 1 shows OLS estimates. Columns 2-6 show IV estimates and differ by the number of temperature spline terms in \(f()\). Panel A (B) shows 2SLS (LIML) IV estimates. All models include quadratic \(ENSO_t + ENSO_{t-1}\) terms and incorporate country fixed effects, year fixed effects, and country-specific linear trends as included instruments. Percentage change shown in the variance of welfare for a one-standard-deviation increase in Moran’s \(I\) relative to the historical mean. Standard errors clustered at the year level in parentheses; p-values in brackets.

address whether weak instruments are a concern. First, across columns 2 to 6, the Cragg-Donald joint F-statistic for both first-stage regressions is above the Stock-Yogo critical values for 10% maximal LIML size, which rejects the presence of weak instruments. However, Stock-Yogo critical values are only valid for iid errors. While we also report the Kleibergen-Paap F-statistic, which is more appropriate given our clustered error structure (Kleibergen and Paap, 2006), there are no established critical values for non-iid errors. We therefore cannot entirely rule out the presence of
weak instruments solely by looking at first-stage F-statistics. Thus, we turn to inference methods that are robust to the presence of weak instruments. For each IV model in columns 2 to 6, we present the p-value from the Anderson-Rubin test of the null hypothesis that $\beta_0$ and $\beta_1$ in equation (6) are jointly zero (Anderson and Rubin, 1949). This null hypothesis is strongly rejected.

The combined evidence from these various diagnostics suggests that weak instruments are not a concern. This gives us confidence that our LIML estimates are unbiased and correctly sized. With that in hand, we turn next to selecting the number of spline terms in $f()$ across columns 2 to 6. We employ the Bayesian Information Criterion (BIC) statistic from a joint seemingly unrelated regression of first-stage equations (7) and (8) to address the trade-off between capturing nonlinearities in $f()$ and having too many spline terms in $f()$. Table 2 shows that the BIC statistic is minimized with four temperature spline terms in column 4. This corresponds to the specification with the most precise LIML estimates of $\beta_0$ and $\beta_1$, with p-values of 0.001 and 0.03, respectively, and will serve as our benchmark model moving forward. However, it is important to observe that the number of splines terms in $f()$ is largely inconsequential for our estimates. The point estimates of $\beta_0$ and $\beta_1$ do not vary much across columns 2 to 6. Estimates of $\beta_0$ consistently have p-values near or below 0.01. The LIML estimates of $\beta_1$ have p-values ranging from 0.03 to 0.11.

To quantify these estimates in welfare terms, suppose that the cross-sectional global spatial correlation of agricultural productivity were to increase by one standard deviation relative to the historical mean. Applying the expression for the variance of welfare in equation (2) to our LIML estimates in panel B of Table 2, we find that a one standard deviation increase in the spatial correlation of productivity leads to a 2% increase in the global variance of welfare across various temperature spline specifications (see Appendix D.1 for details).

4.3 Additional robustness checks

This section presents several robustness checks of our main empirical result. They are designed to test the validity of our statistical assumptions, the interpretation of our results, and consequences of our data construction choices. Our benchmark model throughout is that shown in column 2, panel B of Table 2.

**Randomization inference** Our main source of identifying variation is global time-series fluctuations in the ENSO cycle, as shown in Figure 8. While it is plausible that ENSO is uncorrelated with unobserved determinants of domestic shares of expenditure over a large sample of years, spurious correlations could occur within a 53-year sample period. This would lead to biased estimates.

To examine the relevance of this concern, we conduct a placebo test by randomly reshuffling years in our panel data, breaking the time-series link between domestic shares of expenditure and ENSO-driven changes in country-level cereal yields and the global spatial correlation in yields. This allows us to obtain an empirical distribution of our reduced-form coefficients, $\beta_0$ and $\beta_1$, under placebo conditions and compute the probability of observing our benchmark estimates if years were randomly assigned.
The left and right panels of Figure 13 shows the empirical distribution for $\beta_0$ and $\beta_1$, respectively, for 10,000 randomly reshuffled years without replacement. The vertical line shows the location of our estimated $\beta_0$ and $\beta_1$ from the observed data. We find that it is highly unlikely that our main result is due to small-sample bias.

Figure 13: Robustness: Randomization inference

**Notes:** Empirical distributions of $\beta_0$ (left panel) and $\beta_1$ (right panel) from 10,000 random assignments of years. Vertical lines show estimates of $\beta_0$ and $\beta_1$ from observed data using benchmark model from column 2, panel B of Table 2.

**Standard errors** Standard errors are clustered at the year level in our benchmark model because ENSO treatment occurs at the global time-series level. Table F.2 considers alternative error structures. Column 1 reproduces our benchmark results. To account for serial correlation, column 2 allows year-level clustering and common serial correlation across countries within a 10-year rolling window following Driscoll and Kraay (1998). Column 3 allows differential serial correlation and heteroskedasticity across countries over our entire sample period by clustering standard errors by both year and country. Allowing both forms of serial correlation has little effect on standard errors. Finally, if instruments are weak, standard errors from the LIML estimator may be too small (Hansen, Hausman and Newey, 2008). Column 4 applies the Bekker (1994) adjustment to our benchmark LIML estimates. This only slightly inflates our standard errors, which is unsurprising because the various tests in Table 2 do not suggest that our instruments are weak.

**Controlling for time-varying trade costs** Our IV model correctly identifies $\beta_0$ and $\beta_1$ when ENSO conditions influence a country’s domestic share of cereal expenditure only through its effects on local yields and the global spatial correlation in yields.\(^\text{16}\) While it is unlikely that ENSO, as a

\(^\text{16}\) For example, Hsiang, Meng and Cane (2011) show over the same period that warmer ENSO conditions increase the likelihood of civil conflicts in the tropics. This relationship, however, need not imply an exclusion-restriction violation. Suppose ENSO increases civil conflicts in the tropics only through lowered cereal yields. In that scenario, civil conflict would serve as a “bad control” in our IV specification, potentially biasing our coefficients of interest (see Angrist and Pischke 2009, p. 64-68). Our exclusion-restriction assumption is invalid only if ENSO increases civil conflicts partially through non-agricultural channels and civil conflicts affect domestic share of expenditure by, for example, raising international trade costs relative to internal trade costs. Because the current climate-conflict literature currently supports both agricultural and non-agricultural channels (Hsiang, Burke and Miguel, 2013), the
naturally occurring climatic phenomenon, is affected by economic activity, the exclusion restriction could be violated if ENSO affects domestic cereal expenditure outside of its influence on cereal yields. For example, as noted above, a violation would occur if ENSO were to directly affect trade costs.

Table 3: Controlling for time-varying trade costs
Outcome is log domestic share of expenditure

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln A_{it} (\beta_0) )</td>
<td>2.114</td>
<td>2.178</td>
<td>2.163</td>
<td>2.492</td>
<td>2.297</td>
<td>2.270</td>
</tr>
<tr>
<td>( \ln A_{it} \times I_{it} (\beta_1) )</td>
<td>-4.144</td>
<td>-4.254</td>
<td>-4.189</td>
<td>-4.748</td>
<td>-4.227</td>
<td>-4.281</td>
</tr>
<tr>
<td>ln oil price \times average ln ( \lambda_{ii} )</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>ln oil price \times centrality</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year FE \times average ln ( \lambda_{ii} )</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Year FE \times centrality</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Precipitation</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>5452</td>
<td>5452</td>
<td>5452</td>
<td>5452</td>
<td>5452</td>
<td>5452</td>
</tr>
</tbody>
</table>

Notes: Estimates of \( \beta_0 \) and \( \beta_1 \) from equation (6). Column 1 replicates benchmark model from column 2, panel B, of Table 2. Column 2 (3) controls for the interaction of global log oil price and cross-sectional average log domestic share of expenditure (output-weighted inverse distance averaged across all other countries). Column 4 (5) controls for the interaction of year fixed effects and cross-sectional average log domestic share of expenditure (output-weighted inverse distance averaged across all other countries). Column 6 controls for quadratic precipitation terms. Standard errors clustered at the year levels in parentheses; p-values in brackets.

To address this potential violation of the exclusion restriction, Table 3 augments our benchmark model with additional controls designed to capture time-and-country-varying trade costs. Column 1 replicates our benchmark result. In column 2, we add a country-year-varying proxy for trade costs by interacting the global annual crude oil price with the country’s average log domestic share of expenditure over our sample period. Column 3 uses an alternative measure of cross-sectional trade openness by interacting the global oil price with a country’s centrality, measured as a country’s average output weighted inverse distance to every other country, where output weights is the time-series averaged log agricultural output of the trading partner. In both cases, these proxies for trade costs do not meaningfully alter our estimates of \( \beta_0 \) and \( \beta_1 \). Columns 4 and 5 provide a more flexible specification by interacting year fixed effects with these two cross-sectional measures of trade openness used in columns 2 and 3. Again, our coefficients of interest are relatively unaffected by the inclusion of these controls, suggesting that unobserved shocks to trade costs are not correlated inclusion of conflict as a control would not deliver a unique interpretation: it either jeopardizes a valid identification strategy or show that our instrumental-variable strategy is invalid.
with our ENSO-driven instruments. Finally, ENSO also alters local precipitation. If precipitation is also a determinant of trade costs, there may be an exclusion restriction violation. In column 6, we include quadratic terms for total annual precipitation for each country and find that it does not alter our main estimates.

**Sample split** Table F.3 examines whether $\beta_0$ and $\beta_1$ varies over our sample period. Column 1 shows our benchmark result. Column 2 shows estimates using the years 1961-1987, the first half of our sample period. Column 3 restricts the years to 1988-2013, the second half of our sample period. While estimates from the second half of our sample period are smaller in absolute magnitude than those from the first half, the differences are not statistically significant.

**Dynamic effects** Finally, Table 4 empirically estimates dynamic responses that the static model presented in Section 2 necessarily omits. Column 1 replicates our benchmark contemporaneous-productivity specification for a sample in which $t$ is restricted to 1962-2012, the sample period that allows for both lead and lagged yields.

Improvements since the 1980s in the forecasting of strong ENSO events (Chen et al., 2004; Shrader, 2017) could allow the domestic share of expenditure to respond to future ENSO-driven cereal yields. To examine whether agricultural trade anticipates future ENSO events, column 2 tests for the effects of lead log yields, as instrumented by ENSO in years $t + 1$ and $t$. Future ENSO-driven yields do not influence the domestic share of expenditure.

Past yields might influence the domestic share of expenditure if past productivity affects contemporaneous productivity through intertemporal channels such as depletion of soil nutrients or if past output is stored to facilitate current consumption. Cereal storage, in particular, has been shown to facilitate consumption smoothing in many settings (Williams and Wright, 2005; Roberts and Schlenker, 2013). We address this in two ways. Column 3 examines the effects of lagged log yields generally, as instrumented by ENSO in years $t − 1$ and $t − 2$. We find that past ENSO-driven yields do not influence the domestic share of expenditure. Our standard measure of domestic expenditure is contemporaneous output minus exports; this includes potential changes in stored cereal inventories. In column 4, we use a measure of domestic expenditure that removes changes in cereal inventory. The estimated coefficients are smaller in absolute magnitude than our benchmark estimates; however, they are not statistically different.

**ENSO and local temperature definitions** Table F.4 considers alternative definitions of ENSO and country-level local temperatures. Column 1, panel A reproduces our benchmark results using the NINO4 measure as our ENSO index and crop-area-weighted country-level temperatures. In columns 2, 3 and 4, we use NINO3, NINO34, and NINO12, alternative measures of ENSO that differ by the spatial area over which average sea-surface temperature is calculated (see Figure E.1).

---

17 This measure is contemporaneous output minus exports minus change in cereal inventory, where the latter is defined as the difference in stored cereals in year $t$ minus stored cereals in year $t − 1$. This implicitly assumes that all stored cereals are domestically produced. The sample is smaller due to observations with missing storage data.
Table 4: Dynamic effects  
Outcome is log domestic share of expenditure

<table>
<thead>
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<th>(1)</th>
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<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln A_{it}$</td>
<td>2.217</td>
<td>1.326</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.651)</td>
<td>(0.634)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.001]</td>
<td>[0.041]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln A_{it} \times I_t$</td>
<td>-4.152</td>
<td>-3.233</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.874)</td>
<td>(1.590)</td>
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<tr>
<td></td>
<td>[0.031]</td>
<td>[0.047]</td>
<td></td>
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</tr>
<tr>
<td>$\ln A_{it+1}$</td>
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<td></td>
<td>0.724</td>
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<tr>
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<td></td>
<td></td>
<td>(0.503)</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>[0.156]</td>
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<tr>
<td>$\ln A_{it+1} \times I_{t+1}$</td>
<td>-0.830</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>(1.642)</td>
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<td></td>
<td></td>
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<td>[0.615]</td>
<td></td>
</tr>
<tr>
<td>$\ln A_{it-1}$</td>
<td></td>
<td></td>
<td>0.851</td>
<td></td>
</tr>
<tr>
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<td>(0.526)</td>
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<td></td>
<td></td>
<td></td>
<td>[0.112]</td>
<td></td>
</tr>
<tr>
<td>$\ln A_{it-1} \times I_{t-1}$</td>
<td>-2.039</td>
<td></td>
<td></td>
<td></td>
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<td>(1.354)</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>[0.138]</td>
<td></td>
</tr>
</tbody>
</table>

Remove storage behavior? No No No Yes
Observations 5237 5236 5235 5191

Notes: Estimates of $\beta_0$ and $\beta_1$ from equation (6). Column 1 reproduces benchmark model using log yields in year $t$ instrumented by December ENSO in years $t$ and $t-1$. Column 2 uses log yields in year $t+1$, instrumented by December ENSO conditions in years $t+1$ and $t$. Column 3 uses log yields in year $t-1$, instrumented by December ENSO conditions in years $t-1$ and $t-2$. Column 4 uses log yields in year $t$ to examine effects on a measure of domestic share of expenditure that includes stored cereals. Sample period for 2nd stage equation is 1962-2012 for columns 1-3 and 1961-2013 for column 4. Standard errors clustered at the year level in parentheses; p-values in brackets.

In panel B, we construct country-level temperature from pixel-level temperature data by taking the pixel average across the all area of a country rather than weight by only crop area.\textsuperscript{18} Our results are largely unaffected by these two data construction choices.

**Domestic expenditure share construction** As detailed in Appendix B, we do not observe cereal prices for all cereal-country-year observations with positive cereal output. Our benchmark measure of domestic share of expenditure imputes missing cereal-level prices using the average export-volume-weighted cereal export unit value for that country and year. While this imputation

\textsuperscript{18} Our sample of countries increases slightly when using area-weighted temperature compared with using crop area-weighted temperature because a handful of small-sized countries have no agricultural activity in the Ramankutty et al. (2008) dataset.
increases the number of observations in our estimation sample, this procedure could bias our estimates if it introduces measurement error into our outcome variable that is correlated with our instrumented regressors.

Table F.5 alternative approximations for the domestic expenditure share. Column 1 reproduces our benchmark result. Columns 2 through 4 consider alternative price imputations. Column 2 imputes missing export unit values using producer prices. Columns 3 and 4 impute missing cereal prices using the lowest and highest observed export unit values, rather than the average, for a given country and year. All three alternative imputation methods yield estimates of $\beta_0$ and $\beta_1$ that are statistically indistinguishable from the benchmark estimate in column 1.

5 Application: Inequality under future climate change

In this section, we demonstrate how to incorporate our general-equilibrium mechanism into partial-equilibrium forecasts of economic outcomes under different productivity distributions. Recent reviews of the climate change impact literature emphasize the need to consider general-equilibrium effects in projections of economic outcomes under climate change (Dell, Jones and Olken, 2014; Hsiang, 2016). To that end, we incorporate changes in the spatial correlation of productivities due to climate change into projections of future welfare inequality and show how they differ from partial-equilibrium projections that hold spatial correlation fixed.

Because our exercise serves only to highlight the implications of incorporating this particular general-equilibrium mechanism, let us also emphasize what this projection omits. First, with the exception of changes in agricultural productivity due to climate-driven changes in local temperature over the 21st century, we hold all other economic variables fixed at recent historical values. Thus, we do not take into account important trends such as technological change. Second, we apply estimates based on past exogenous annual changes in agricultural productivity to future long-term productivity changes due to climate change. This implies that we omit possible adaptations in anticipation of future climate change (Deschênes and Greenstone, 2007; Hsiang, 2016). Third, we do not consider other potential general-equilibrium adjustments such as factor reallocation across sectors and across crops within the agricultural sector. All three practices are standard in econometric estimates of climate impacts and may ultimately result in different realized climate impacts than what we project.

Section 5.1 reports climate change’s anticipated effects on the global variance and spatial correlation of agricultural productivity. Section 5.2 shows how incorporating these changes in the spatial correlation of productivities affects welfare projections.

\footnote{See Appendix B regarding concerns with FAO’s producer prices.}

\footnote{There is currently no scientific consensus on how ENSO will be affected by anthropogenic climate change (?). Our projection exercise therefore assumes ENSO is stationary over the 21st century and does not contribute to long-run changes in the global spatial correlation of agricultural productivities.}
5.1 Agricultural productivity under climate change

To examine how climate change will affect agricultural productivity, we estimate a nonlinear log cereal yield response function using historical variation in temperatures across countries and years. Specifically, for the period 1961-2013, we estimate:

\[
\ln A_{it} = k(T_{it}) + X_{it}\Psi + \nu_{it}
\]

(9)

where \(k()\) is a restricted cubic spline and the benchmark set of controls in \(X_{it}\) include country fixed effects, year fixed effects, and country-specific quadratic trends. Figure 14 shows the estimated cubic spline response function, \(k()\), using four temperature spline terms. It also shows two cross-sectional temperature distributions: observed temperatures in 2013 and the forecast for 2099 under a business-as-usual (Representative Concentration Pathway 8.5) climate scenario obtained from the Coupled Model Intercomparison Project (CMIP5) multi-model ensemble mean.\(^{21}\) Column 1 of Table F.6 shows that the coefficients of this functional form are jointly statistically significant with a productivity-maximizing temperature around 9°C. Table F.6 also indicates that the predicted optimal temperature is relatively insensitive to the number of knots in the spline function and to the inclusion of precipitation controls.

Next, we combine the estimated coefficients in equation (9) with local temperature projections under a business-as-usual climate scenario to project log cereal yields in the 2014-2099 period. All other variables in equation (9) are fixed at 2013 levels. Figure 15 maps the projected change in country-level log cereal yields under climate change between 2013-2099. Consistent with the nonlinear yield response function shown in Figure 14, climate change lowers agricultural productivities across much of the world with the exception of a few upper-latitude countries that experience modest gains.

Climate change alters two important moments of the cross-country agricultural productivity distribution. First, the variance of agricultural productivity increases. In 2013, of the 12 countries with temperatures below the global productivity-maximizing temperature, 10 had productivities above the cross-sectional mean (see Figure E.3).\(^{22}\) As temperatures increase under climate change, these countries with already high relative productivity will gain further by moving towards the productivity-maximizing temperature shown in Figure 14. Concurrently nearly all other countries will experience productivity losses as they move away from the optimal temperature. Because the gains from climate change are experienced almost exclusively by relatively high productivity countries, there is a resulting increasing in the cross-country variance of productivity, depicted by

\(^{21}\) The Coupled Model Intercomparison Project is a coordinated effort by the climate-science community to harmonize model runs across various climate models. The average climate projection across CMIP models is known as the multi-model ensemble mean. CMIP5 was used to inform the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (see Taylor, Stouffer and Meehl (2012) for details).

\(^{22}\) Figure E.3 shows that the unconditional relationship between log productivity and temperature is very similar to the conditional relationship depicted in Figure 14, \(k(T_{it})\) which controls for \(X_{it}\). Thus, we can describe how climate change alters the variance and spatial correlation of productivity in terms of the nonlinear shape of \(k(T_{it})\), even though productivity incorporates other determinants contained in controls \(X_{it}\Psi\) and residual \(\nu_{it}\) from equation (9).
Figure 14: Estimated temperature response function for log cereal yields

Notes: Gray solid line shows $k()$ in equation (9), the predicted relationship between crop area-weighted country-level temperature and log cereal yields, estimated during 1961-2013. Restricted cubic spline estimated using four spline terms with knots placed along the temperature support according to Harrell (2001). Gray dashed line shows additional predicted log cereal yields using extrapolated temperature in 2099. Estimated model corresponds to column 1 of Table F.6. Orange line shows the distribution of observed country-level temperature in 2013. Red line shows country-level projected temperature in 2099 from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

Second, as temperatures increase across the planet, the spatial correlation of agricultural productivities increases. This is due to the non-monotone yield response function shown in Figure 14 and the fact that surface temperatures are generally decreasing in distance to the equator. Absent climate change, mid-latitude locations experience the productivity-maximizing temperature. Locations closer to and farther from the equator both generally exhibit lower yields. As climate change increases temperatures across the globe, latitudes closer to the poles now experience the productivity-maximizing temperature, with less productive locations becoming more bunched around the equator. This bifurcation of global agriculture into high-productivity poles and a low-productivity band around the equator increases the spatial correlation of agricultural productivity. The resulting increase in Moran’s $I$ for agricultural productivity under climate change...
Figure 15: Change in log cereal yields under climate change (2013-2099)

Notes: Map shows the projected change in country-level log cereal yields under climate change between 2013-2099. Projected change in log yields obtained after estimating equation (9) with four spline terms as shown in column 1 of Table F.6. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

Figure 16: Variance and spatial correlation of agriculture productivity under climate change

Notes: Gray (blue) series shows the change in the global variance (Moran’s I) of log cereal yields over the 21st century under climate change. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario. Change is indicated by the blue series in Figure 16.

Thus plays a second-order role in determining changes in the spatial correlation of productivity. For example, the projected temperature change over the 21st century for Gabon, the country located closest to the equator, is 3.4°C. For Finland, the country located closest to the north pole, the projected temperature change is 2.9°C.
5.2 Welfare projections and changes in spatial structure

The change in the spatial correlation of agricultural productivity due to climate change is consequential for global welfare inequality. To demonstrate this, we combine projected local agricultural productivity under climate change with our estimates of $\hat{\beta}_0$ and $\hat{\beta}_1$ in Section 4 to project future domestic shares of expenditure via equation (6) and welfare variance via equation (2) (see Appendix D.2 for details). We consider two scenarios. In the first scenario, we omit general-equilibrium effects by fixing the spatial correlation of temperature-predicted agricultural productivities to its 2013 value. In the second scenario, the spatial correlation of productivities increases with climate change as depicted in Figure 16.

Figure 17: Variance in climate-driven welfare over the 21st century

![Graph showing variance in climate-driven welfare over the 21st century.

Notes: Gray (red) line shows the change in the variance of welfare when omitting (including) changes in the spatial correlation of log cereal yields over the 21st century under climate change. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

The projected change in the variance of welfare over the 21st century is shown in Figure 17. The gray line shows the projection that omits changes in spatial correlation and the red line shows the projection that include such changes. Omitting changes in spatial correlation, the projected increase in the variance of agricultural productivity generates a projected increase in the variance of welfare. The projection that incorporates increases in the spatial correlation of agricultural productivity due to climate change predicts a 19% greater increase in welfare inequality between 2013-2099 compared to the projection that holds spatial correlation fixed.

How do the projections differ across countries? Figure 18 maps the difference between the two projections.24 Including an increase in the spatial correlation of productivity causes the gains from trade to be lower in less productive countries and higher in more productive countries than in a

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24 See equation (D.14) at the end of Appendix D.3.
Figure 18: Differences in projected welfare changes due to change in spatial correlation (2013-2099)

**Notes:** Map shows the difference in projected country-level welfare change over 2013-2099 between projections that include (Figure D.2) and omit (Figure D.1) changes in spatial correlation. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

...projection that holds spatial correlation fixed. In particular, Figure 18 shows that most countries in Africa, and a few in Asia and South America have lower gains from trade in the projection that incorporates changes in spatial correlation. This is because the relatively high local temperatures that drive yield losses in these countries is compounded by similar temperatures simultaneously experienced by neighboring countries. In the simplest terms, a key feature of climate change is that it makes Ethiopia and Kenya less productive at the same time, lowering the gains from trade compared to a scenario in which each country warms independently. By the same logic, parts of Europe and North American have higher gains from trade when the projection includes increases in spatial correlation. The relatively milder temperatures experienced by these countries is accompanied by similar temperatures over neighboring locations.

Figure 19 depicts climate-change forecasts for each country in terms of the predicted change in agricultural productivity from Figure 15 and the difference in projected welfare from omitting the change in spatial correlation shown in Figure 18. The vast majority of countries suffer a decrease in agricultural productivity as a result of increased temperature. As in Figure 18, the strongest contrast in Figure 19 is between outcomes for African and European economies. While there is substantial heterogeneity in the productivity declines across countries within each continent, most economies in Africa, and a few in South America and Asia, experience productivity losses that would be considerably amplified by changes in spatial correlation. By contrast, most European economies have reduced projected welfare losses when changing spatial correlation is considered. For the few economies with increased productivity under climate change, the differences across projections are close to zero.

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See Figure E.4 for the same plot with country identifiers.
6 Conclusion

This paper studies how the spatial arrangement of the global productivity distribution shapes the distribution of welfare across the globe. In particular, we theoretically show that, holding the unconditional moments of the productivity distribution fixed, greater spatial correlation of productivity increases dispersion in welfare. The increase in spatial correlation causes high-productivity locations to enjoy larger gains from trade than they would if productivity were spatially uncorrelated.

To empirically investigate this relationship, we exploit a global natural experiment that is well-suited for identifying general-equilibrium effects following a change in the spatial structure of the international trade network. Specifically, we use the El Niño-Southern Oscillation, a naturally occurring global climatic phenomenon, to examine how the spatial correlation of agricultural productivity governs the response of the domestic share of expenditure, a sufficient statistic for the gains from trade in a broad class of trade models, to local productivity. Using data from the past...
five decades of agricultural trade, we find that high-productivity locations enjoy larger gains from trade when agricultural productivity is more spatially correlated, as predicted.

The interplay between local productivity and the gains from trade is potentially important in many domains. Many economically valuable endowments – such as human capital, energy resources, minerals, and wildlife stocks – tend to exhibit substantial spatial correlation. Furthermore, the spatial correlation of these endowments may change following the relocation of existing endowments, the discovery of new uses for existing endowments, or the discovery of new endowments. This paper provides a framework for analyzing the general-equilibrium welfare consequences of such system-wide changes to the global trade network. In settings in which welfare differences are arbitrated away by mobile factors of production, we expect that greater spatial correlation of productivity would make population density, rather than welfare per capita, more unequal across locations. Our application in this paper demonstrates that incorporating changes in the spatial correlation of productivities substantially alters predictions about global welfare inequality when forecasting the consequences of anthropogenic climate change.
References


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Appendix

A Theory appendix

A.1 General economic environment

This appendix section provides details of perfect-competition results presented in Section 2 and extends them to the Krugman (1980) model of monopolistic competition.

A.1.1 Perfect-competition microfoundations

Production function. In the Armington model, each country $i$ produces a distinct variety using a linear production technology such that one unit of labor yields $A_i$ units of output. Under perfect competition, its price is $w_i/A_i$ and thus the Dixit-Stigliz price index is

$$P_j = \left( \sum_{i=1}^{N} \left( w_i \tau_{ij} / A_i \right)^{1-\sigma} \right)^{1/(1-\sigma)}.$$

In the Eaton and Kortum (2002) model, there is a continuum of varieties, and each country’s efficiency in producing them follows a Fréchet distribution with location parameter $T_i$ and dispersion parameter $\vartheta$.

Gravity equation. Written in terms of expenditure shares, the gravity equation is

$$\lambda_{ij} = \frac{\chi_i (\tau_{ij} w_i)^{-\epsilon}}{\sum_{i=1}^{N} \chi_i (\tau_{ij} w_i)^{-\epsilon}}.$$

In the Armington model, $\epsilon = \sigma - 1$ and $\chi_i = A_i^\epsilon$. In the Eaton-Kortum model without intermediate inputs, $\epsilon = \vartheta$ and $\chi_i = T_i$. Thus, the equilibrium trade flows associated with a productivity distribution $\{A_i\}$ and trade elasticity $\epsilon$ in the Armington model are equal to the equilibrium trade flows for an Eaton-Kortum model in which efficiency distributions have location parameters $T_i = A_i^{1/\epsilon}$.

Welfare. Equation (1) is an immediate consequence of the main result in Arkolakis, Costinot and Rodríguez-Clare (2012). They show that, in a broad class of models, the gains from trade relative to autarky are equal to $-\frac{1}{\epsilon} \ln \lambda_{ii}$. In our theoretical environment, autarky welfare is equal to $\ln A_i + \gamma$, as implied by equation (1). $\gamma$ is a function of structural parameters. In the Armington model with symmetric preferences, $\gamma$ is zero. In the Eaton and Kortum (2002) model, $\gamma = \left[ \Gamma \left( 1 + \frac{1-\sigma}{\sigma} \right) \right]^{1/(1-\sigma)}$ where $\Gamma$ is the gamma function.

A.1.2 Krugman (1980) microfoundations

We now discuss the case of monopolistic competition with homogeneous firms, in which the measure of varieties available in equilibrium is endogenously determined. Consider a many-country version of the Krugman (1980) model in which fixed costs $f_j$ and marginal costs $c_j$ may vary across countries. Denote the equilibrium number of homogeneous firms producing in country $j$ by $n_j$.

Gravity equation. In the free-entry equilibrium, $\epsilon = \sigma - 1$, $n_i = L_i / (\sigma f_i)$, and $\chi_i = n_i c_i^{-\epsilon}$.
Welfare. In this setting, real per capita consumption is
\[
\ln \left( \frac{C_i}{L_i} \right) = \frac{1}{\epsilon} \ln n_i - \ln c_i + \ln \left( \frac{\sigma - 1}{\sigma} \right) - \frac{1}{\epsilon} \ln \lambda_{ii}
\]
If population size \( L_i \) and fixed costs \( f_i \) are country-invariant (\( n_i = n \ \forall j \)) and we interpret productivity as shifting marginal costs, \( A_i = c_i^{-1} \), then this is equivalent to equation (1) with \( \gamma = \frac{1}{\epsilon} \ln n + \ln \left( \frac{\sigma - 1}{\sigma} \right) \). If population size \( L_i \) and marginal costs \( c_i \) are country-invariant and we interpret productivity as shifting fixed costs, \( A_i = f_i^{-1/\epsilon} \), then this is equivalent to equation (1) with \( \gamma = \frac{1}{\epsilon} \ln (L/\sigma) + \ln \left( \frac{\sigma - 1}{\sigma} \right) \).

In the case of countries with heterogeneous population sizes, equation (1) must be extended to replace \( \gamma \) with a location-specific \( \gamma_i \) that depends on structural parameters other than productivity. For example, if productivity shifts marginal costs, \( A_i = c_i^{-1} \), then we obtain
\[
\ln \left( \frac{C_i}{L_i} \right) = \ln A_i + \gamma_i - \frac{1}{\epsilon} \ln \lambda_{ii}, \quad (1')
\]
where \( \gamma_i = \frac{1}{\epsilon} \ln n_i + \ln \left( \frac{\sigma - 1}{\sigma} \right) \). If we assume that \( \text{cov}(\ln A_i^u, \gamma_i) = \text{cov}(\ln A_i^c, \gamma_i) \), we obtain an extension of equation (3):
\[
\text{var} \left( \ln C_i^c / L_i \right) - \text{var} \left( \ln C_i^u / L_i \right) = -\frac{2}{\epsilon} \left[ \text{cov} \left( \ln A_i^c, \ln \lambda_{ii}^c \right) - \text{cov} \left( \ln A_i^u, \ln \lambda_{ii}^u \right) \right] - \frac{2}{\epsilon} \left[ \text{cov} \left( \gamma_i, \ln \lambda_{ii}^c \right) - \text{cov} \left( \gamma_i, \ln \lambda_{ii}^u \right) \right] + \frac{1}{\epsilon^2} \left[ \text{var} \left( \ln \lambda_{ii}^c \right) - \text{var} \left( \ln \lambda_{ii}^u \right) \right]. \quad (3')
\]

A.1.3 The case of symmetric trade costs

Starting from the equilibrium system of equations and using the assumption of symmetric trade costs (\( \tau_{ij} = \tau_{ji} \)):
\[
Y_i = w_i L_i = \sum_j \left( \frac{w_i}{A_i} \right)^{-\epsilon} \tau_{ij}^{-\epsilon} w_j L_j \Phi_j = \left( \frac{w_i}{A_i} \right)^{-\epsilon} \Omega_i
\]
\[
\Rightarrow \frac{w_i}{A_i} = \left( \frac{\Omega_i}{A_i L_i} \right)^{1/\epsilon}
\]
\[
\Rightarrow \Phi_j = \sum_j \tau_{ji}^{-\epsilon} \left( \frac{w_j}{A_j} \right)^{-\epsilon} = \sum_j \tau_{ji}^{-\epsilon} (A_j L_j / \Omega_j)^{\epsilon}
\]
\[
= \sum_j \tau_{ji}^{-\epsilon} (A_j L_j / \Phi_j)^{1/\epsilon}
\]
The last equality exploits the fact that we can normalize incomes such that \( \Phi_i = \Omega_i \) when trade is balanced and \( \tau_{ij}^{-\epsilon} \) is symmetric, as established in Anderson and van Wincoop (2003) and Head and Mayer (2014).
Since \( \lambda_{ii} = \left( \frac{w_i/A_i}{\Phi_i} \right)^{-\epsilon} \), the above expression for \( w_i/A_i \) and the assumption of symmetric trade costs yield the result that

\[
\lambda_{ii} = \frac{(\Omega_i/(A_iL_i))^{1+1}}{\Phi_i} = (A_iL_i)^{\frac{1}{1+1}} \Phi_i^{\frac{2+1}{1+1}}
\]

Thus, in the case in which \( L_i = L \forall i \), \( \text{var}(\ln \lambda_{ii}) = \frac{1+2\epsilon}{1+\epsilon} \text{cov}(\ln \Phi_i, \ln \lambda_{ii}) \).

Comparing these outcomes for productivity distributions \( A^c \) and \( A^u \) in the case in which \( L_i = L \forall i \),

\[
\text{var}(\ln \lambda_{ii}) - \text{var}(\ln \lambda_{ii}) = \frac{\epsilon}{\epsilon + 1} \left[ \text{cov}(\ln A_i^c, \ln \lambda_{ii}^c) - \text{cov}(\ln A_i^u, \ln \lambda_{ii}^u) \right] - \frac{1+2\epsilon}{1+\epsilon} \left[ \text{cov}(\ln \Phi_i^c, \ln \lambda_{ii}^c) - \text{cov}(\ln \Phi_i^u, \ln \lambda_{ii}^u) \right].
\]

4.2 Spatial correlation and the covariance of productivity and gains from trade

This appendix section contains the proof of the four-country case presented in Section 2.2.1 and details the construction and parameterization of the illustrative examples presented in Section 2.2.

4.2.1 Four-country case

The proof of Proposition 1 follows.

\( A^c \) is more spatially correlated than \( A^u \)

**Proof.** Recall that Moran’s \( I \) is given by:

\[
I(\ln A, W) = \frac{N}{\sum_i \sum_j \omega_{ij}} \sum_i (\ln A_i - \ln \bar{A}) \sum_j \omega_{ij} (\ln A_j - \ln \bar{A}) \sum_i (\ln A_i - \ln \bar{A})^2
\]

where \( \omega_{ij} \) are spatial weights. Define the spatial weight matrix

\[
\{\omega_{ij}\} = \begin{bmatrix}
\omega_0 & \omega_1 & \omega_2 & \omega_1 \\
\omega_1 & \omega_0 & \omega_1 & \omega_2 \\
\omega_2 & \omega_1 & \omega_0 & \omega_1 \\
\omega_1 & \omega_2 & \omega_1 & \omega_0
\end{bmatrix}
\]

Thus, there is a one-to-one mapping between \( \omega_{ij} \) and \( \tau_{ij} \). \( \omega_1 \) is the spatial weight associated with trade cost \( d_1 \); \( \omega_2 \) is the spatial weight associated with trade cost \( d_2 \).

The average log productivity is given by \( \ln \bar{A} = \frac{1}{2} \ln \bar{a} \). For the correlated state, \( \ln A^c = (\ln \bar{a}, \ln \bar{a}, 0, 0) \), so the demeaned log productivity vector is equal to \( \ln \tilde{A}^c = (\frac{1}{2} \ln \bar{a}, \frac{1}{2} \ln \bar{a}, -\frac{1}{2} \ln \bar{a}, -\frac{1}{2} \ln \bar{a}) \). For the uncorrelated state, \( \ln A^u = (\ln \bar{a}, 0, 0, 0) \) and \( \ln \tilde{A}^u = (\frac{1}{2} \ln \bar{a}, -\frac{1}{2} \ln \bar{a}, \frac{1}{2} \ln \bar{a}, -\frac{1}{2} \ln \bar{a}) \).

\( \ln A^c \) is more spatially correlated than \( \ln A^u \) if and only if \( I(\ln A^c, W) > I(\ln A^u, W) \iff \sum_i \ln \tilde{A}^c_i \sum_j \omega_{ij} \ln \tilde{A}^c_j > \sum_i \ln \tilde{A}^u_i \sum_j \omega_{ij} \ln \tilde{A}^u_j \).
The relevant terms are as follows:

\[
\sum_j \omega_{ij} \ln \hat{A}_j^c = \left\{ \begin{array}{ll}
\frac{1}{2} (\omega_0 - \omega_2) \ln \hat{a} & \text{for } i = 1, 2 \\
-\frac{1}{2} (\omega_0 - \omega_2) \ln \hat{a} & \text{for } i = 3, 4
\end{array} \right.
\]

\[
\sum_i \ln \hat{A}_i^c \sum_j \omega_{ij} \ln \hat{A}_j^c = (\omega_0 - \omega_2) (\ln \hat{a})^2
\]

\[
\sum_j \omega_{ij} \ln \hat{A}_j^u = \left\{ \begin{array}{ll}
\frac{1}{2} (\omega_0 - 2\omega_1 + \omega_2) \ln \hat{a} & \text{for } i = 1, 3 \\
-\frac{1}{2} (\omega_0 - 2\omega_1 + \omega_2) \ln \hat{a} & \text{for } i = 2, 4
\end{array} \right.
\]

\[
\sum_i \ln \hat{A}_i^u \sum_j \omega_{ij} \ln \hat{A}_j^u = (\omega_0 - 2\omega_1 + \omega_2) (\ln \hat{a})^2
\]

\[
I(\ln A^c, W) > I(\ln A^u, W) \iff \omega_0 - \omega_2 > \omega_0 - 2\omega_1 + \omega_2 \iff \omega_1 > \omega_2.
\]

**Equilibrium for the correlated state:** \( A^c = (\hat{a}, \hat{a}, 1, 1) \)

By symmetry, the equilibrium incomes and market access of countries 1 and 2 are identical, \( Y_1 = Y_2 \) and \( \Phi_1 = \Phi_2 \). Similarly, countries 3 and 4 have identical outcomes: \( Y_3 = Y_4 \) and \( \Phi_3 = \Phi_4 \). As a result, the equilibrium incomes that solve \( Y_i = \sum_{j=1}^{N} \lambda_{ij} Y_j \) can without loss of generality be characterized by the scalar \( x \equiv Y_1/Y_4 \), the relative income levels.

\[
Y_1 = \lambda_{11} Y_1 + \lambda_{12} Y_2 + \lambda_{13} Y_3 + \lambda_{14} Y_4 \Rightarrow x = \frac{\lambda_{13} + \lambda_{14}}{1 - \lambda_{11} - \lambda_{12}}
\]

Equilibrium expenditure shares can be expressed as \( \lambda_{ij} = A_i^c Y_i^{1-\epsilon} \tau_{ij}^{\epsilon}/\Phi_j \). Thus \( \lambda_{ij} A_i^c Y_i^{1-\epsilon} = \tau_{ij}^{\epsilon}/\Phi_j \) and

\[
x = \frac{\tau_{13}^{\epsilon}/\Phi_3 + \tau_{14}^{\epsilon}/\Phi_4}{\hat{a}^{1-\epsilon} Y_1^{1-\epsilon} - \tau_{11}^{\epsilon}/\Phi_1 - \tau_{12}^{\epsilon}/\Phi_2}.
\]

Using the facts that \( \Phi_1 = \Phi_2 = Y_1^{-\epsilon} \hat{a}^{\epsilon} (1 + d_1^{\epsilon}) + Y_3^{-\epsilon} (d_2^{\epsilon} + d_1^{\epsilon}) \) and \( \Phi_3 = \Phi_4 = Y_1^{-\epsilon} \hat{a}^{\epsilon} (d_2^{\epsilon} + d_1^{\epsilon}) + Y_3^{-\epsilon} (1 + d_1^{\epsilon}) \), it can be shown that the equilibrium value of \( x \) is the solution to the equation

\[
x^{2\epsilon+1} + \frac{d_2^{\epsilon} + d_1^{\epsilon}}{1 + d_1^{\epsilon}} \hat{a}^{\epsilon} (x^{\epsilon+1} - x^{\epsilon}) - \hat{a}^{2\epsilon} = 0. \tag{A.1}
\]

**Equilibrium for the uncorrelated state:** \( A^u = (\hat{a}, \hat{a}, 1) \)

Analogous to the correlated state, this case can be solved by exploiting the facts that countries 1 and 3 have identical outcomes, \( Y_1 = Y_3 \) and \( \Phi_1 = \Phi_3 \), and countries 2 and 4 have identical outcomes: \( Y_2 = Y_4 \) and \( \Phi_2 = \Phi_4 \). The equation that characterizes equilibrium relative income \( x \) is

\[
x^{2\epsilon+1} + \frac{d_2^{\epsilon} + d_1^{\epsilon}}{1 + d_2^{\epsilon}} \hat{a}^{\epsilon} (x^{\epsilon+1} - x^{\epsilon}) - \hat{a}^{2\epsilon} = 0. \tag{A.2}
\]
Note that $0 < r^c < r^u < 1$ since $d_1^2 > d_2 > d_1 > 0$.

### Comparing equilibria

Equations (A.1) and (A.2) show that relative income in each equilibrium is given by the zeros of the following generalized polynomial

$$R(x; r) = x^{2\epsilon + 1} + r\tilde{a}^\epsilon (x^{\epsilon + 1} - x) - \tilde{a}^{2\epsilon}$$

when $r > 0$ is evaluated at $r^c$ and $r^u$, respectively. By Descartes’ rule of signs, $R(x; r)$ has exactly one real positive zero (for a given value of $r$) (Jameson, 2006).\(^\text{26}\) Denote this zero of $R(x; r)$ by $x^*(r)$.

We prove that $x^*(r)$ is decreasing by contradiction. Let $r_1 < r_2$ and denote by $x^*_1$ and $x^*_2$ their respective unique positive zeros. Suppose that $x^*_1 < x^*_2$. Consider the function $F(x) = R(x; r_1) - R(x; r_2) = (r_2 - r_1)\tilde{a}^\epsilon(x - 1)$. It is evident that $F(0) = F(1) = 0$, $F(x) < 0 \forall x \in (0, 1)$, and $F(x) > 0 \forall x > 1$. When evaluated at $x^*_1$, $F(x^*_1) = R(x^*_1; r_2) - R(x^*_1; r_1) = R(x^*_1; r_2)$, since $x^*_1$ is a zero of $R(x; r_1)$.

Note that $R(x; r)$ is continuous in $x$ and that $R(0; r) < 0$. Therefore, $R(x; r_2) < 0 \forall x \in (0, x^*_2)$. Since $x^*_1 \in (0, x^*_2)$ by assumption, $F(x^*_1) = R(x^*_1; r_2) < 0$. Since $F(x) > 0 \forall x > 1$, we conclude that $x^*_1 \in (0, 1)$. We also know that $\forall x > x^*_1, R(x; r_1) > 0$ since $R(x^*_1; r_1) = 0$ and $\lim_{x \to +\infty} R(x; r_1) = +\infty$. Together, these results imply that $R(1; r_1) > 0$. Yet, $R(1; r_1) = 1 - \tilde{a}^{2\epsilon} < 0$ as $\tilde{a} > 1$. Thus, we have a contradiction. We conclude that $r_1 < r_2 \Rightarrow x^*_1 > x^*_2$.

Denote the equilibrium relative incomes by $x_c$ and $x_u$. Since $r^u > r^c$, $x_u < x_c$. The ratio of equilibrium incomes is greater in the correlated case. Since the countries are of equal size, the ratio of equilibrium incomes $x$ is also the more productive economy’s “double-factoral terms of trade”. Thus, the more productive economies’ double-factoral terms of trade are greater in the correlated case.

**cov($\ln A_i, \ln \lambda_{ii}$) is lower in the spatially correlated case**

**Proof.** Equilibrium domestic shares of expenditure can be expressed as $\lambda_{ii} = A_i^c Y_i^{-\epsilon}/\Phi_i$. For the correlated state $A^c$, $\Phi_1 = \Phi_2 = Y_1^{-\epsilon}\tilde{a}^\epsilon(1 + d_1^{-\epsilon}) + Y_3^{-\epsilon}(d_2^{-\epsilon} + d_1^{-\epsilon})$ and $\Phi_3 = \Phi_4 = Y_1^{-\epsilon}\tilde{a}^\epsilon(d_2^{-\epsilon} + d_1^{-\epsilon}) + Y_3^{-\epsilon}(1 + d_1^{-\epsilon})$, so

$$\lambda_{11}^c = \lambda_{22}^c = \frac{A_1^c Y_1^{-\epsilon}}{\Phi_1} = \frac{1}{1 + d_1^{-\epsilon} + \tilde{a}^{-\epsilon}x_c^{-\epsilon}(d_2^{-\epsilon} + d_1^{-\epsilon})} = \frac{1}{(1 + d_1^{-\epsilon})(1 + \tilde{a}^{-\epsilon}x_c^{-\epsilon})}$$

$$\lambda_{33}^c = \lambda_{44}^c = \frac{A_3^c Y_3^{-\epsilon}}{\Phi_3} = \frac{1}{1 + d_1^{-\epsilon} + \tilde{a}^{-\epsilon}x_c^{-\epsilon}(d_2^{-\epsilon} + d_1^{-\epsilon})} = \frac{1}{(1 + d_1^{-\epsilon})(1 + \tilde{a}^{-\epsilon}x_c^{-\epsilon})}$$

For the uncorrelated state $A^u$, $\Phi_1 = \Phi_3 = Y_1^{-\epsilon}\tilde{a}^\epsilon(1 + d_2^{-\epsilon}) + 2Y_2^{-\epsilon}d_1^{-\epsilon}$ and $\Phi_2 = \Phi_4 = Y_2^{-\epsilon}(1 +

\(^{26}\) It also has either 0 or 2 negative zeros that are obviously not of interest.
In both equilibria, 
\[
\lambda_{11}^u = \lambda_{33}^u = \frac{1}{d_1^\epsilon} = \frac{1}{1 + d_1^\epsilon},
\]
\[
\lambda_{22}^u = \lambda_{44}^u = \frac{1}{d_2^\epsilon} = \frac{1}{1 + d_2^\epsilon}.
\]

Thus, we obtain the following demeaned values of the log domestic shares of expenditure
\[
\frac{\ln \lambda_{11}}{\ln \lambda_{44}} = -\frac{1}{2} \left[ \ln \left( 1 + x^\epsilon \tilde{a}^{-\epsilon} r \right) - \ln \left( 1 + \tilde{a}^\epsilon x^{-\epsilon} r \right) \right]
\]
when evaluated at \((r^c, x_c)\) and \((r^u, x_u)\) for the two respective equilibria.

The covariance of productivity and the domestic share of expenditure is therefore
\[
cov(\ln A_i, \ln \lambda_{ii}) = -\frac{1}{4} \ln \tilde{a} \left[ \ln \left( 1 + x^\epsilon \tilde{a}^{-\epsilon} r \right) - \ln \left( 1 + \tilde{a}^\epsilon x^{-\epsilon} r \right) \right]
\]
Recall that \(\epsilon\) and \(\tilde{a}\) are fixed parameters while \(x\) is a function of \(r\). This covariance is positive because \(\tilde{a} > x\).

It can be shown that \(cov(\ln A_i, \ln \lambda_{ii})\) is increasing in \(r\).
\[
\frac{dcov(\ln A_i, \ln \lambda_{ii})}{dr} \propto d\ln \left( \frac{1 + x^\epsilon \tilde{a}^{-\epsilon} r}{1 + \tilde{a}^\epsilon \tilde{a}^{-\epsilon} x^{-\epsilon} r} \right) \propto \left( \frac{\tilde{a}}{x} \right)^\epsilon - \left( \frac{x}{\tilde{a}} \right)^\epsilon - \frac{r \epsilon}{x} \left[ 2 + x^\epsilon \tilde{a}^{-\epsilon} x^{-\epsilon} \tilde{a}^\epsilon \right] \frac{dx}{dr} > 0
\]
Since \(r^u > r^c\), the covariance of productivity and the domestic share of expenditure is lower for \(A^c\) than \(A^u\). Thus, the covariance of productivity and the equilibrium gains from trade, \(cov(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii})\), is greater for \(A^c\) than \(A^u\).

\[\textit{var}(\ln(C_i/L)) \textit{ is greater in the spatially correlated case}\]

**Proof.** In both equilibria,
\[
\text{var}(\ln \lambda_{ii}) = \frac{2}{4} \left( \ln \lambda_{11} \right)^2 + \frac{2}{4} \left( \ln \lambda_{44} \right)^2 = \left( \ln \lambda_{11} \right)^2 = \frac{4}{(\ln \tilde{a})^2} \left( \text{cov}(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii}) \right)^2.
\]
Therefore
\[
\text{var}(\ln(C_i/L)) = \text{var}(A_i) + 2\text{cov}(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii}) + \frac{1}{\epsilon^2} \text{var}(\ln \lambda_{ii})
\]
\[
= \text{var}(A_i) + 2\text{cov}(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii}) + \frac{4}{(\ln \tilde{a})^2} \left( \text{cov}(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii}) \right)^2
\]
\[\text{27} \tilde{a} > x \text{ because } x \text{ is the largest positive zero of } R(x; r), R(x'; r) < 0 \forall x' \in (0, x), \text{ and } R(\tilde{a}; r) = (1+r)(\tilde{a}^{-1})\tilde{a}^{2e} > 0.
\]

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Recall that $\text{cov}(\ln A_i, \frac{1}{\epsilon} \ln \lambda_{ii})$ if and only if

$$2 + \frac{8}{(\ln \overline{a})^2} \text{cov}(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii}) > 0 \iff \ln \tilde{a} > \frac{1}{\epsilon} \ln \left(1 + \tilde{a}^\epsilon x - \epsilon \tilde{r} \right) \frac{1}{1 + x^\epsilon \tilde{a} - \epsilon \tilde{r}}$$

This inequality is true. The triangle inequality for trade costs, $d_2 < d_1$, implies that $r^u < 1$. If $r < 1$ and $\epsilon \geq 1$, then $R(\sqrt{\tilde{a}}; r) \leq 0$. Thus, $x^r(r) \geq \sqrt{\tilde{a}} \forall r \in (0, 1)$. That implies the following inequality:

$$\frac{1 + \tilde{a}^\epsilon x - \epsilon \tilde{r}}{1 + x^\epsilon \tilde{a} - \epsilon \tilde{r}} \leq \frac{\tilde{a}^\epsilon x - \epsilon (1 + r)}{x^\epsilon \tilde{a} - \epsilon (1 + r)} = \left(\frac{\tilde{a}}{x}\right)^{2\epsilon} \leq \left(\frac{\tilde{a}}{\sqrt{\tilde{a}}}\right)^{2\epsilon} = \tilde{a}^\epsilon$$

Thus, $\text{var}(\ln(C_i/L))$ is increasing in $\text{cov}(\ln A_i, -\frac{1}{\epsilon} \ln \lambda_{ii})$.

$\Box$

$\mathbb{E}(\ln(C_i/L))$ is lower in the spatially correlated case

**Proof.** By equation (1), the difference in average welfare between the uncorrelated and correlated states is

$$\mathbb{E}(\ln(C_i^u/L)) - \mathbb{E}(\ln(C_i^c/L)) = -\frac{1}{4\epsilon} \sum_{i=1}^{4} [\ln \lambda_{ii}^u - \ln \lambda_{ii}^c] = \frac{1}{4\epsilon} \ln \left(\prod_{i=1}^{4} \frac{\lambda_{ii}^c}{\lambda_{ii}^u}\right).$$

Due to the symmetry of the problem, $\lambda_{11}^c = \lambda_{22}^c$, $\lambda_{33}^c = \lambda_{44}^c$, $\lambda_{11}^u = \lambda_{33}^u$ and $\lambda_{22}^u = \lambda_{44}^u$. Consequently,

$$\mathbb{E}(\ln(C_i^u/L)) - \mathbb{E}(\ln(C_i^c/L)) = \frac{1}{2\epsilon} \ln \left(\frac{\lambda_{11}^c \lambda_{44}^c}{\lambda_{11}^u \lambda_{44}^u}\right).$$

The following results were obtained in proving that $\text{cov}(\ln A_i, \ln \lambda_{ii})$ is lower in the spatially correlated case:

$$\frac{\lambda_{11}^c}{\lambda_{11}^u} = 1 + d_2^\epsilon \frac{1 + (\frac{x}{a})^\epsilon r^u}{1 + d_1^\epsilon \frac{1 + (\frac{x}{a})^\epsilon r^c}{1 + d_2^\epsilon \frac{1}{1 + d_1^\epsilon}}}, \quad \frac{\lambda_{44}^c}{\lambda_{44}^u} = 1 + d_1^\epsilon \frac{1 + (\frac{x}{a})^\epsilon r^u}{1 + d_2^\epsilon \frac{1 + (\frac{x}{a})^\epsilon r^c}{1 + d_1^\epsilon \frac{1}{1 + d_2^\epsilon}}}.$$

Recall that $r^c = \frac{d_1^\epsilon + d_2^\epsilon}{1 + d_1^\epsilon}$ and $r^u = \frac{d_2^\epsilon + d_4^\epsilon}{1 + d_2^\epsilon}$. It follows that $\frac{1 + r^c}{1 + r^u} = \frac{1 + d_1^\epsilon}{1 + d_2^\epsilon}$ and therefore

$$\frac{\lambda_{11}^c}{\lambda_{11}^u} = 1 + r^c \frac{1 + (\frac{x}{a})^\epsilon r^u}{1 + r^u \frac{1 + (\frac{x}{a})^\epsilon r^c}{1 + r^c \frac{1}{1 + r^u}}}, \quad \frac{\lambda_{44}^c}{\lambda_{44}^u} = 1 + r^c \frac{1 + (\frac{x}{a})^\epsilon r^u}{1 + r^u \frac{1 + (\frac{x}{a})^\epsilon r^c}{1 + r^c \frac{1}{1 + r^u}}}.$$

\[R(\sqrt{\tilde{a}}; r) = \tilde{a}^{\frac{2\epsilon + 1}{\epsilon}} + r\tilde{a}^\epsilon (\tilde{a}^{\frac{2\epsilon}{\epsilon}} - \tilde{a}^{\frac{1}{\epsilon}}) - \tilde{a}^{2\epsilon} = \tilde{a}^\epsilon \left(\frac{\tilde{a}^{\frac{2\epsilon}{\epsilon}} + r\tilde{a}^{\frac{1}{\epsilon}} (\tilde{a}^{\frac{2\epsilon}{\epsilon}} - 1)}{1}ight) \leq \tilde{a}^\epsilon \left(\frac{\tilde{a}^{\frac{2\epsilon}{\epsilon}} - \tilde{a}^{\frac{1}{\epsilon}} (1 + \tilde{a}^{\frac{2\epsilon}{\epsilon}})}{1}ight) \leq 0\]
Combining the above expressions yields
\[
\frac{\lambda^c_{11}\lambda^u_{44}}{\lambda^u_{11}\lambda^c_{44}} = \left(1 + r^c\right)^2 \frac{1 + r^uV\left(\frac{x_u}{a}\right) + \left(r^u\right)^2}{1 + r^cV\left(\frac{x_c}{a}\right) + \left(r^c\right)^2}
\]
where \( V(\cdot) \) denotes the function \( V(x) = x + x^{-1} \), which for \( x \in (0,1) \) is greater than 2 and decreasing. From proofs above, we know that \( 1 > r^u > r^c > 0 \) and \( \bar{a} > x_c > x_u > 1 \). Therefore \( 1 > (x_c/\bar{a})^\epsilon > (x_u/\bar{a})^\epsilon > 0 \) and \( V((x_u/\bar{a})^\epsilon) > V((x_c/\bar{a})^\epsilon) > 2 \). Now consider the ratio
\[
Q(r) = \frac{1 + rV\left(\frac{x^*(r)}{a}\right) + r^2}{(1 + r)^2} = 1 + \frac{r}{1 + r}\left(V\left(\frac{x^*(r)}{a}\right)^\epsilon - 2\right).
\]
Since \( r^u > r^c > 0 \), we have \( \frac{r^u}{1 + r^u} > \frac{r^c}{1 + r^c} \). Combining this result with the fact that \( V\left(\frac{x^*(r)}{a}\right) - 2 > V\left(\frac{x^*(r)}{a}\right)^\epsilon - 2 > 0 \) leads to \( Q(r^u) > Q(r^c) \). As a consequence:
\[
\frac{\lambda^c_{11}\lambda^u_{44}}{\lambda^u_{11}\lambda^c_{44}} = Q(r^u) > Q(r^c) \Rightarrow \ln\left(\frac{\lambda^c_{11}\lambda^u_{44}}{\lambda^u_{11}\lambda^c_{44}}\right) > 0 \Rightarrow \mathbb{E}(\ln(C^u_i/L)) > \mathbb{E}(\ln(C^c_i/L))
\]

\[\square\]

### A.2.2 Circular geography

Figures 2 and 3 present an illustrative example in which we parameterize \( A_i \) and \( \tau_{ij} \) on a circular geography. As stated in the main text, \( N = 50, \epsilon = 1, \) and \( L_i = 1 \) \( \forall i \). Countries have locations given by \( l_i = \frac{\pi}{N}(2i - 1 - N) \) for \( i = 1, \ldots, N \). Productivity \( \ln A_i \) has a mean value of 10 and follows a sinewave with amplitude 1 and frequency \( \theta \).\(^{29}\) Bilateral trade costs are given by \( \ln \tau_{ij} = .8\ln(1 + ||l_i - l_j||) \), where \( ||l_i - l_j|| \) is the distance between locations \( i \) and \( j \) on the circle.

Figures 2 and 3 depict demeaned distributions. Table A.1 reports the means and variances of countries' welfare per capita under autarky and trade.

<table>
<thead>
<tr>
<th>Frequency of ( \ln A ) sine wave (( \theta ))</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autarky welfare (( \ln A )) mean</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Autarky welfare (( \ln A )) variance</td>
<td>0.510204</td>
<td>0.510204</td>
<td>0.510204</td>
<td>0.510204</td>
</tr>
<tr>
<td>Trading-equilibrium welfare (( \ln C/L )) mean</td>
<td>12.2654</td>
<td>12.2769</td>
<td>12.2807</td>
<td>12.2836</td>
</tr>
<tr>
<td>Trading-equilibrium welfare (( \ln C/L )) variance</td>
<td>0.298203</td>
<td>0.226274</td>
<td>0.203006</td>
<td>0.184882</td>
</tr>
</tbody>
</table>

Figure 4 introduces heterogeneous sizes to the parameterization used in Figures 2 and 3. Size \( \ln L_i \) is the sum of a sinewave with mean value 10, amplitude 1, and frequency \( \theta_L = 1 \) and Gaussian

\(^{29}\) The standard deviation of a sine wave is proportional to its amplitude and independent of its frequency. This is true for both the function and our \( N \)-point discretization.
noise $\sim \mathcal{N}(0, 1)$.

Figure 5 depicts the expenditure-productivity relationship in a circular geography with equal-sized countries for three selected productivity vectors. These productivity distributions differ only in their spatial correlation. They were generated by shuffling a vector $\ln A_0 \sim \mathcal{N}(0, 1)$.

A.2.3 Randomly generated geography

In Figure 6, we examine how the relationship between productivity and domestic share of expenditure depends on the spatial correlation of productivity in a randomly generated geography. We draw $N = 50$ locations’ coordinates on a plane $l_j \in \mathbb{R}^2$ from a standard normal distribution. We generate bilateral, distance-related trade costs using $\ln \tau_{ij} = \tau \ln (1 + d_{ij})$, where distance $d_{ij} = ||l_i - l_j||$ is the Euclidean norm on $\mathbb{R}^2$ and $\tau$ is a positive scaling factor. Countries are of equal size, $L_j = 1 \ \forall j$.

The trade elasticity $\epsilon = 4$.

To construct $M$ productivity distributions that have identical first and second moments and different spatial covariances, we employ a procedure that makes use of the eigenvectors of a transformation of the spatial weight matrix. Let $I$ denote the identity matrix and consider $J = ee^\top$, where $e$ is the constant vector of ones. The object of interest is the matrix $\Pi = CWC$ where $C$ corresponds to the centering matrix: $C = I - \frac{1}{N} J$ and $W$ is our spatial weight matrix. It can be shown that the upper and lower bounds of Moran’s $I$ are given by: $\lambda_{\text{max}} \frac{N}{W_0}$ and $\lambda_{\text{min}} \frac{N}{W_0}$ where $\lambda_{\text{max}}$ and $\lambda_{\text{min}}$ denote the largest and the smallest eigenvalues of $\Pi$ respectively and $W_0 = \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}$.

More generally, Moran’s $I$ will be equal to $\lambda_i \frac{N}{W_0}$ when evaluated at the $i$th eigenvector. It can also be shown that the non-constant eigenvectors of $\Pi$ are centered and have identical second moments.

With these eigenvectors in hand, we apply a translation $T_c : v \rightarrow v + c$ with $c \in \mathbb{R}^2_+$ to the non-constant eigenvectors of $\Pi$. We employ linear combinations of the strictly positive vectors produced by this transformation to produce a set of $M$ productivity distributions denoted $(A_1, \ldots, A_M)$. By construction, these productivity distributions have identical first and second moments but vary in their spatial covariance as measured by Moran’s $I$.

A.3 Multiple-sector case

This appendix section provides details of the multi-sector economic environment summarized in Section 2.3.

Preferences. Individuals in country $i$ have preferences that are Cobb-Douglas over sectors $s = 1, \ldots, S$ and constant elasticity of substitution (CES) within sectors. Thus, the relevant price indices are

$$ P_i = \prod_{s=1}^{S} P_{is}^{\alpha_{is}} \quad \text{and} \quad P_{is} = \left( \int_{\omega_s} p_i(\omega_s)^{1-\sigma_s} d\omega_s \right)^{1/(1-\sigma_s)}, $$

where $\alpha_{is} \geq 0$ are expenditure shares ($\sum_{s=1}^{S} \alpha_{is} = 1$) and $\sigma_s$ are sectoral elasticities of substitution across varieties.

Production. Productivity in country $j$ in sector $s$ is $A_{is}$.
Trade costs. Selling one unit to \( j \) from \( i \) in sector \( s \) requires producing \( \tau_{ijs} \geq 1 \) units, with \( \tau_{iis} = 1 \).

Gravity equation. Denote sales from \( i \) to \( j \) in sector \( s \) by \( X_{ijs} \). Across sectors, Cobb-Douglas preferences cause optimizing consumers to spend \( \alpha_{js} \) of their total expenditure in sector \( s \), \( X_{js} = \alpha_{js} X_j \). Within each sector, CES preferences result in the share of expenditure by \( j \) on goods from \( i \) in sector \( s \) taking the form of a gravity equation:

\[
\lambda_{ijs} = \frac{X_{ijs}}{X_{js}} = \frac{\chi_{is}(\tau_{ijs}w_i)^{-\epsilon_s}}{\sum_{l=1}^{N} \chi_{ls}(\tau_{ljs}w_l)^{-\epsilon_s}} = \frac{\chi_{is}(\tau_{ijs}w_i)^{-\epsilon_s}}{\Phi_{js}}.
\]

Equilibrium. In a competitive equilibrium, labor-market clearing, goods-market clearing, and budget constraints are satisfied such that total income \( Y_i = w_i L_i \) and sectoral income \( Y_{is} = w_i L_{is} \) satisfy \( Y_{is} = \sum_{j=1}^{N} X_{ijs} \), \( Y_i = \sum_{s=1}^{S} Y_{is} \), and \( X_{is} = \alpha_{is} Y_i \) for all countries. The equilibrium system of equations is

\[
Y_{is} = \sum_{j=1}^{N} \lambda_{ijs} \alpha_{js} \sum_{s'=1}^{S} Y_{jss'}.
\]

In this environment, real consumption per capita is

\[
\ln \left( \frac{C_i}{L_i} \right) = \sum_{s=1}^{S} \alpha_{is} \left( \ln A_{is} + \gamma_s - \frac{1}{\epsilon_s} \ln \lambda_{iis} \right).
\]

The first two terms, \( \sum_{s=1}^{S} \alpha_{is} (\ln A_{is} + \gamma_s) \), are per capita welfare in autarky, and the final term, \( -\sum_{s=1}^{S} \frac{\alpha_{is}}{\epsilon_s} \ln \lambda_{iis} \), summarizes the gains from trade.

Dispersion in per capita welfare across countries thus depends on the exogenous variation in productivities \( A_{is} \) and the endogenous variation in domestic shares of expenditure \( \lambda_{iis} \). For the sake of expositional brevity, assume that expenditures shares are common across countries, \( \alpha_{is} = \alpha_s \forall i \). In that case, the variance of per capita welfare is

\[
\text{var} \left( \ln \left( \frac{C_i}{L_i} \right) \right) = \text{var} \left( \sum_{s=1}^{S} \alpha_{is} \ln A_{is} \right) + \text{var} \left( \sum_{s=1}^{S} \frac{\alpha_{is}}{\epsilon_s} \ln \lambda_{iis} \right) - 2 \sum_{s=1}^{S} \sum_{s'=1}^{S} \frac{\alpha_{is} \alpha_{is'}}{\epsilon_s \epsilon_{s'}} \text{cov} (\ln A_{is}, \ln \lambda_{iis'})
\]

To examine the role of spatial correlation, consider two productivity distributions – a correlated state \( c \) and an uncorrelated state \( u \). Assume that unconditional variance of the productivity distributions is the same, \( \text{var} \left( \sum_{s=1}^{S} \alpha_{is} \ln A^c_{is} \right) = \text{var} \left( \sum_{s=1}^{S} \alpha_{is} \ln A^u_{is} \right) \). The difference in welfare dispersion then depends on the covariance of productivities and domestic shares of expenditure, both within and across sectors, and between domestic shares of expenditure.
\[ \text{var} \left( \ln \left( C_i^c / L_i \right) \right) - \text{var} \left( \ln \left( C_i^u / L_i \right) \right) = 2 \sum_{s=1}^{S} \sum_{s' = 1}^{S} \frac{\alpha_s \alpha_{s'}}{\varepsilon_s \varepsilon_{s'}} \left\{ \text{cov} \left( \ln A_{is}^u, \ln \lambda_{iis'}^u \right) - \text{cov} \left( \ln A_{is}^c, \ln \lambda_{iis'}^c \right) \right\} \\
\quad - \sum_{s=1}^{S} \sum_{s' = 1}^{S} \frac{\alpha_s \alpha_{s'}}{\varepsilon_s \varepsilon_{s'}} \left\{ \text{cov} \left( \ln \lambda_{iis}^u, \ln \lambda_{iis'}^u \right) - \text{cov} \left( \ln \lambda_{iis}^c, \ln \lambda_{iis'}^c \right) \right\} \]

(A.3)

Just as in the single-sector case, for typical values of the sectoral trade elasticities, \(2 \alpha_s \alpha_{s'} / \varepsilon_s \varepsilon_{s'}\) is an order of magnitude larger than \(\alpha_s \alpha_{s'} / \varepsilon_s \varepsilon_{s'}\). Thus, the difference in welfare dispersion is governed by the \(\text{cov} \left( \ln A_{is}^u, \ln \lambda_{iis'}^u \right)\) terms, provided that the block of \(\text{cov} \left( \ln A_{is}^c, \ln \lambda_{iis'}^c \right)\) terms is the same order of magnitude as the block of \(\text{cov} \left( \ln \lambda_{iis}^u, \ln \lambda_{iis'}^u \right)\) terms.

Under what circumstances is studying differences in \(\text{cov} \left( \ln A_{is}^u, \ln \lambda_{iis'}^u \right)\) in one sector alone informative about welfare dispersion? For simplicity, consider the two-sector case and three possible relationships between the two sectors: perfectly correlated productivities, perfectly anti-correlated productivities, and orthogonal productivities.

In the perfectly correlated case, there is little scope for adjustment across sectors, and thus outcomes are similar to those obtained in the one-sector environment. In fact, if all sectors have perfectly correlated productivities (\(A_{is} \propto A_i \forall s\)), perfectly correlated spatial linkages (\(\tau_{ij} \propto \tau_{ij} \forall s\)) and equal trade elasticities (\(\varepsilon_s = \varepsilon \forall s\)), then expenditure shares are equal across sectors, \(\lambda_{iis} = \lambda_{ij}\), and the difference in welfare dispersion in equation (A.3) is exactly proportionate to the single-sector expression in equation (3).

If sectoral productivities are perfectly anti-correlated, then outcomes in one sector may be exactly offset by outcomes in another, leaving welfare unchanged. That is, it is possible to construct circumstances in which the sum of covariances of productivities and domestic shares of expenditure within sectors is exactly the opposite of the sum of cross-sector covariances. Consider the two-sector case with equal expenditure shares \(\alpha_1 = \alpha_2 = \frac{1}{2} \forall j\) and equal trade elasticities \(\varepsilon_1 = \varepsilon_2 = \varepsilon\). If the two sectors’ productivities are perfectly anti-correlated, such that \(\ln A_{11} + \ln A_{22}\) is a constant, then it can be shown that \(\sum_{s=1}^{S} \sum_{s' = 1}^{S} \frac{\alpha_s \alpha_{s'}}{\varepsilon_s \varepsilon_{s'}} \text{cov} \left( \ln A_{is}^u, \ln \lambda_{iis'}^u \right) = 0\). Thus, our predictions about trade flows are valid, but the welfare consequences of these changes are fully offset by the non-agricultural sector’s anti-correlated changes.

What about the orthogonal case? Figure 7 depicts a two-sector sine-wave economy with two symmetric sectors that differ only in their sine-wave frequency. Table A.2 reports the means and variances of countries’ welfare per capita under autarky and trade. Compared to Table A.1, the variance of autarky welfare is lower because autarky welfare is the simple average of two sectors’ (orthogonal) productivities with the same mean and variance. The mean trading-equilibrium welfare is higher (the gains from trade are larger) in the multi-sector case due to gains from specialization according to comparative advantage. This additional margin of adjustment also dampens the degree to which greater spatial correlation of productivity in one of the two sectors affects the variance.
Table A.2: Outcomes for two-sector sine-wave economy

<table>
<thead>
<tr>
<th>Frequency of $\ln A_1$ sine wave ($\theta_1$)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autarky welfare ($\frac{1}{2} \ln A_1 + \frac{1}{2} \ln A_2$) mean</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Autarky welfare ($\frac{1}{2} \ln A_1 + \frac{1}{2} \ln A_2$) variance</td>
<td>0.255102</td>
<td>0.255102</td>
<td>0.255102</td>
<td>0.255102</td>
</tr>
<tr>
<td>Trading-equilibrium welfare ($\ln C/L$) mean</td>
<td>12.3610</td>
<td>12.3699</td>
<td>12.3721</td>
<td>12.3736</td>
</tr>
<tr>
<td>Trading-equilibrium welfare ($\ln C/L$) variance</td>
<td>0.114255</td>
<td>0.097649</td>
<td>0.092189</td>
<td>0.087935</td>
</tr>
</tbody>
</table>

of welfare in the trading equilibrium, but our main prediction still holds in this multi-sector setting with orthogonal productivities.

B Data sources and construction

Agricultural data Our cereal data cover barley, maize, millet, oats, rice, rye, sorghum, and wheat. We use cereal-level measures of output (in metric tons, 1961-2013), yield (in metric tons per hectare, 1961-2013), trade quantity (in metric tons, 1961-2013), trade value (in nominal USD, 1961-2013), producer prices (in nominal local currency, 1966-2013), and change in storage (in metric tons, 1961-2013) for each country and year obtained from FAOstat.\footnote{Available at \url{http://www.fao.org/faostat/en/#data}.} The gravity analysis in Table C.1 uses bilateral values of cereal trade flows (exporter-importer-year value in current USD) for 1986-2013 obtained from FAOstat.

Domestic share of expenditure aggregated across cereals $c = 1, \ldots, C$ for country $i$ in year $t$ is

$$
\lambda^0_{cit} = \frac{\sum_{c=1}^{C} X_{cit}}{\sum_{c=1}^{C} X_{cit} + \sum_{j \neq i}^{N-1} \sum_{c=1}^{C} X_{cjit}}
$$

where $X_{cjit}$ is the value of cereal $c$ sold to $i$ by $j$ in year $t$. We observe $X_{cjit}$ for $j \neq i$. We must construct $X_{cit}$ using data on output quantities, export quantities, and prices. $X_{cit} = (q_{cit} - \text{exports}_{citi}) \cdot p_{cit}$, where $q_{cit}$ is domestic output quantity, $\text{exports}_{citi}$ is export quantity, and $p_{cit}$ is domestic price.

There are two potential data sources for price $p_{cit}$, neither of which are ideal. The first data source is export unit values, $\frac{\sum_{j \neq i} X_{cjit}}{\sum_{j \neq i} X_{cij}}$, which are observed when a country exports a cereal. Unfortunately, only 53% of the cereal-country-year observations in our sample with positive output quantities have positive export quantities. The second price measure, producer prices in nominal local currency, presents two challenges. First, producer prices are available for only 59% of the cereal-country-year observations with positive cereal output. Second, due to resource constraints at the time, the FAO did not standardize the collection of 1966-1990 producer prices as it did for prices since 1991. As such, FAO warns against the combined use of the full 1966-2013 panel and notes that the FAO is “not in a position to give any explanation for the existing differences”

In light of these limitations and to ensure sufficient statistical power in our estimation, we elect to approximate domestic expenditure $\sum_{c=1}^{C} x_{cit}$ by domestic quantity times average price, $\left(\sum_{c=1}^{C} (q_{cit} - x_{cit})\right) \left(\frac{\sum_{c=1}^{C} X_{cit}}{\sum_{c=1}^{C} x_{cit}}\right)$. This measure is available for every year that a country exports at least one cereal, yielding a sizable estimation sample. This approximation of domestic expenditure $\sum_{c=1}^{C} X_{cit}$ makes our outcome variable a noisy measure the domestic share of expenditure. Table F.5 presents results for alternative approximations of the domestic share of expenditure.

Finally, our measure of cereal yield in country $i$ and year $t$ is area-weighted cereal-level yield.

**ENSO index** Annual ENSO variations can be detected using different indices, with the most commonly used being equatorial Pacific sea surface temperature (SST) anomalies. We primarily utilize 1960-2013 values of the monthly Kaplan NINO4 index which averages SST over the area 5°S-5°N, 160°E-150°W. For robustness checks in Table F.4, we also use the NINO3 (5°S-5°N, 150°W-90°W), NINO34 (5°S-5°N, 170°W - 120°W), and NINO12 (10°S-0°, 90°W-80°W) indices (Kaplan et al., 1998).

**Historical temperature and precipitation** Global temperature (in degrees centigrade) and precipitation (in mm/month) variable constructed from monthly gridded global weather data at a 0.5° latitude by 0.5° longitude resolution from the Center for Climatic Research at the University of Delaware (Legates and Willmott, 1990a, b). 1960-2013 monthly data was first spatially aggregated from pixel to country-level using cross-sectional crop area weights from Ramankutty et al. (2008). Annual values constructed by averaging January-December monthly values.

**Projected temperature under climate change** Global multi-model ensemble mean temperature temperature (in degrees centigrade) from monthly gridded global data at the 2.5° latitude by 2.5° longitude resolution from the Coupled Model Intercomparison Project version 5 (CMIP5). 2014-2099 monthly data was first spatially aggregated from pixel to country-level using cross-sectional crop area weights from Ramankutty et al. (2008). For robustness checks in Table F.4, we also aggregate temperature from pixel to country-level using total country area. Annual values values constructed by averaging monthly values.

**Geography** Country latitude and longitude are defined as crop area-weighted average using the global cross-sectional distribution of crop area in 2000 (Ramankutty et al., 2008). Great-circle distances between these country centroids are computed using the haversine formula.

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33 Available at [https://climexp.knmi.nl/selectfield_cmip5.cgi](https://climexp.knmi.nl/selectfield_cmip5.cgi)
Global oil prices Monthly West Texas Intermediate crude oil spot price obtained from the St. Louis Federal Reserve.\textsuperscript{34} 1961-2013 annual values constructed by averaging January-December monthly values.

C Additional empirical results

C.1 Gravity estimates for cereals trade

The theoretical model of Section 2 assumes that trade in cereals follows a gravity specification for exporter $i$, importer $j$ and year $t$:

$$\ln X_{ijt} = -\epsilon \ln \tau_{ij} + \ln \left( \frac{X_{it}}{w_{it}^{\epsilon}} \right) + \ln \left( \frac{X_{jt}}{\Phi_{jt}} \right)$$

Estimating this log-linear equation using bilateral trade flows in cereals yields patterns similar to those found in aggregate trade flows (e.g., Head and Mayer 2014). Bilateral cereal trade flows are available from FAOStat starting in 1986. As is standard, we estimate in our panel setting using bilateral distance as a (time-invariant) source of variation in bilateral trade costs while employing exporter-year ($it$) fixed effects and importer-year ($jt$) fixed effects. Table C.1 reports the results. While the estimated distance coefficient of -1.5 differs from the coefficient of -1.0 typically estimated for aggregate trade flows, the regression exhibits the typical explanatory power, accounting for the majority of the variation in cereal trade flows. In addition, 61\% of countries that trade cereals in a given year both import and export cereals that year. At the level of importer-exporter pairs, 24\% of trading pairs sell cereal in both directions. Thus, cereals are far from homogeneous commodities, and international trade in cereals is well described by the gravity specification.

\textsuperscript{34}Available at \url{https://fred.stlouisfed.org/series/WTISPLC}
Table C.1: Gravity regression for international trade in cereals

<table>
<thead>
<tr>
<th>Outcome is log import value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln distance$_{ij}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>R-squared</td>
</tr>
<tr>
<td>Country-level intra-industry trade share</td>
</tr>
<tr>
<td>Bilateral intra-industry trade share</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Notes: OLS estimates of gravity model for bilateral (importer-reported) trade value during 1986-2013. All models include importer-year and exporter-year fixed effects. Intraindustry trade shares are fraction of country-year and country-pair-year observations with positive exports and imports, conditional on positive exports or imports. Standard errors clustered at the importer and exporter levels in parentheses; p-value in brackets.

D Welfare calculations

This section details the welfare calculations in the main text.

D.1 Calculating historical variance of welfare effect

This section details the within-sample welfare calculation discussed in Section 4.2 and shown in Table 2. Recall the expression for the variance of welfare in equation (2):

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

We employ this expression to quantify the magnitude of our reduced-form results in welfare terms. Consider the following thought experiment: suppose the spatial correlation of productivity increases from the 1961-2013 historical mean, \( \bar{I} = .214 \), by one standard deviation, \( \sigma_I = .0191 \). What is the resulting percentage change in the cross-sectional variance of welfare, holding everything else fixed? We denote these two hypothetical states as uncorrelated state \( u \) and correlated state \( c \).

For the uncorrelated state, we define variance productivity as the average cross-sectional productivity variance during 1961-2013:

$$\text{var}(\ln A_i^u) \equiv E_t[\text{var}_t(\ln A_{it}|t)] \quad (D.1)$$

Next, we define covariance between productivity and domestic share of expenditure during the
uncorrelated state as the average cross-sectional covariance during 1961-2013:

\[ \text{cov}(\ln A_{ui}, \ln \lambda_{ii}^u) \equiv E_t[\text{cov}_i(\ln A_{iti}, \ln \lambda_{iti}|t)] \] (D.2)

We further define the variance of domestic share of expenditure during the uncorrelated states as the average variance during 1961-2013:

\[ \text{var}(\ln \lambda_{iiu}) \equiv E_t[\text{var}_i(\ln \lambda_{iti}|t)] \] (D.3)

Note that the values in definitions (D.1), (D.2), (D.3) can be directly computed from data since \( \ln A_{iti} \) and \( \ln \lambda_{iti} \) are observed.

For the correlated state \( c \), \( \text{var}(\ln A_{ci}) \) is also given by definitions (D.1) since we assume productivity variance is unaltered by changes in spatial correlation. \( \text{cov}(\ln A_{ci}, \ln \lambda_{cci}) \) and \( \text{var}(\lambda_{cci}) \), however, have to be calculated as one does not directly observe data from a year in which only \( I_t = \bar{I} + \sigma_I \) while everything else is fixed at the historical mean. To do this, first recall our reduced-form expression for \( \ln \lambda_{iti} \) from equation (6):

\[ \ln \lambda_{iti} = \beta_0 \ln A_{iti} + \beta_1 \ln A_{iti} I_t + Z_{iti} \hat{\Pi} + \mu_{iti} \]

Our estimates of this equation can be employed to construct each component of equation (2) for the correlated state. The covariance between productivity and domestic share of expenditure during the correlated state is:

\[ \text{cov}(\ln A_{ci}, \ln \lambda_{cci}) \equiv (\hat{\beta}_0 + \hat{\beta}_1 (\bar{I} + \sigma_I)) E_t[\text{var}_i(\ln A_{iti}|t)] + E_t[\text{cov}_i(\ln A_{iti}, Z_{iti} \hat{\Pi}|t)] + E_t[\text{cov}_i(\ln A_{iti}, \mu_{iti}|t)] \] (D.4)

The variance of domestic share of expenditure during the correlated state is:

\[ \text{var}(\ln \lambda_{ci}) \equiv (\hat{\beta}_0^2 + 2\hat{\beta}_0 \hat{\beta}_1 (\bar{I} + \sigma_I) + \hat{\beta}_1^2 (\bar{I} + \sigma_I)^2) E_t[\text{var}_i(\ln A_{iti}|t)] + E_t[\text{var}_i(\ln \mu_{iti}|t)] + 2(\hat{\beta}_0 + \hat{\beta}_1 (\bar{I} + \sigma_I)) E_t[\text{cov}_i(\ln A_{iti}, Z_{iti} \hat{\Pi}|t)] + 2E_t[\text{cov}_i(\ln A_{iti}, \mu_{iti}|t)] + 2E_t[\text{cov}_i(Z_{iti} \hat{\Pi}, \mu_{iti}|t)] \] (D.5)

Each term in equations (D.4) and (D.5) is either directly observable or can be obtained by estimating equation (6). For example, for the model estimated in column 2, panel B of Table 2, with \( \hat{\beta}_0 = 2.114 \)
and $\hat{\beta}_1 = -4.144$, we have:

$$E_t[\text{var}_i(\ln A_{it}|t)] = .453$$
$$E_t[\text{var}_i(Z_{it}\hat{\Pi}|t)] = 1.04$$
$$E_t[\text{var}_i(\hat{\mu}_{it}|t)] = .083$$
$$E_t[\text{cov}_i(\ln A_{it}, Z_{it}\hat{\Pi}|t)] = -.497$$
$$E_t[\text{cov}_i(\ln A_{it}, \hat{\mu}_{it}|t)] = -.026$$
$$E_t[\text{cov}_i(Z_{it}\hat{\Pi}, \hat{\mu}_{it}|t)] = -.001$$

Applying equation (2), the percentage change in the variance of welfare in the correlated state, relative to the uncorrelated state, is

$$\frac{\text{var} \left( \ln \frac{C^c_{it}}{L_{it}} \right) - \text{var} \left( \ln \frac{C^u_{it}}{L_{it}} \right)}{\text{var} \left( \ln \left( C^u_{it} / L_{it} \right) \right)} = \frac{\text{var} \left( \ln A^c_{it} \right) - \frac{2}{\epsilon} \text{cov} \left( \ln A^c_{it}, \ln \lambda^c_{it} \right) + \frac{1}{\epsilon^2} \text{var} \left( \ln \lambda^c_{it} \right) - 1 \right)}{\text{var} \left( \ln A^u_{it} \right) - \frac{2}{\epsilon} \text{cov} \left( \ln A^u_{it}, \ln \lambda^u_{it} \right) + \frac{1}{\epsilon^2} \text{var} \left( \ln \lambda^u_{it} \right) - 1 \right)}$$

(D.6)

To complete the calculation, let the agricultural trade elasticity be $\epsilon = 8.59$ (Caliendo and Parro, 2015). Values from equation (D.6) are shown in Table 2.

**D.2 Calculating change in variance of welfare under climate change**

In Section 5.2, we calculate the percentage change in the variance of welfare between the end of our estimation period, $\bar{t} = 2013$, and the end of our projection period, $T = 2099$, under climate change, holding everything else fixed. Compared with the welfare calculation described in Appendix D.1 and reported in Table 2, there is an added complication: climate change also changes the variance of productivity.

To begin, recall equation (9) for $\ln A_{it}$ during the estimation period, $t \in [\bar{t}, \bar{t}]$:

$$\ln A_{it} = k(T_{it}) + X_{it} \Psi + \nu_{it}$$

Using equation (9) and our business-as-usual CMIP5 ensemble mean projected temperatures under climate change, we first compute country-year agricultural productivity under climate change during the projection period $t \in [\bar{t} + 1, T]$:

$$\hat{\ln} A_{it} = \hat{k}(T_{it}) + X_{it} \hat{\Psi} + \hat{\nu}_{it}$$

(D.7)

Figure 14 shows $\hat{k}(\cdot)$ for our benchmark specification. Figure 15 shows the associated change in log agricultural productivity, $\hat{\ln} A_{i,2099} - \ln A_{i,2013}$, for each country. In the left panel of Figure 17, the gray line shows $\text{var}(\hat{\ln} A_{it})$ while the blue line shows $\hat{I}_t$ computed using $\hat{\ln} A_{it}$ for each projection year.

To compute the change in variance of welfare from the end of the estimation period, $\bar{t}$, to any
We consider two scenarios for obtaining future domestic share of expenditure, \( \hat{\ln} \lambda_{it} \). In the first scenario, the projection omits changes in the spatial structure in the sense that the spatial correlation of productivities is fixed at its value at the end of the estimation period, \( I_{\bar{t}} \), throughout the projection period. In the second projection, we allow climate change to alter the spatial correlation of productivity.

Variance projection omitting changes in spatial structure
Holding the spatial correlation of productivity fixed, the domestic share of expenditure during the projection period, \( t \in [\bar{t} + 1, T] \), is computed using our benchmark estimate of equation (6):

\[
\ln \lambda_{it}^n = (\beta_0 + \beta_1 I_{\bar{t}}) \ln A_{it} + Z_{it} \hat{\Pi} + \hat{\mu}_{it}
\]  

(D.9)

Equations (D.7) and (D.9) allows construction of \( \text{var}(\ln \lambda_{it}^n) \) and \( \text{cov}(\ln A_{it}, \ln \lambda_{it}^n) \) for each year in the projection period. These are then fed into equation (D.8) to compute the change in the variance of welfare since 2013 over the 21st century for the projection that omits changes in spatial structure. That projected welfare variance is shown as the solid gray line in the right panel of Figure 17.

Variance projection including changes in spatial structure
Allowing the spatial correlation of productivity to vary under climate change, the domestic share of expenditure during the projection period, \( t \in [\bar{t} + 1, T] \), is computed using our benchmark estimate of equation (6):

\[
\ln \lambda_{it}^s = (\beta_0 + \beta_1 \hat{I}_{\bar{t}}) \ln A_{it} + Z_{it} \hat{\Pi} + \hat{\mu}_{it}
\]  

(D.10)

Equations (D.7) and (D.10) allows construction of \( \text{var}(\ln \lambda_{it}^s) \) and \( \text{cov}(\ln A_{it}, \ln \lambda_{it}^s) \) for each year in the projection period. These are then fed into equation (D.8) to compute the change in the variance of welfare since 2013 over the 21st century for the projection that includes changes in spatial structure. That projected welfare variance is shown as the solid red line in the right panel of Figure 17.

Difference across projections
For the period from 2013-2099, we calculate the percentage difference in the change in welfare variance between projections that include and omit changes in
spatial structure:

\[
\frac{\text{var} \left( \ln \left( \frac{C_{i,2009}}{L_{i,2009}} \right) \right)}{\text{var} \left( \ln \left( \frac{C_{n,2009}}{L_{n,2009}} \right) \right)} - \frac{\text{var} \left( \ln \left( \frac{C_{i,2013}}{L_{i,2013}} \right) \right)}{\text{var} \left( \ln \left( \frac{C_{n,2013}}{L_{n,2013}} \right) \right)} - 1 \quad (D.11)
\]

With baseline parameters, allowing climate change to alter the spatial correlation of productivities predicts a 20% greater increase in welfare variance than when spatial correlation is held fixed.

D.3 Calculating change in country-level welfare under climate change

From equation (1), the expression for welfare of country \(i\) in year \(t\) is

\[
\ln \left( \frac{C_{it}}{L_{it}} \right) = \ln A_{it} + \gamma - \frac{1}{\epsilon} \ln \lambda_{it}.
\]

For the projection period, the productivity of country \(i\), \(\hat{\ln} A_{it}\) is given by equation (D.7). Next, we calculate the difference in welfare projections for individual countries between projections that include and omit changes in spatial structure.

Country welfare projection omitting changes in spatial structure  

Holding the spatial correlation of productivity fixed, the other component of welfare during the projection period, \(t \in [\bar{t} + 1, T]\), is:

\[
\hat{\ln} \lambda_{it}^n = (\hat{\beta}_0 + \hat{\beta}_1 \hat{I}_t) \hat{\ln} A_{it} + \hat{\kappa} \hat{I}_t + Z_{it} \hat{\Pi} + \hat{\mu}_{it} \quad (D.12)
\]

where spatial correlation affects both the average domestic share of expenditure (\(\kappa\)) and its relationship to domestic productivity (\(\beta_1\)).

\(^{35}\) The difference in country \(i\) welfare between end of the estimation period and the end of the projection period is:

\[
\ln \left( \frac{C_{i,T}}{L_{i,T}} \right) - \ln \left( \frac{C_{i,\bar{t}}}{L_{i,\bar{t}}} \right) = \left[ \hat{\ln} A_{iT} - \ln A_{i\bar{t}} \right] - \left( \frac{1}{\epsilon} \right) \left[ (\hat{\beta}_0 + \hat{\beta}_1 \hat{I}_t)(\hat{\ln} A_{iT} - \ln A_{i\bar{t}}) \right] \quad (D.13)
\]

Figure D.1 shows the change in welfare for each country under this projection.

Country welfare projection including changes in spatial structure  

Allowing the spatial correlation of productivity to vary under climate change, the other component of welfare during the projection period, \(t \in [\bar{t} + 1, T]\) is:

\[
\hat{\ln} \lambda_{it}^s = (\hat{\beta}_0 + \hat{\beta}_1 \hat{I}_t) \hat{\ln} A_{it} + \hat{\kappa} \hat{I}_t + Z_{it} \hat{\Pi} + \hat{\mu}_{it}
\]

Similarly, the difference in country \(i\) welfare between end of the estimation period and the end of

\(^{35}\) To obtain \(\kappa\), we first recover year fixed effects from equation (6). \(\hat{\kappa} = 2.45\) is the coefficient from a linear regression of year fixed effects on \(I_t\) and a linear time trend.
Figure D.1: Welfare change under projection that omits changes in spatial structure (2013-2099)

Notes: Map shows the projected 2013-2099 welfare changes from the projection that omits changes in spatial structure under a business-as-usual CMIP5 ensemble mean climate projection.

the projection period is:

$$\ln(C^s_{it}/L^s_{it})-\ln(C^m_{it}/L^m_{it}) = [\ln(A^s_{iT} - \ln(A^m_{it}) - (1/\epsilon) \left( (\hat{\beta}_0 + \hat{\beta}_1 I^s_T) \ln A^s_{iT} - (\hat{\beta}_0 + \hat{\beta}_1 I^m_t) \ln A^m_{it} + \hat{\kappa} (I^s_T - I^m_t) \right]$$

Figure D.2 shows the change in welfare for each country under this projection.

Figure D.2: Welfare change under projection that includes changes in spatial structure (2013-2099)

Notes: Map shows the projected 2013-2099 welfare changes from the projection that includes changes in spatial structure under a business-as-usual CMIP5 ensemble mean climate projection.

Difference across projections  The difference in country welfare between projections that include and omit changes in spatial structure is:

$$[\ln(C^s_{iT}/L^s_{iT}) - \ln(C^m_{it}/L^m_{it})] - [\ln(C^m_{iT}/L^m_{iT}) - \ln(C^s_{it}/L^s_{it})] = -(1/\epsilon) \left[ (\hat{\beta}_1 \ln A^s_{iT} + \hat{\kappa}) (I^s_T - I^m_t) \right]$$  \hspace{1cm} (D.14)
Figure 18 shows the country-level difference across projections.
E Appendix figures

Figure E.1: Location of ENSO sea-surface temperature measurements

Notes: ENSO indices defined as average sea surface temperature over a region minus the long-term mean sea surface temperature for that region. Spatial definitions for standard ENSO indices: NINO4 (5°S-5°N, 160°E-150°W), NINO3 (5°S-5°N, 150°W-90°W), NINO34 (5°S-5°N, 170°W - 120°W), and NINO12 (10°S-0°, 90°W-80°W).
Figure E.2: Monthly ENSO index for top 10 positive events


Figure E.3: Observed log cereal yields and temperature in 2013

Notes: Observed country-level log cereal yields in 2013 with cross-sectional mean removed plotted against temperature in 2013. From equation (9), observed log cereal yield is the sum of the nonlinear temperature relationship \( k(T_{it}) \), controls \( x_{it} \Psi \), and the residual term \( \nu_{it} \). Vertical line shows the log cereal yield maximizing temperature from Figure 14.
Figure E.4: Differences in welfare projections due to change in spatial correlation and projected yield changes

Notes: Scatter shows the difference in projected country-level welfare change between projections that include and omit changes in spatial correlation (from Figure 18) plotted against change in log cereal yields (from Figure 15) over 2013-2099 under climate change. Countries labeled by ISO3 identifier.
## F Appendix tables

Table F.1: Statistical significance of first-stage coefficients

<table>
<thead>
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<th>(5)</th>
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<tbody>
<tr>
<td>$\alpha'_{11}$ joint F-stat p-value</td>
<td>0.022</td>
<td>0.007</td>
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<td>0.011</td>
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</tr>
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<td>$\alpha'_{12}$ joint F-stat p-value</td>
<td>0.006</td>
<td>0.038</td>
<td>0.097</td>
<td>0.178</td>
<td>0.218</td>
</tr>
<tr>
<td>$\alpha'_{21}$ joint F-stat p-value</td>
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<td>0.004</td>
<td>0.007</td>
<td>0.006</td>
<td>0.003</td>
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<td>$\alpha'_{22}$ joint F-stat p-value</td>
<td>0.041</td>
<td>0.062</td>
<td>0.028</td>
<td>0.041</td>
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<td>Number of temperature splines in $f()$</td>
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Notes: Shows p-values from joint significance F-tests across the elements of each vector of first-stage coefficients, $A_{11}$ and $A_{12}$ from equation (7), $A_{21}$ and $A_{22}$ from equation (8). Columns 1-5 correspond to the first-stage IV specifications in columns 2-6 of Table 2.

Table F.2: Alternative error structures

Outcome is log domestic share of expenditure

<table>
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<tbody>
<tr>
<td>$\ln A_{it}$ ($\beta_0$)</td>
<td>2.114</td>
<td>2.114</td>
<td>2.114</td>
<td>2.114</td>
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<tr>
<td></td>
<td>(0.604)</td>
<td>(0.581)</td>
<td>(0.830)</td>
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<td>[0.014]</td>
<td>[0.004]</td>
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<tr>
<td>$\ln A_{it} \times I_t$ ($\beta_1$)</td>
<td>-4.144</td>
<td>-4.144</td>
<td>-4.144</td>
<td>-4.144</td>
</tr>
<tr>
<td></td>
<td>(1.834)</td>
<td>(1.659)</td>
<td>(2.157)</td>
<td>(1.939)</td>
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<td></td>
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<td>[0.037]</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
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<td>5452</td>
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</table>

Notes: Estimates of $\beta_0$ and $\beta_1$ from equation (6). Column 1 reproduces benchmark estimates from column 4, panel B of Table 2 with year-level clustered standard errors. Column 2 allows year-level clustering and common serial correlation across countries within a 10-year window. Column 3 allows year and country-level clustering. Column 4 allows year-level clustering with a Bekker (1994) adjustment. Standard error in parentheses; p-values in brackets.
Table F.3: Sample split  
Outcome is log domestic share of expenditure

<table>
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<td>(12.564)</td>
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<td>[0.028]</td>
<td>[0.715]</td>
<td>[0.108]</td>
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</table>

Observations 5452 2655 2793  

Notes: Estimates of $\beta_0$ and $\beta_1$ from equation (6). Column 1 reproduces benchmark estimates from column 4, panel B of Table 2. Column 2 restricts sample to 1961-1987. Column 3 restricts sample to 1988-2013. Standard errors clustered at year level in parentheses; p-values in brackets.

Table F.4: ENSO and local temperature definitions  
Outcome is log domestic share of expenditure

Panel A: Crop-area-weighted country temperature

<table>
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<td>$\ln A_{it} , (\beta_0)$</td>
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<td>2.722</td>
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<td>$\ln A_{it} \times I_t , (\beta_1)$</td>
<td>-4.144</td>
<td>-4.064</td>
<td>-4.465</td>
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<tr>
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<td>(2.406)</td>
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<td>[0.098]</td>
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Observations 5452 5452 5452 5452  

Panel B: Total-area-weighted country temperature

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<td>$\ln A_{it} , (\beta_0)$</td>
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ENSO index 4 3 34 12  
Observations 5605 5605 5605 5605  

Notes: Estimates of $\beta_0$ and $\beta_1$ from equation (6). Panel A uses crop-area-weighted country-level temperatures. Panel B uses all-area-weighted country-level temperatures. Columns 1 to 4 use NINO4, NINO3, NINO34, and NINO12 as ENSO index. Standard errors clustered at year level in parentheses; p-values in brackets.
Table F.5: Alternative domestic expenditure share constructions  
Outcome is log domestic share of expenditure

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<td>[0.002]</td>
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<td>3.963</td>
<td>3.864</td>
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<td>Anderson-Rubin weak-id robust joint p-value</td>
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Notes: Estimates of $\beta_0$ and $\beta_1$ from equation (6). Column 1 reproduces benchmark estimates from column 4, panel B of Table 2 with average export-volume-weighted cereal export unit value used for imputing cereal-level prices in constructing domestic expenditure share. Column 2 uses cereal-level export unit values with missing observations imputed using producer prices to construct domestic expenditure. Columns 3 and 4 use cereal-level export unit values with missing observations imputed using the lowest and highest observed export unit value for a given country and year, respectively. Standard errors clustered at year level in parentheses; p-values in brackets.
Table F.6: Log cereal yield and local temperature

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tbody>
<tr>
<td>Temperature 1st term</td>
<td>0.004</td>
<td>0.004</td>
<td>0.005</td>
<td>0.005</td>
<td>0.007</td>
<td>0.005</td>
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<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.011)</td>
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<td>0.686</td>
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<td>0.629</td>
<td>0.631</td>
<td>0.519</td>
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<td>Temperature 2nd term</td>
<td>-0.183</td>
<td>-0.165</td>
<td>-0.222</td>
<td>-0.203</td>
<td>-0.126</td>
<td>-0.100</td>
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<td></td>
<td>(0.041)</td>
<td>(0.040)</td>
<td>(0.071)</td>
<td>(0.071)</td>
<td>(0.060)</td>
<td>(0.059)</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.003</td>
<td>0.006</td>
<td>0.041</td>
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<tr>
<td>Temperature 3rd term</td>
<td>0.650</td>
<td>0.599</td>
<td>0.418</td>
<td>0.393</td>
<td>0.020</td>
<td>-0.031</td>
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<tr>
<td></td>
<td>(0.160)</td>
<td>(0.159)</td>
<td>(0.196)</td>
<td>(0.196)</td>
<td>(0.212)</td>
<td>(0.205)</td>
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<tr>
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<td>0.000</td>
<td>0.000</td>
<td>0.038</td>
<td>0.050</td>
<td>0.924</td>
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<td>Temperature 4th term</td>
<td>-1.162</td>
<td>-1.100</td>
<td>0.356</td>
<td>0.248</td>
<td>1.320</td>
<td>1.394</td>
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<tr>
<td></td>
<td>(0.533)</td>
<td>(0.539)</td>
<td>(0.649)</td>
<td>(0.644)</td>
<td>(0.674)</td>
<td>(0.658)</td>
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<tr>
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<td>0.034</td>
<td>0.047</td>
<td>0.586</td>
<td>0.702</td>
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<tr>
<td>Temperature 5th term</td>
<td>-2.204</td>
<td>-1.801</td>
<td>-2.895</td>
<td>-3.370</td>
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</tr>
<tr>
<td></td>
<td>(1.775)</td>
<td>(1.760)</td>
<td>(1.880)</td>
<td>(1.864)</td>
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<td></td>
<td>0.220</td>
<td>0.311</td>
<td>0.130</td>
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<td>Temperature 6th term</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.814)</td>
<td>(3.791)</td>
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<tr>
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<td>(0.001)</td>
<td>(0.001)</td>
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<tr>
<td>Precipitation squared</td>
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<tr>
<td></td>
<td>(0.000)</td>
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<tr>
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<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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<td>Temp. joint p-value</td>
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<td>0.0030</td>
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<td>8.87</td>
<td>8.94</td>
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</table>

Notes: Estimates of cubic spline terms for $b()$ in equation (9). The number of knots placed along the temperature support according to Harrell (2001) varies across columns. Odd (even) numbered columns exclude (include) quadratic precipitation terms. P-value from a joint significance test of temperature terms shown. Standard errors clustered at year level in parentheses; p-values in brackets.