The Spatial Structure of Endowments, 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 in most African, South American, and many Asian countries.

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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 are more similar, 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. Greater spatial correlation of productivities increases welfare inequality by increasing the correlation between productivity and the 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 4%.

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 restructuring of productivities across the planet. Looking at one country's productivity change in isolation is not sufficient to summarize the economic consequences of climate change for that country. 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 29% higher increase in the inequality of welfare 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 and South America, and many in Asia. 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 (Nunn 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 incorporates 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 covari-

ance 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 *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.

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

$$P_j = \left(\int_{\omega \in \Omega} p_j(\omega)^{1-\sigma} d\omega \right)^{1/(1-\sigma)}.$$

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.

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, $p_j(\omega) \leq \tau_{ij} p_i(\omega)$.

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:[1]

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

where χ_i is a function of A_i and other structural parameters that are not trade costs, ϵ 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). Φ_j is a (decreasing) transformation of j's price index that summarizes consumers' access to goods from every source.

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

[1] Appendix C.1 shows that the gravity model fits trade in cereals well.

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

$$\ln\left(C_i/L_i\right) = \ln A_i + \gamma - \frac{1}{\epsilon} \ln \lambda_{ii}, \tag{1}$$

where γ 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 ϵ 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 exogenous productivities and endogenous gains from trade, and the variance of those gains.

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

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, $var(\ln A_i^c) = var(\ln A_i^u)$. Under this assumption, the difference in welfare dispersion between the correlated and uncorrelated states is

$$\begin{aligned} var\left(\ln\left(C_i^c/L_i\right)\right) - var\left(\ln\left(C_i^u/L_i\right)\right) = &-\frac{2}{\epsilon}\left[cov\left(\ln A_i^c, \ln \lambda_{ii}^c\right) - cov\left(\ln A_i^u, \ln \lambda_{ii}^u\right)\right] \\ &+ \frac{1}{\epsilon^2}\left[var\left(\ln \lambda_{ii}^c\right) - var\left(\ln \lambda_{ii}^u\right)\right]. \end{aligned} \tag{3}$$

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 $var\left(\ln \lambda_{ii}^c\right) - var\left(\ln \lambda_{ii}^u\right)$ is the same order of magnitude or smaller than $cov\left(\ln A_i^c, \ln \lambda_{ii}^c\right) - cov\left(\ln A_i^u, \ln \lambda_{ii}^u\right)$, this means that the second term on the right side of equation (3) is an order of magnitude smaller than the the first term. Appendix A.1.3 shows that, if trade costs are symmetric ($\tau_{ij} = \tau_{ji}$) and countries equal sized ($L_i = L\ \forall i$), $var\left(\ln \lambda_{ii}^c\right) - var\left(\ln \lambda_{ii}^u\right) = \frac{\epsilon}{\epsilon+1}\left[cov(\ln A_i^c, \ln \lambda_{ii}^c) - cov(\ln A_i^u, \ln \lambda_{ii}^u)\right] + \frac{1+2\epsilon}{1+\epsilon}\left[cov(\ln \Phi_i^c, \ln \lambda_{ii}^c) - cov(\ln \Phi_i^u, \ln \lambda_{ii}^u)\right]$. Heuristically, the latter term is of smaller magnitude, since Φ_i is a price-index term that is a weighted sum of all other countries' prices. Thus,

The first-order difference in welfare dispersion is governed by the covariance of the exogenous productivities and the endogenous 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 $cov\left(\ln A_i^c, \ln \lambda_{ii}^c\right) < cov\left(\ln A_i^u, \ln \lambda_{ii}^u\right)$ and thus that $var\left(\ln\left(C_i^c/L_i\right)\right) > var\left(\ln\left(C_i^u/L_i\right)\right)$.

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

This section illustrates how the spatial correlation of productivity may influence the covariance of autarky welfare and gains from trade, and thus the variance of welfare, per equation (3). 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

$$\tau \equiv \begin{bmatrix} 1 & d_1 & d_2 & d_1 \\ d_1 & 1 & d_1 & d_2 \\ d_2 & d_1 & 1 & d_1 \\ d_1 & d_2 & d_1 & 1 \end{bmatrix}, \quad 1 < d_1 < d_2 < d_1^2 \tag{4}$$

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. What are the consequences for trade and welfare?

Proposition 1 shows that the "regional" arrangement of productivities exhibits greater spatial

$var\left(\ln \lambda_{ii}^c\right) - var\left(\ln \lambda_{ii}^u\right)$ is the same order of magnitude as $cov\left(\ln A_i^c, \ln \lambda_{ii}^c\right) - cov\left(\ln A_i^u, \ln \lambda_{ii}^u\right)$.

correlation, as measured by Moran's I.[3] 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 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 τ_{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 w_{ij} and τ_{ij} and assigns a higher weight to the pairs with $\tau_{ij} = d_1$ than pairs with $\tau_{ij} = d_2$.*
- *The covariance of productivity and the domestic share of expenditure is lower for the more spatially correlated productivity distribution: $cov(\ln A_i^c, \ln \lambda_{ii}^c) < cov(\ln A_i^u, \ln \lambda_{ii}^u)$.*
- *The variance of welfare across counties is greater for the more spatially correlated productivity distribution: $var(\ln(C_i^c/L)) > var(\ln(C_i^u/L))$.*

This four-country case establishes our prediction linking the spatial correlation of productivity to welfare inequality. Next, we illustrate this logic for 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 θ over the circle's circumference. This functional form has two convenient properties. First, the spatial correlation of productivity is governed by the frequency θ: 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 θ alone.[4]

Figure 1 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 frequencies of $\theta = 1$ and $\theta = 4$. It is clear that the spatial correlation of productivity is greater in

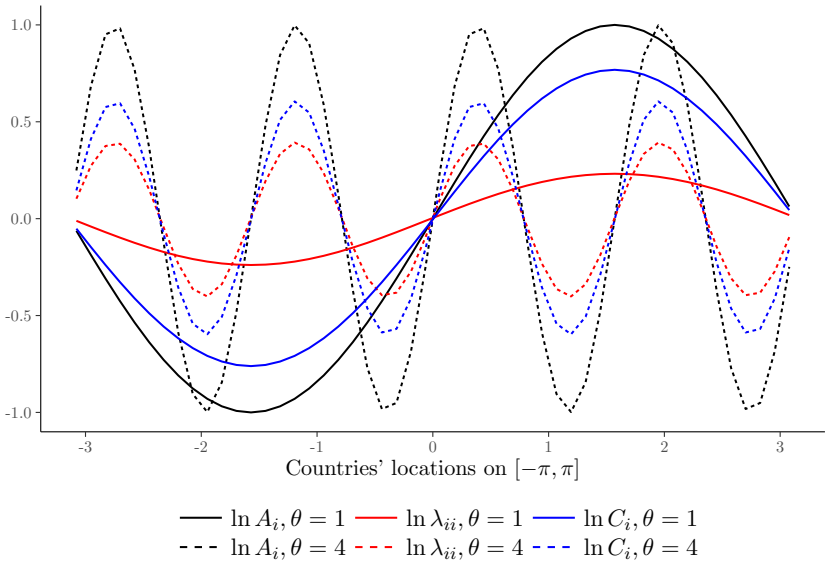
[3] Moran's I is a commonly used measure of global spatial correlation that can be computed for any geography endowed with a distance metric. Formally, Moran's I for $\ln A_{it}$ in year t is

$$I_t = \frac{N}{\sum_i \sum_{j \neq i} w_{ij}} \frac{\sum_i \sum_{j \neq i} w_{ij} \left(\ln A_{it} - \overline{\ln A_t}\right)\left(\ln A_{jt} - \overline{\ln A_t}\right)}{\sum_\ell \left(\ln A_{\ell t} - \overline{\ln A_t}\right)^2},$$

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

[4] Details of the parameters underlying Figure 1 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 1: Ideal environment: Circular geography with productivity sine wave



NOTES: This figure depicts an economy with a circular geography and a productivity distribution that follows a sine wave with frequency θ. 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.

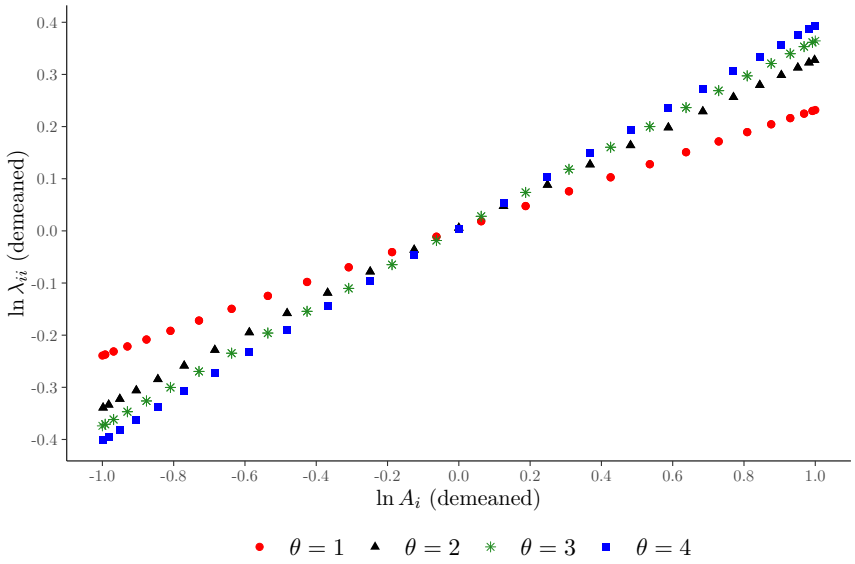
the $\theta = 1$ case, as location "zero" divides the circle into two contiguous regions with above-average and below-average productivity. In the $\theta = 4$ case, lower spatial correlation means that locations of opposing productivity are more closely situated. In the case of higher spatial correlation, $\theta = 1$, 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.[5]

Figure 2 depicts the expenditure-productivity relationship in our sine-wave example for more values of the sine-wave frequency, θ. 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.[6] 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. Intuitively, when productivities are more spatially correlated, an increase in a location's own productivity level is accompanied by higher productivity levels in its nearby

[5] In this particular parameterization, average welfare is slightly lower when productivity is more spatially correlated. See Table A.1 for details.

[6] This pattern is exhibited for many parameter values in our numerical simulations. We have yet to prove this result analytically.

Figure 2: One-sector sine-wave economy: $cov(\ln \lambda_{ii}, \ln A_i)$



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 θ. Geographic locations and trade costs as in Figure 1. See Appendix A.2 for parameterization details.

trading partners, such that its gains from trade are larger than they would otherwise be. Thus, the spatial correlation of productivity governs the variance of welfare across countries through its effect on the covariance of $\ln \lambda_{ii}$ and $\ln A_i$.

2.2.3 Asymmetric environments

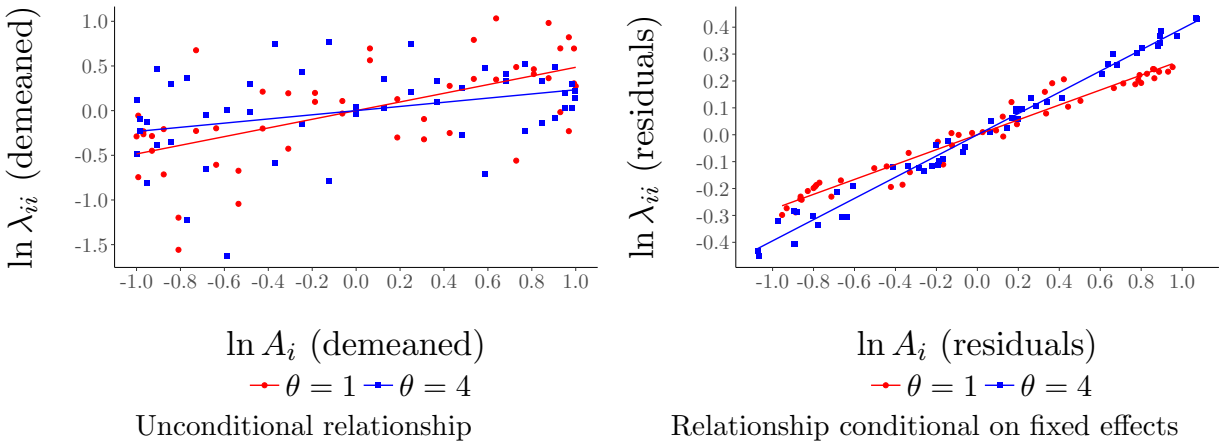
Our stylized, many-country example in Section 2.2.2 demonstrates the consequence of spatial correlation of productivity for global welfare inequality in an ideal environment that holds fixed all other economic elements. Compared to such an environment, any empirical setting is more complicated because (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 2. 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 3, 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 θ is lower, controlling for heterogeneous sizes.

Figure 3: Circular geography with heterogeneous sizes and productivity sine wave



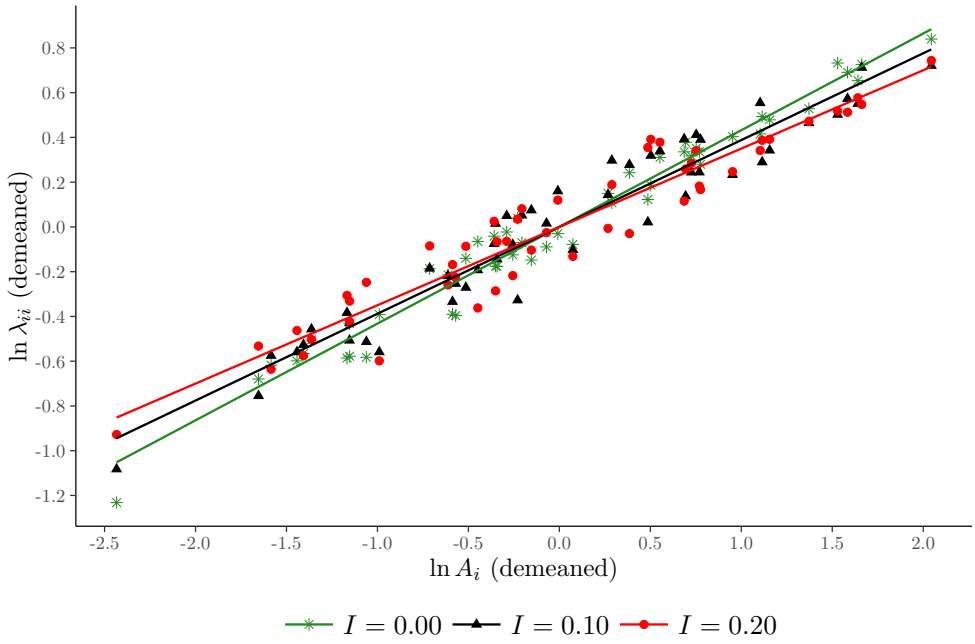
NOTES: This figure depicts the λ_{ii}–A_i relationship for an economy with a circular geography and a productivity distribution that follows a sine wave with frequency θ. Geographic locations and trade costs as in Figure 1. Country sizes L_i are positively correlated with A_i in the $\theta = 1$ state.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

Since actual productivity does not exhibit a sine-wave distribution, we cannot conduct our empirical examination in terms of the frequency θ. 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.[7] Figure 4 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

[7] See Appendix A.2 for details.

Figure 4: Circular geography with equal-sized countries and arbitrary productivities



NOTES: This figure depicts the λ_{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 1. See Appendix A.2 for parameterization details.

activity, regardless of the distribution of productivities. All else equal, remote countries exhibit a higher domestic share of expenditure. This variation is absorbed by country fixed effects.

Figure 5 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.[8] The vertical axis is the coefficient from a linear regression of the domestic share of expenditure on own productivity,

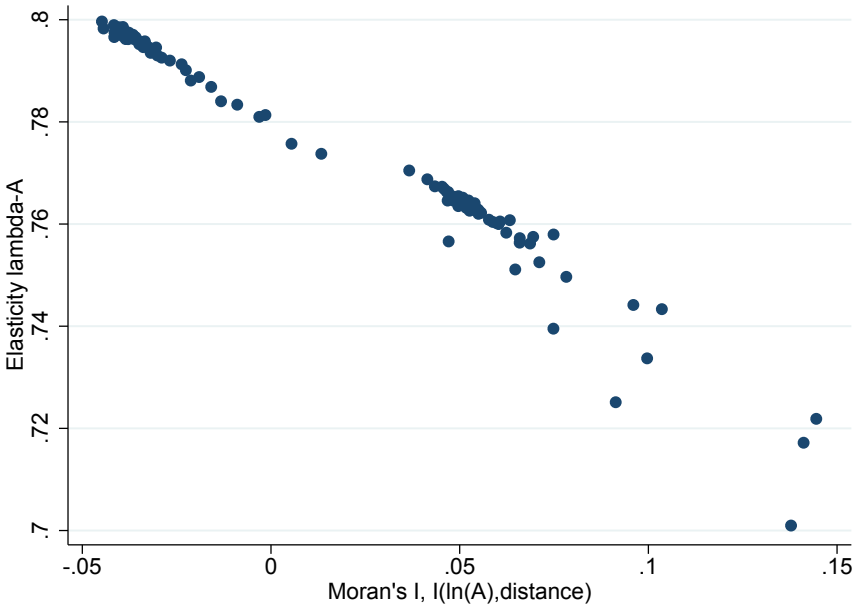
$$\ln \lambda_{iit} = \beta_t \ln A_{it} + \pi_i^I + \pi_t^T + \epsilon_{it}, \tag{5}$$

for country i at "time" t, where each t denotes an equilibrium associated with a different productivity distribution. The country fixed effects π_i^I control for differences in countries' time-invariant determinants of the domestic share of expenditure, such as remoteness. The "year" fixed effects π_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 β_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

[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.

and the spatial correlation of productivities. While the relationship is not literally monotonic, the elasticity of λ_{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 5: Random-geography economy



NOTES: This figure depicts how $cov(\ln \lambda_{ii}, \ln A_i)$ 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 λ_{ii} with respect to A_i is $\hat{\beta}_t$ estimated from $\ln \lambda_{iit} = \beta_t \ln A_{it} + \pi_i^I + \pi_t^T + \epsilon_{it}$, as described in the text. See Appendix A.2 for parameterization details.

2.3 Multiple-sector case

This section extends our predictions to an economy with multiple sectors. An empirical investigation of the previous section's prediction requires exogenous variation in the global productivity distribution. Our empirical strategy exploits such variation in the agricultural sector, which constitutes a small share of global trade. This section demonstrates that our prediction about the spatial correlation of productivity and the productivity-expenditure relationship holds for each sector in a multi-sector gravity model of trade. Moreover, the multi-sector welfare expression is analogous to the single-sector case, summing over sectors using their expenditure shares. Greater spatial correlation in a single sector implies greater dispersion in welfare across countries, provided that sectors' productivities are not perfectly anti-correlated. Thus, the previous section's predictions about trade in one sector can be empirically investigated in a multi-sector world.

Real consumption per capita in the multi-sector version of our economic environment is akin to equation (1), summing over sectors using their expenditure shares. We assume that consumers

have Cobb-Douglas preferences over sectors $s = 1, \ldots, S$ with expenditure shares $\alpha_{js} \geq 0$ and CES preferences over varieties within sectors. As shown in Appendix A.3, real consumption per capita in this environment is

$$\ln\left(C_j/L_j\right) = \sum_{s=1}^{S} \alpha_{js} \left(\ln A_{js} + \gamma_s - \frac{1}{\epsilon_s} \ln \lambda_{jjs} \right), \tag{6}$$

where γ_s depends on sectoral structural parameters other than productivity and ϵ_s is the sectoral trade elasticity. The first two terms, $\sum_{s=1}^{S} \alpha_{js} \left(\ln A_{js} + \gamma_s \right)$, are per capita welfare under autarky, and the final term, $-\sum_{s=1}^{S} \frac{\alpha_{js}}{\epsilon_s} \ln \lambda_{jjs}$, summarizes the gains from trade. Dispersion in per capita welfare across locations thus depends on the exogenous variation in productivities A_{js} and the endogenous variation in domestic shares of expenditure λ_{jjs}. We again compare two productivity distributions, correlated c and uncorrelated u, that have the same unconditional variance of productivity, $var\left(\sum_{s=1}^{S} \alpha_{js} \ln A_{js}^{c}\right) = var\left(\sum_{s=1}^{S} \alpha_{js} \ln A_{js}^{u}\right)$. For the sake of expositional brevity, assume also that expenditures shares are common across countries, $\alpha_{js} = \alpha_s \ \forall j$. We can then obtain the multi-sector analogue of equation (3):

$$\begin{aligned} var\left(\ln\left(C_j^c/L_j\right)\right) - var\left(\ln\left(C_j^u/L_j\right)\right) = & \ 2 \sum_{s=1}^{S} \sum_{s'=1}^{S} \frac{\alpha_s \alpha_{s'}}{\epsilon_{s'}} \left\{ cov\left(\ln A_{js}^{u}, \ln \lambda_{jjs'}^{u}\right) - cov\left(\ln A_{js}^{c}, \ln \lambda_{jjs'}^{c}\right) \right\} \\ & - \sum_{s=1}^{S} \sum_{s'=1}^{S} \frac{\alpha_s \alpha_{s'}}{\epsilon_s \epsilon_{s'}} \left\{ cov\left(\ln \lambda_{jjs}^{u}, \ln \lambda_{jjs'}^{u}\right) - cov\left(\ln \lambda_{jjs}^{c}, \ln \lambda_{jjs'}^{c}\right) \right\} \end{aligned} \tag{7}$$

Just as in the single-sector case, for typical values of the sectoral trade elasticities, $2\frac{\alpha_s \alpha_{s'}}{\epsilon_{s'}}$ is an order of magnitude larger than $\frac{\alpha_s \alpha_{s'}}{\epsilon_s \epsilon_{s'}}$. Thus, the difference in welfare dispersion is governed by the $cov\left(\ln A_{js}, \ln \lambda_{jjs'}\right)$ terms, provided that the block of $cov\left(\ln A_{js}, \ln \lambda_{jjs'}\right)$ terms is the same order of magnitude as the block of $cov\left(\ln \lambda_{jjs}, \ln \lambda_{jjs'}\right)$ terms.

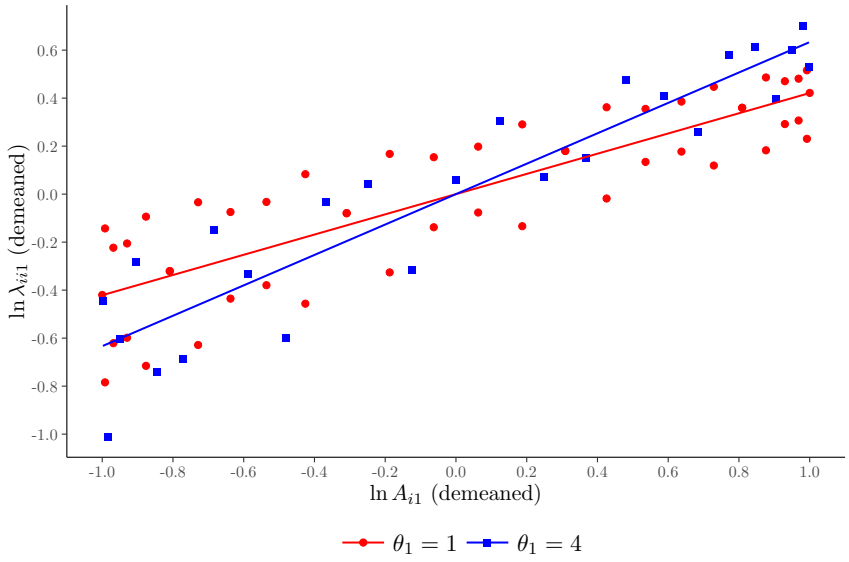
Under what circumstances is studying differences in $cov\left(\ln A_{js}, \ln \lambda_{jjs}\right)$ in one sector alone informative about welfare dispersion? For simplicity, consider the two-sector case and three possible relationships between the two sectors: perfectly correlated productivities, perfectly 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.[9] 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.[10]

[9] In fact, if all sectors have perfectly correlated productivities ($A_{is} \propto A_i \ \forall s$), perfectly correlated spatial linkages ($\tau_{ijs} \propto \tau_{ij} \ \forall s$) and equal trade elasticities ($\epsilon_s = \epsilon \ \forall s$), then expenditure shares are equal across sectors, $\lambda_{ijs} = \lambda_{ij}$, and the difference in welfare dispersion in equation (7) is exactly proportionate to the single-sector expression in equation (3).

[10] Consider the two-sector case with equal expenditure shares $\alpha_1 = \alpha_2 = \frac{1}{2} \ \forall j$ and equal trade elasticities $\epsilon_1 =$

In the orthogonal case of our illustrative sine-wave example, the presence of an additional sector introduces an additional margin of adjustment that does not qualitatively alter the economic mechanism. Naturally, this additional margin dampens the magnitude of welfare dispersion relative to the perfectly correlated case. To produce a multi-sector analogue of the sine-wave example presented in Section 2.2, we consider two symmetric sectors that differ only in their sine-wave frequency, so that their productivities are orthogonal by construction. The result is depicted in Figure 6, which is the multi-sector analogue of the example presented in Figure 2. The idiosyncratic, orthogonal variation in the second sector's productivity adds noise to the relationship between the domestic share of expenditure and productivity, but it does not change the basic pattern. 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.[11]

Figure 6: Two-sector sine-wave economy: $cov(\ln \lambda_{ii1}, \ln A_{i1})$



NOTES: This figure depicts the λ_{iis}–A_{is} relationship for $s = 1$ in a two-sector economy in which sectoral productivity follows a sine wave with frequency θ_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 τ_{ijs}, expenditure shares $\alpha_{j1} = \alpha_{j2} = \frac{1}{2}$, 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 θ_1 is lower), $cov(\ln \lambda_{ii1}, \ln A_{i1})$ is lower.

Thus, greater spatial correlation of productivity in one sector dampens the covariance of productivities and domestic expenditure shares. This is associated with greater dispersion in welfare, unless in the extreme case that there is an exact opposite pattern in the spatial distribution of productivity in other sectors. Having established that the spatial correlation of productivity may

$\epsilon_2 = \epsilon$. If the two sectors' productivities are perfectly anti-correlated, such that $\ln A_{j1} + \ln A_{j2}$ is a constant, then it can be shown that $\sum_{s=1}^{S} \sum_{s'=1}^{S} \frac{\alpha_s \alpha_{s'}}{\epsilon_{s'}} cov\left(\ln A_{js}, \ln \lambda_{jjs'}\right) = 0$.

[11] See Table A.2 in Appendix A.2 for details of this example.

have important consequences for the distribution of welfare gains in a trading equilibrium, we next turn to an empirical setting in which there is exogenous variation in productivity.

3 The El Niño-Southern Oscillation

This section describes the exogenous variation in productivities that we employ to test whether greater spatial correlation of productivities increases the covariance of productivity and gains from trade. Causal empirical validation of this relationship requires a reshuffling of local productivities that alters the global spatial correlation of productivities but is orthogonal to other determinants of the gains from trade.

To illustrate how one can identify such a relationship, it is helpful to imagine an ideal experiment, akin to the simulations summarized in Figure 5, in which the researcher can manipulate a fixed set of productivities across the world. To construct a spatially uncorrelated state of the world, the researcher would change productivities to exhibit a more checkered-like spatial pattern. To construct a more spatially correlated state, productivities would be rearranged such that similar productivities are clustered together.

Such an ideal experiment 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 summarizes the basic physics of ENSO and empirically demonstrates that it drives annual changes in the spatial correlation of agricultural productivity around the planet.

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 conditions 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).[12] 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 enables ENSO to have very broad spatial 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 abnormally warm temperature across the tropics and subtropics while almost simultaneously there is a spatially contiguous area of abnormally 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.[13]

ENSO conditions are typically summarized by the average sea-surface temperature over a fixed area in the tropical Pacific. In our analysis, we follow the climatology literature by employing the widely used NINO3.4 index, a statistic defined as average ocean temperature (in degrees Celsius) over a rectangular area bounded by 5°N - 5°S, 170°W - 120°W (see map in Figure E.1). Henceforth, we refer to this simply as the ENSO index.

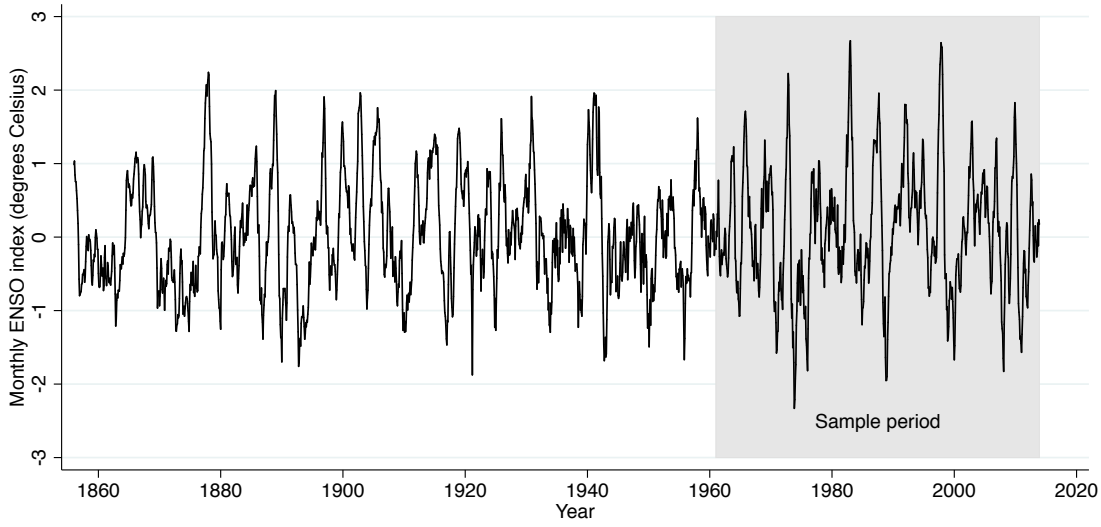
Figure 7 plots the monthly ENSO index for 1856-2013, which extends further back than our sample period of 1961-2013. Observe that the index fluctuates between positive and negative

[12] 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).

[13] 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).

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.

Figure 7: Monthly ENSO index (1856-2013)

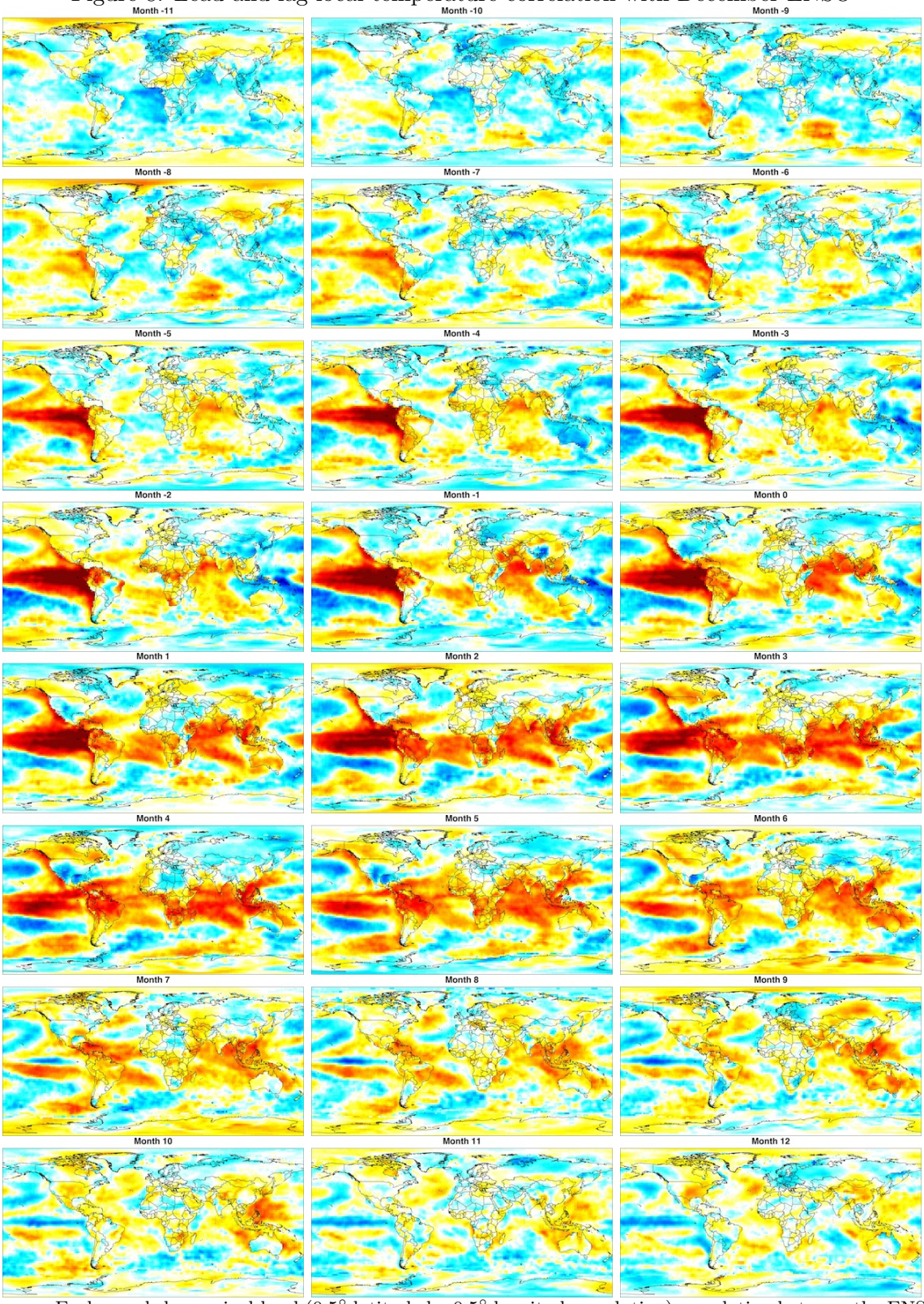


NOTES: Monthly ENSO index (NINO3.4) during 1856-2013. Shaded area shows our 1961-2013 sample period.

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 8 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 8: 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.

Figure 8 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.

3.2 ENSO and the spatial correlation of agricultural productivity

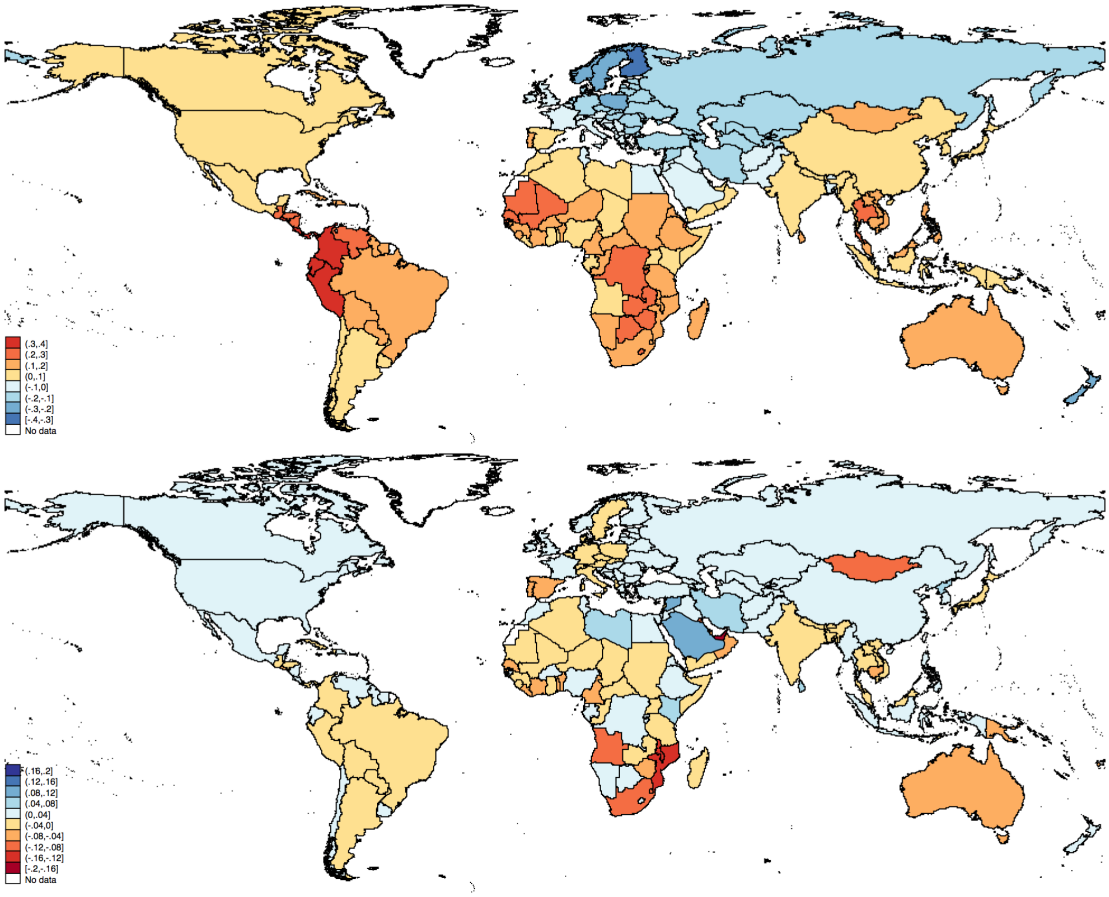
The spatial and temporal patterns shown in Figure 8 suggest that ENSO could drive global spatial correlation in cereal yields, a productivity measure that is both directly observed at the country-level with near global data coverage and has previously been documented to be sensitive to local temperature conditions (Schlenker and Roberts, 2009; Hsiang and Meng, 2015). To demonstrate this at an annual time scale, for which productivity and trade data is available, Figure 9 shows the country-level sum of the effects of 1-degree increases in the 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 agricultural productivity. Consistent with the tropical climatic dynamics discussed above, increases in the ENSO index tend to raise temperatures and lower agricultural productivities for countries closer to the tropics and drive cooler temperatures and increased agricultural productivities in higher-latitude countries.

Figure 9 suggests that ENSO could drive global spatial correlation in agricultural productivity, 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, with the spatial weight equal to the inverse great-circle distance between countries' area-weighted centroids.

Figure 10 shows a relationship between ENSO and the global spatial correlation in temperature (left panel) and agricultural productivity (right panel). To characterize the ENSO phenomenon in terms of a scalar, we oversimplify the timing issues discussed above by plotting the average of the 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 agricultural productivity. ENSO, in this simple bivariate model, explains 13% and 10% of annual variation in the global spatial correlations of temperature and agricultural productivity, respectively.

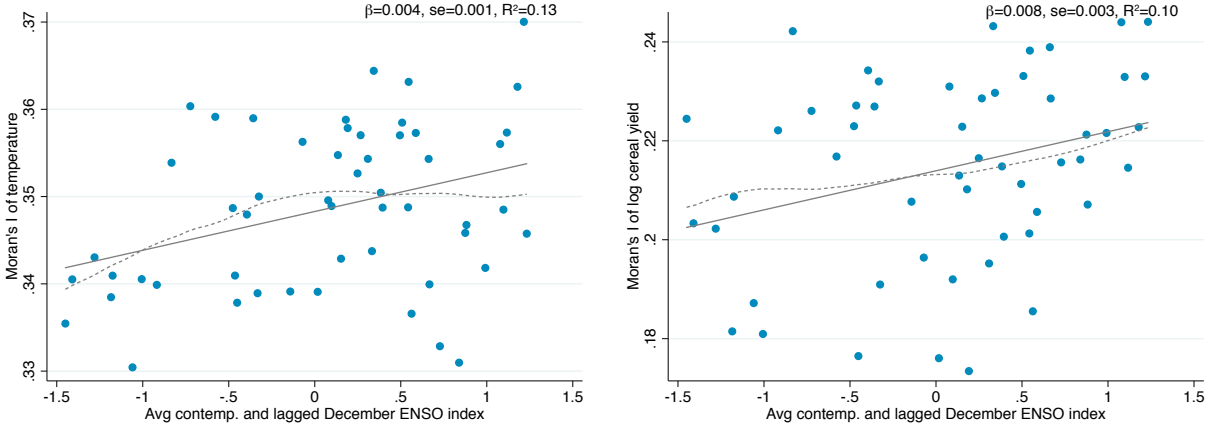
To relax the timing simplification of Figure 10, Table 1 presents regressions of the annual Moran's I statistic for log cereal yields on flexible polynomial functions of December ENSO in year t and $t-1$. Two results are evident: (1) spatial correlation in cereal yields responds to the interaction of contemporaneous and lagged ENSO, and (2) there appears to be nonlinearity in the response function as captured by the precision of several quadratic ENSO coefficients. These findings inform our choice of functional form in Section 4. Finally, consistent with our theoretical framework in Section 2.1, ENSO appears to affect neither the global mean nor the variance of agricultural productivity, as shown by the left and right panels of Figure 11, respectively. That is,

Figure 9: ENSO's spatial effects on temperature and log cereal yields



NOTES: Maps show the sum of country-specific coefficients on $ENSO_t$ and $ENSO_{t-1}$ for crop-area weighted temperature (top panel) and log cereal yields (bottom panel) after controlling for country fixed effects and country-specific time trends.

Figure 10: ENSO and Moran's I for temperatures and log cereal yields



NOTES: Left (right) panel shows the relationship between Moran's I of crop-weighted country-level temperature (log cereal yields) in year t and averaged contemporaneous and lagged December ENSO. Linear fit shown as solid line. Local polynomial fit shown as dashed line.

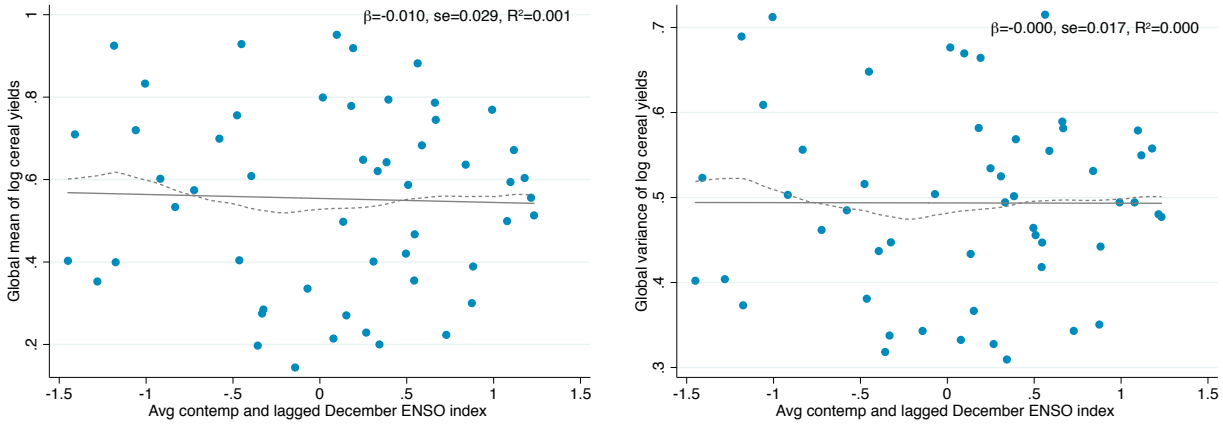
one can think of ENSO as reshuffling agricultural productivities around the world while holding the unconditional first and second moments of agricultural productivity fixed.

Table 1: ENSO and Moran's I in log cereal yields
Outcome is Moran-I in log cereal yields

	(1)	(2)	(3)	(4)
$ENSO_t$	0.005***	0.005***	0.006***	0.004
	(0.001)	(0.001)	(0.002)	(0.003)
$ENSO_t^2$			-0.002	0.001
			(0.002)	(0.002)
$ENSO_{t-1}$	0.003**	0.004**	0.003**	0.004**
	(0.001)	(0.002)	(0.001)	(0.002)
$ENSO_{t-1}^2$			0.001	0.002**
			(0.001)	(0.001)
$ENSO_t$ x $ENSO_{t-1}$		0.004**		0.002
		(0.002)		(0.002)
$ENSO_t^2$ x $ENSO_{t-1}^2$				-0.002*
				(0.001)
Observations	53	53	53	53

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<0.01, ** p<0.05, * p<0.1.

Figure 11: ENSO and the global cross-sectional mean and variance in log cereal yields



NOTES: Left (right) panel shows the relationship between the mean (variance) of cross-sectional country log cereal yields and averaged contemporaneous and lagged December ENSO. Linear fit shown as solid line. Local polynomial fit shown as dashed line.

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.

4.1 Estimation strategy

We empirically estimate a variant of equation (5), which was 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:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \Pi' \mathbb{Z}_{it} + \mu_{it} \tag{8}$$

where λ_{iit} is country i's 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. $\mathbb{Z}_{it}$ 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 $\mathbb{Z}_{it}$. In addition, $\mathbb{Z}_{it}$ includes country-specific time trends. μ_{it} is an error term.

β_0 and β_1 are our two reduced-form parameters.[14] β_0 captures the relationship between a country's gains from trade and productivity when productivity is spatially uncorrelated (when Moran's I is zero). β_1 captures the degree to which the global spatial correlation of productivities mediates this relationship between gains from trade and productivity.

An estimate of $\widehat{\beta}_1 < 0$ would imply that greater spatial correlation of productivity increases the global variance of welfare. Recall from Section 2.1 that an increase in the spatial correlation of productivities increases welfare dispersion by increasing the covariance of productivity and the gains from trade. We find that greater spatial correlation lowers the covariance of productivity and the domestic share of expenditure ($\widehat{\beta}_1 < 0$). Provided that the trade elasticity ϵ 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 (8) may be problematic to the extent that expenditure shares and

[14] Note that compared with equation (5), equation (8) further imposes the functional-form assumption that the $\ln \lambda_{iit} - \ln A_{it}$ relationship is linear in Moran's I. We verify this assumption below.

productivity are simultaneously determined or if there are omitted determinants of expenditure shares that are correlated with productivity, even after conditioning on $\mathbb{Z}_{it}$. For example, demand shocks could affect expenditure shares and elicit supply responses that change average yields. Similarly, if domestic cereal output requires imported intermediate goods, then unobserved trade cost shocks may jointly affect domestic cereal yields and domestic share of expenditure.

Our instrumental-variables (IV) strategy exploits the change in local yields and the global spatial correlation of yields as ENSO "reshuffles" agricultural productivity around the world, as described in Section 3. Because ENSO is a naturally occurring climatic phenomenon, this ENSO-driven variation is arguably uncorrelated with unobserved determinants of domestic expenditure shares.[15] Specifically, we employ the ENSO-predicted values of productivity and productivity interacted with spatial correlation as our instrumental variables.[16] To construct our instrumental variables, we estimate the effect of ENSO on each country's cereal yield and on the global spatial correlation in yields:

$$\ln A_{it} = f_i(\mathbf{ENSO}_t) + \Omega_1' \mathbb{Z}_{it} + \omega_{1it} \tag{9}$$

$$I_t = g(\mathbf{ENSO}_t) + \Omega_2' \mathbb{W}_t + \omega_{2t} \tag{10}$$

where we define $\mathbf{ENSO}_t \equiv \{ENSO_t, ENSO_{t-1}\}$ because the impact of a given ENSO event can influence socio-economic outcomes across two calendar years, as discussed in Section 3.1. The contemporaneous and lagged ENSO effects on country-level cereal yields and global spatial correlation in yields are dictated by the country-specific function $f_i()$ and the global function $g()$, both of which will take on different functional forms as a robustness check.[17] Equation (9) has the same vector of panel semi-parametric controls, $\mathbb{Z}_{it}$, as equation (8). $\mathbb{W}_t$ in equation (10) includes a global time trend with the same polynomial order as time trends in equation (8).

Equations (9) and (10) provide two instruments, $\widehat{f}_i(\mathbf{ENSO}_t)$ and $\widehat{f}_i(\mathbf{ENSO}_t)\widehat{g}_i(\mathbf{ENSO}_t)$, that

[15] As noted in Section 3.1, while ENSO has the broadest spatial effect on temperatures around the world, it can also affect other local weather variables on a smaller spatial scale. By directly estimating country-specific ENSO effects on agricultural productivity, our approach allows ENSO to flexibly affect the spatial structure of productivity through any combination of local weather variables.

[16] Prominent examples in which predicted variables are used as instruments can be found in health (Currie and Gruber, 1996; Cutler and Gruber, 1996; Schlenker and Walker, 2015) and public economics (Moffitt and Wilhelm, 2000; Gruber and Saez, 2002; Dahl and Lochner, 2012). While the use of predicted regressors in OLS estimation necessitates adjusting standard errors for the regressors' sampling variability, this issue does not arise in an IV setting with predicted instruments. This is because instrumenting an endogenous variable retains that variable's sampling variability (see Wooldridge 2002, p.117).

[17] Rather than separately estimating equations (9) and (10), an alternative approach would be to only estimate equation (9), obtain ENSO-predicted yields, $\widehat{f}_i(\mathbf{ENSO}_t)$, and use it to construct a predicted Moran's I statistic. Such an approach, however, implicitly assumes that $I_t = I(\{\widehat{f}_i(\mathbf{ENSO}_t)\})$ has the correct functional form. Our approach, which follows Kelejian (1971) and Amemiya (1974), allows for more flexible estimation of $g()$.

we use to estimate the following first-stage regressions, one for each of our endogenous variables:[18]

$$\ln A_{it} = \alpha_{11}\widehat{f}_i(\mathbf{ENSO}_t) + \alpha_{12}\widehat{f}_i(\mathbf{ENSO}_t)\widehat{g}(\mathbf{ENSO}_t) + \Gamma_1'\mathbb{Z}_{it} + \upsilon_{1it} \tag{11}$$

$$\ln A_{it}I_t = \alpha_{21}\widehat{f}_i(\mathbf{ENSO}_t) + \alpha_{22}\widehat{f}_i(\mathbf{ENSO}_t)\widehat{g}(\mathbf{ENSO}_t) + \Gamma_2'\mathbb{Z}_{it} + \upsilon_{2it} \tag{12}$$

where the vector of semi-parametric controls, $\mathbb{Z}_{it}$, includes the same variables as in equations (8) and (9). The second stage of our IV estimator is equation (8). Standard errors are clustered at both the country and continent-year levels to allow arbitrary forms of serial correlation and heteroskedasticity within a country and spatial correlation and heteroskedasticity across countries within a particular continent and year. In a robustness check, we cluster at the country and year levels.

There are several potential concerns regarding this approach. First, as with any IV estimator, our instruments should satisfy the exclusion restriction and generate sufficiently strong first-stage regressions. We conduct several indirect tests of our exclusion-restriction assumption in Section 4.3 and demonstrate that our estimates pass standard weak-instrument tests. Second, because our estimation uses a global climatic index to drive both country-level agricultural productivity and the global spatial correlation in that productivity, estimates of β_0 and β_1 are identified through a nonlinear function of $\mathbf{ENSO}_t$. In what follows, we show that we recover very similar estimates of β_0 and β_1 under a variety of functional forms for $f_i()$ and $g_i()$. This suggests that our main result is not driven by any particular nonlinear transformation of $\mathbf{ENSO}_t$.

4.2 Main results

It is instructive to first consider the analogous OLS regression of equation (8), as shown in column 1 of Table 2. The top panel includes linear country-specific trends, while the bottom panel includes quadratic country-specific trends. Both models include country and year fixed effects. OLS estimates of β_0 are statistically precise and positive. However, OLS estimates of β_1 are noisy and also positive.

To address the potential bias of OLS estimates due to the endogeneity of cereal yields, columns 2 through 5 of Table 2 report IV estimates of β_0 and β_1 from equation (8) by varying (i) the polynomial order of the ENSO function in $f_i()$ and $g()$ in equations (9) and (10) (across columns) and (ii) the polynomial order of time trends in equations (8)-(12) (across panels). All models incorporate country and year fixed effects as included instruments.

Across the various IV specifications in columns 2 through 5 of Table 2, we consistently find statistically significant estimates with $\widehat{\beta}_0 > 0$ and $\widehat{\beta}_1 < 0$. These results are relatively insensitive to the polynomial order of time trends. More importantly, our estimates are fairly stable across dif-

[18] Our IV approach has the advantaged of being exactly identified: there are two endogenous variables and two instruments. Alternatively, one could eliminate the prediction step in equations (9) and (10) and estimate $\widehat{f}_i(\mathbf{ENSO}_t)$ and $\widehat{g}(\mathbf{ENSO}_t)$ directly within equations (11) and (12). However, because $f_i()$ involves country-specific parameters, such an approach would result in a highly over-identified IV setting that may be more vulnerable to weak-instrument concerns (see Angrist and Pischke 2009, p.209).

Table 2: Main result: Domestic share of expenditure and spatial correlation of productivity

Outcome is log domestic share of expenditure					
	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
			Panel A: Linear trends		
$\ln A_{it}$ (β_0)	0.363**	3.754***	3.785***	2.133***	2.219***
	(0.166)	(1.248)	(1.158)	(0.791)	(0.757)
$\ln A_{it} \times I_t$ (β_1)	0.645	-14.333**	-14.471***	-7.382**	-7.783**
	(0.757)	(5.810)	(5.445)	(3.510)	(3.328)
Pct. change in welfare variance from 1 s.d. increase in I_t	-0.300	6.510**	6.571***	3.389**	3.571**
	(0.353)	(2.601)	(2.409)	(1.643)	(1.567)
ENSO poly. order for predicting $\ln A_{it}$		1	1	2	2
ENSO poly. order for predicting I_t		1	2	1	2
Cragg-Donald F-stat		22.73	24.55	63.92	67.20
Kleibergen-Paap F-stat		29.56	17.10	15.12	16.86
Anderson-Rubin weak-id robust p-value		4.66e-07	2.72e-08	0	0
Observations	5681	5681	5681	5681	5681
			Panel B: Quadratic trends		
$\ln A_{it}$ (β_0)	0.406*	3.473***	3.575***	3.100**	3.091***
	(0.210)	(1.300)	(1.029)	(1.240)	(0.982)
$\ln A_{it} \times I_t$ (β_1)	0.501	-13.471**	-13.952***	-12.073**	-12.028***
	(0.894)	(6.210)	(4.892)	(5.722)	(4.411)
Pct. change in welfare variance from 1 s.d. increase in I_t	-0.233	6.127**	6.341***	5.503**	5.483***
	(0.415)	(2.711)	(2.142)	(2.597)	(2.052)
ENSO poly. order for predicting $\ln A_{it}$		1	1	2	2
ENSO poly. order for predicting I_t		1	2	1	2
Cragg-Donald F-stat		17.09	20.80	24.62	25.77
Kleibergen-Paap F-stat		11.21	11.03	6	11.60
Anderson-Rubin weak-id robust p-value		5.62e-05	4.63e-06	5.13e-07	3.10e-08
Observations	5681	5681	5681	5681	5681

NOTES: Estimates of equation (8). Column 1 shows OLS estimates. Columns 2-5 show IV estimates. Columns 2-5 differ in the ENSO functional form used for predicting instruments. All models incorporate country and year fixed effects as included instruments. Panel A (B) includes global or country-specific linear (quadratic) trends in equations (8)-(12). 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 country and continent-year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

ferent combinations of linear and quadratic $\mathbf{ENSO_t}$ functions in $f_i()$ and $g()$ used to generate our instruments. The similar reduced-form coefficients obtained from different nonlinear transforma-

tions of $\mathbf{ENSO_t}$ shows that our results are not uniquely identified by any particular functional-form assumption.

To assess instrument relevance, Table 2 shows several first-stage tests. The Cragg-Donald and Kleibergen-Paap F-statistics presents the joint F-statistic for both first-stage regressions under the assumption of iid and cluster-robust errors, respectively (Cragg and Donald, 1993; Kleibergen and Paap, 2006). Because there is no clear relationship between the F-statistics and properties of the IV estimator in cases with multiple endogenous variables and non-iid standard errors, we also present the p-value from the Anderson-Rubin test against a null in which the endogenous regressors in equation (8) are jointly zero (Anderson and Rubin, 1949). This test is robust to the presence of weak instruments. For all IV specifications in Table 2, our estimates exhibit strong first-stage regressions and second-stage estimates that are robust even if instruments were weak.

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 benchmark model in column 5, panel A of Table 2, we find that a one standard deviation increase in the spatial correlation of productivity leads to a 3.6% increase in the global variance of welfare (see Appendix D.1 for details). Across the various IV specifications shown in Table 2, we find a range of welfare effects between 3.4% to 6.6%.

Finally, our ENSO treatment is annual which suggests that error terms across all countries within a year may be correlated. Appendix Table F.1 replicates Table 2 with standard errors that are clustered at the country and year levels. Allowing for arbitrary forms of spatial correlation and heteroskedasticity across all countries within a given year produces smaller standard errors. For all subsequent results, we present the larger standard errors obtained by clustering at the country and continent-year levels.

4.3 Additional robustness checks

This section presents several robustness checks of our main empirical result. They are designed to test both the validity of our statistical modeling assumptions and the interpretation of our results. Our benchmark model throughout is that shown in column 5, panel A of Table 2.

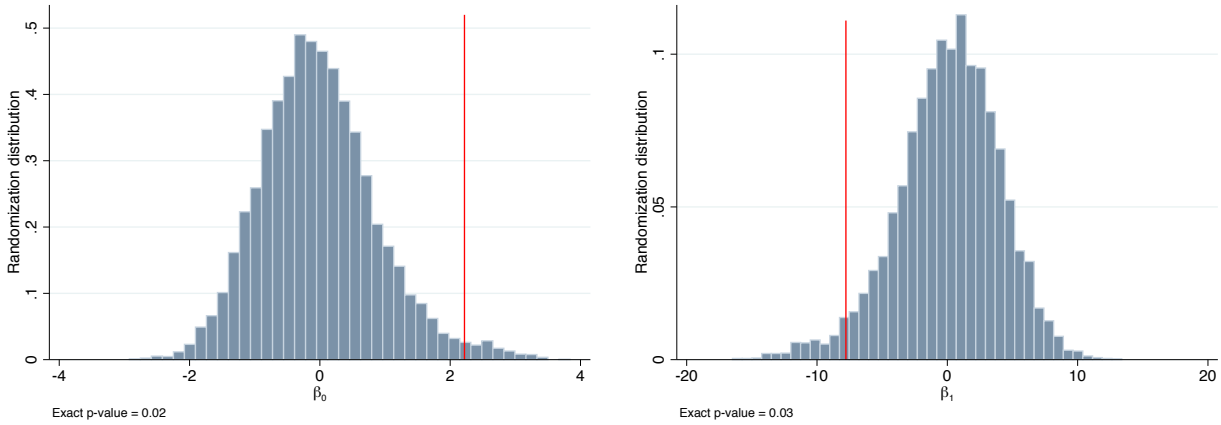
Randomization inference Our main source of identifying variation is global time-series fluctuations in the ENSO cycle, as shown in Figure 7. While it is plausible that ENSO is uncorrelated with unobserved determinants of domestic shares of expenditure over a long time horizon, spurious correlations could occur within a 53-year sample period. This would lead to biased IV 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, β_0 and β_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 12 shows the empirical distribution for $\widehat{\beta}_0$ and $\widehat{\beta}_1$, respectively, for 10,000 randomly reshuffled years without replacement. The vertical line shows the location of our estimated $\widehat{\beta}_0$ and $\widehat{\beta}_1$ from the observed data. The exact p-values for our estimated $\widehat{\beta}_0$ and $\widehat{\beta}_1$ are 0.02 and 0.03, respectively, implying that it is highly unlikely that our main result is due to small-sample bias.

Figure 12: Robustness: Randomization inference



NOTES: Empirical distributions of β_0 (left panel) and β_1 (right panel) from 10,000 random assignments of years. Vertical lines show estimates of β_0 and β_1 from observed data using benchmark model from column 5, panel A of Table 2.

Controlling for time-varying trade costs Our IV model correctly identifies β_0 and β_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.[19] While it is unlikely that ENSO, as a naturally occurring climatic phenomenon, is affected by economic activity, the exclusion violation 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.

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

[19] 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 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.

Table 3: Robustness: Controls for trade costs
Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)
$\ln A_{it}$ (β_0)	2.219***	2.260***	2.231***	2.207***	2.209***
	(0.757)	(0.751)	(0.761)	(0.749)	(0.779)
$\ln A_{it} \times I_t$ (β_1)	-7.783**	-7.982**	-7.815**	-7.800**	-7.702**
	(3.328)	(3.306)	(3.338)	(3.262)	(3.453)
ln oil price × average ln λ_{ii}	No	Yes	No	No	No
ln oil price × centrality	No	No	Yes	No	No
Year FE × average ln λ_{ii}	No	No	No	Yes	No
Year FE × centrality	No	No	No	No	Yes
Cragg-Donald F-stat	67.20	67.23	67.25	69	66.23
Kleibergen-Paap F-stat	16.86	16.99	16.92	17.35	17.48
Anderson-Rubin weak-id robust p-value	0	0	0	1.46e-10	0
Observations	5681	5681	5681	5681	5681

NOTES: Estimates of equation (8). All models incorporate quadratic functions of $\mathbf{ENSO}_t$ to predict $\ln A_{it}$ and I_t, linear time trends, and country and year fixed effects as included instruments. Column 1 replicates column 5, panel A 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). Standard errors clustered at country and continent-year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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 β_0 and β_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 with our ENSO-driven instruments.

Nonlinearity in second-stage regression Our estimated second-stage regression in equation (8) differs from our theory-informed equation (5) by additionally assuming that log domestic share of expenditure is linear in both log cereal yields and the interaction of log cereal yields and Moran's I. We now examine these functional-form assumptions.

Tests of nonlinearity require breaking our main instruments into multiple variables. This potentially creates weaker first-stage regressions. To minimize this concern, we first examine whether log domestic share of expenditure is linear in log cereal yields. Conditional on that linear relationship, we then examine whether the interaction between log yield and the spatial correlation of log yields is linear. The first test is presented in the left panel of Figure E.3 in which a restricted cubic spline

is fitted onto log yields in our benchmark specification for equation (8) but without the interaction term. The relationship between log domestic share of expenditure and log yields appears roughly linear. The right panel of Figure E.3 examines how this relationship varies with Moran's I by discretizing the empirical Moran's I distribution into three equal-sized intervals and estimating a separate slope for each. The linear relationship between log domestic share of expenditure and log yield becomes flatter as Moran's I values increase. Consistent with our theoretical example in Figure 2, this interaction relationship appears monotone and roughly linear with slopes of 0.71, 0.55, and 0.43 for bins centered at Moran's I values of 0.19, 0.21, and 0.23, respectively.

Time-varying parameters Table 4 examines whether β_0 and β_1 vary 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 1988-2013, the second half of our sample period. We do not find that our results differ statistically across the two subsample periods.

Table 4: Robustness: Time-varying parameters
Outcome is log domestic share of expenditure

	(1)	(2)	(3)
$\ln A_{it}$ (β_0)	2.219***	1.633	2.030***
	(0.757)	(0.994)	(0.702)
$\ln A_{it} \times I_t$ (β_1)	-7.783**	-5.278	-7.448**
	(3.328)	(4.615)	(3.087)
Pct. change in welfare variance			
from 1 s.d. increase in I_t	3.850**	2.066	4.116**
	(1.693)	(1.777)	(1.779)
Cragg-Donald F-stat	67.20	32.22	21.84
Kleibergen-Paap F-stat	16.86	8.962	13.19
Anderson-Rubin weak-id robust p-value	0	3.80e-06	1.22e-05
2nd stage sample period	1961-2013	1961-1987	1988-2013
Observations	5681	2757	2919

NOTES: Estimates of equation (8). All models incorporate quadratic functions of $\mathbf{ENSO}_t$ to predict $\ln A_{it}$ and I_t, linear time trends, and country and year fixed effects as included instruments. Column 1 replicates column 5, panel A of Table 2. Column 2 restricts sample to 1961-1987. Column 3 restricts sample to 1988-2013. Standard errors clustered at country and continent-year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dynamic effects Finally, Table 5 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 which 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 contemporary 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. To more directly explore the potential role for stored cereals, column 4 reports our benchmark contemporaneous-productivity specification using a modified measure of the domestic share of expenditure that excludes stored cereals.[20] The estimated coefficients are similar to our benchmark estimates, suggesting that storage behavior is not responsible for the response of expenditure shares to ENSO-driven productivity variation.

5 Application: Inequality under future climate change

In this section, we demonstrate how to incorporate our general-equilibrium mechanism into 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 projections that hold spatial correlation fixed.

The objective is to project future economic impacts of climate change. For country i in year t, the economic outcome of interest y_{it} may be consumption or welfare. Because this outcome is determined in general equilibrium, it is determined by both local temperature, T_{it}, and the global spatial correlation of productivities induced by temperature, I_t. Denote that function as $h(T_{it}; I_t)$. Climate change may affect both arguments.

In Section 5.1, we first discuss an approach to climate impact projections that omits changes in spatial correlation. We then extend this approach by incorporating climate-driven changes in spatial correlation in Section 5.2.

[20] Our standard measure of country-level domestic good consumption is output minus exports. To construct a measure that excludes storage, we further subtract the country-level difference between stored cereals in year $t-1$ and year t. This implicitly assumes that all stored cereals are domestically produced. The sample is smaller due to observations with missing storage data.

Table 5: Robustness: Dynamic effects
Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)
$\ln A_{it}$ (β_{0t})	2.178***			2.096**
	(0.770)			(1.035)
$\ln A_{it} \times I_t$ (β_{1t})	-7.588**			-8.289*
	(3.363)			(4.634)
$\ln A_{i,t+1}$ ($\beta_{0,t+1}$)		0.726		
		(1.180)		
$\ln A_{i,t+1} \times I_{t+1}$ ($\beta_{1,t+1}$)		-2.447		
		(5.423)		
$\ln A_{i,t-1}$ ($\beta_{0,t-1}$)			-0.290	
			(0.911)	
$\ln A_{i,t-1} \times I_{t-1}$ ($\beta_{1,t-1}$)			0.480	
			(4.234)	
Remove storage?	No	No	No	Yes
Cragg-Donald F-stat	65.71	60.99	48.15	50.50
Kleibergen-Paap F-stat	17.53	11.55	11.26	10.25
Anderson-Rubin weak-id robust p-value	0	0.0768	0.282	0.00121
2nd stage sample period	1962-2012	1962-2012	1962-2012	1961-2013
Observations	5458	5457	5456	5367

NOTES: Estimates of equation (8). 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 excludes cereal storage. Sample period for 2nd stage equation is 1962-2012 for columns 1-3 and 1961-2013 for column 4. All models incorporate country fixed effects, year fixed effects, and country-specific trends as included instruments. Standard errors clustered at country and continent-year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.1 Omitting changes in spatial structure

Define $t \in [\underline{t}, \bar{t}]$ as the historical estimation period. The following specification is used to estimate the effect of historical local temperature T_{it}^H on y_{it}:

$$y_{it} = h(T_{it}^H; I_t^H) + \mathbb{X}_{it}\Pi + \nu_{it} \quad \text{for } t \in [\underline{t}, \bar{t}] \tag{13}$$

where $\mathbb{X}_{it}$ is a vector of controls. The nonlinear response function $h()$ is estimated using variation in local temperature T_{it}^H and implicitly depends upon the historical global spatial correlation of temperature-induced productivities, I_t^H. In a second step, a future outcome is projected by evaluating the estimated response function at a future temperature T_{it}^F. In particular, one is typically interested in predicting future outcome levels driven only by temperature changes while holding

everything else fixed to the last estimation year. That projection is

$$\widehat{y}_{it} = \widehat{h}(T_{it}^F; I_t^H) + \mathbb{X}_{i\bar{t}}\widehat{\Pi} + \widehat{\nu_{i\bar{t}}} \quad \text{for } t \in [\bar{t}+1, \mathcal{T}]. \tag{14}$$

This approach assumes that climate change affects local outcome y only through local temperature T_{it}. That is, using historical local temperature variation alone to estimate $h()$ implicitly assumes that climate change does not affect I_t. However, as the next section shows, climate change also alters I_t. This is consequential since a country's welfare depends on its productivity both directly (autarky welfare) and indirectly through any correlation between a country's productivity and its gains from trade, as governed by the spatial correlation of productivities, I_t. Because this approach does not directly estimate the effect of changes in I_t, any changes in the spatial correlation of productivity due to climate change would be omitted from projections using equation (14).

5.2 Including changes in spatial structure

We now illustrate how climate projections are altered by incorporating general-equilibrium effects from climate-driven changes in the spatial correlation of productivities. Before doing so, it is important to highlight two elements of our exercise so that it not be interpreted as a literal prediction of future impacts. First, with the exception of changes in local temperature due to climate change over the 21st century, we hold everything else fixed at recent historical values. Second, we apply estimates based on past exogenous annual changes in agricultural productivity to future long-term productivity changes due to climate change. Both practices are standard in econometric estimates of climate impacts and omit possible adaptations in anticipation of future climate change (Deschênes and Greenstone, 2007; Hsiang, 2016).

Using the same sample period as in Section 4, we first estimate a global nonlinear log cereal yield response function on country-year-level crop-area-weighted temperature. Specifically, for the period 1961-2013, we estimate:

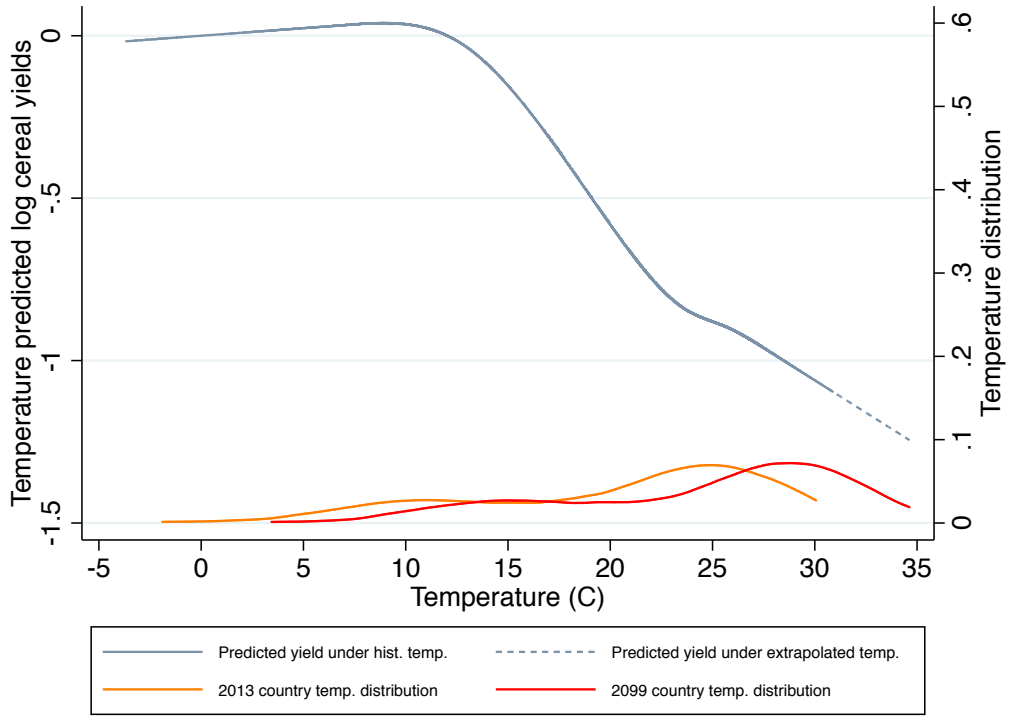
$$\ln A_{it} = k(T_{it}) + \mathbb{X}_{it}\Psi + \nu_{it} \tag{15}$$

where $k()$ is a restricted cubic spline and the set of controls in $\mathbb{X}_{it}$ include quadratic precipitation terms, country fixed effects, year fixed effects, and country-specific quadratic trends.[21] Figure 13 shows the predicted cubic spline response function, $k()$, using six knots, as well as the cross-country distribution of crop-area-weighted temperatures observed in 2013, the end of our estimation period, and under a business-as-usual (Representative Concentration Pathway 8.5) climate scenario in 2099 using the Coupled Model Intercomparison Project (CMIP5) multi-model ensemble mean climate projection.[22] Column 4 of Table F.2 shows that the coefficients of this functional form are jointly

[21] Note that by modeling temperature effects on log cereal yield rather than an economic outcome as shown in equation (13), we are isolating the direct productivity effects of local temperature.

[22] 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

Figure 13: Estimated temperature response function for log cereal yields



NOTES: Gray solid line shows $k()$ in equation (15), the predicted relationship between crop-area-weighted country-level temperature and log cereal yields, estimated during 1961-2013. Restricted cubic spline estimated using six 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 4 of Table F.2. 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.

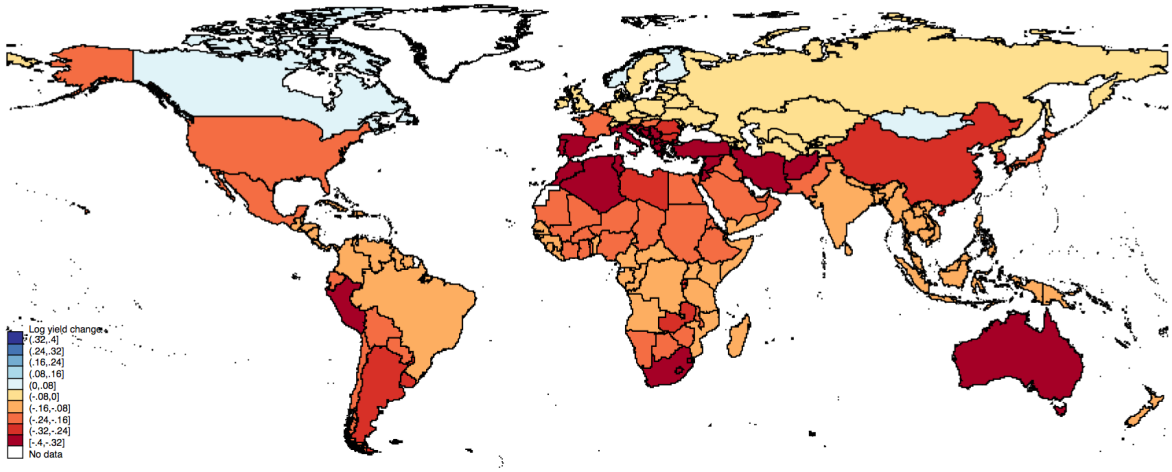
statistically significant with an optimal temperature around 9°C. Table F.2 also indicates that the predicted optimal temperature is relatively insensitive to the number of knots in the spline function and to the omission of precipitation controls. Figure 14 maps the projected change in country-level log cereal yields under climate change between 2013-2099, $\widehat{\ln A}_{i,2099} - \ln A_{i,2013}$. Projections of temperature-driven log cereal yields, $\widehat{\ln A}_{it}$, for each projection year come from combining the estimated coefficients in equation (15) with local temperature projections from the CMIP5 multi-model ensemble mean under a business-as-usual scenario. All other variables in equation (15) are fixed at 2013 levels. Consistent with the nonlinear yield response function shown in Figure 13, 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.[23] First, the variance of agricultural productivity increases. Because climate change

Panel on Climate Change (see Taylor, Stouffer and Meehl (2012) for details).

[23] Because of surface albedo changes due to polar ice melt, there is higher warming in the poles relative to lower

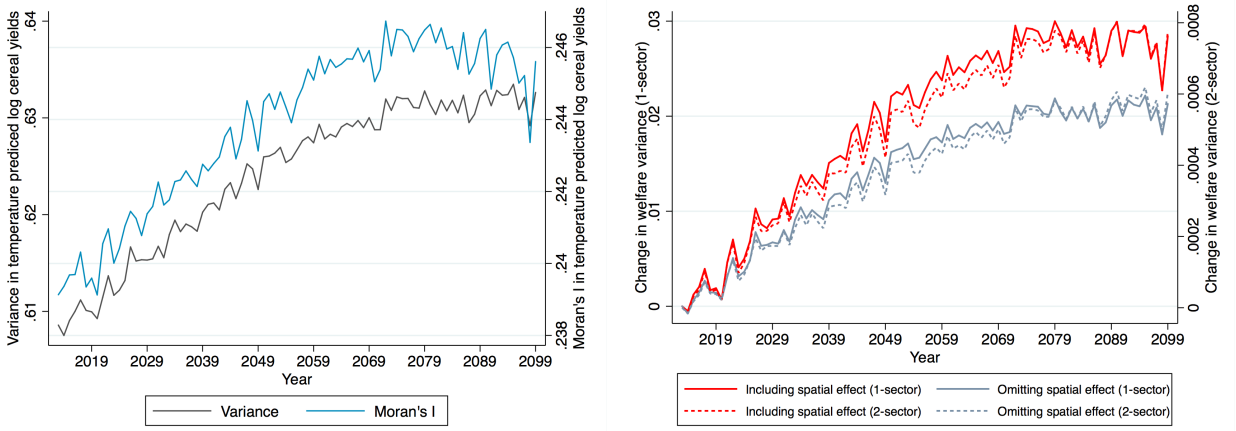
Figure 14: Change in log cereal yields under climate change (2013-2099)



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 (15) with six knots as shown in column 4 of Table F.2. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

raises temperatures across the globe, it shifts countries from the relatively flat portion of the yield response function depicted by the gray line in Figure 13 to the declining portion. This increases the cross-country variance, depicted by the gray line in the left panel of Figure 15.

Figure 15: Variance in climate-driven welfare over the 21st century



NOTES: Left panel shows the change in the global variance (gray line) and Moran's I (blue line) of log cereal yields over the 21st century under climate change. Right panel shows the change in the variance of welfare omitting (gray line) and including (red line) changes in the spatial correlation of log cereal yields over the same period. Solid lines under one-sector (agriculture) model. Dash lines under two-sector (agriculture and non-agriculture) model. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

latitude areas. This implies that the country-specific shift in temperature due to climate change is not spatially uniform. However, this latitude-dependent gradient is relatively small compared to the average global temperature change and 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.

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 13 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 is indicated by the blue line in the left panel of Figure 15.

The change in the spatial correlation of agricultural productivity due to climate change is consequential for global inequality. To calculate the change in the variance of welfare under climate change, we combine projected local agricultural productivity, $\widehat{\ln A}_{it}$, and global spatial correlation of productivity, $\widehat{I}_t$, with our benchmark reduced-form estimates $\widehat{\beta}_0$ and $\widehat{\beta}_1$ in Section 4 to construct future $\widehat{\ln \lambda}_{iit}$ using equation (8). This allows us to construct each component of the welfare variance in equation (2): $var(\widehat{\ln A}_{it})$, $cov(\widehat{\ln A}_{it}, \widehat{\ln \lambda}_{iit})$, and $var(\widehat{\ln \lambda}_{iit})$.

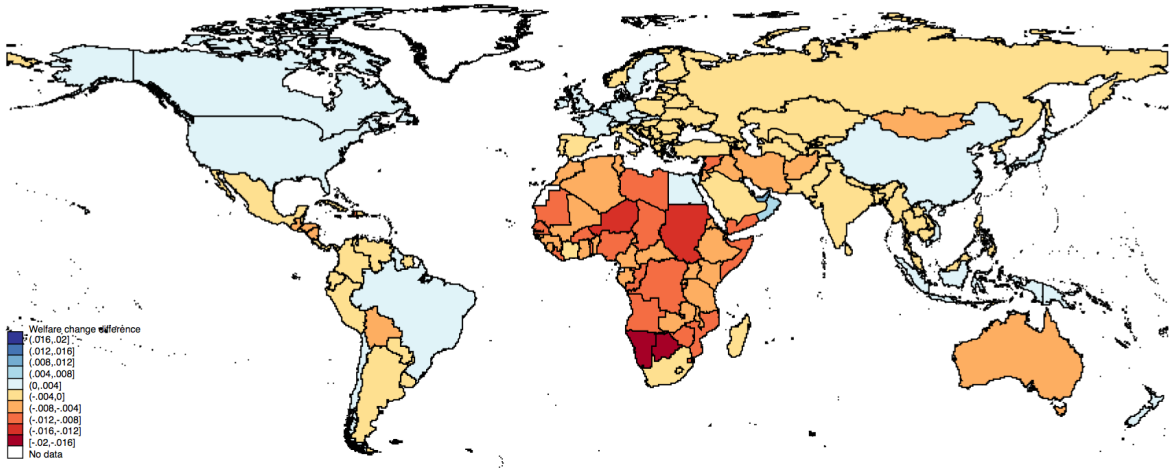
5.3 Comparing projections

To examine the importance of incorporating changes in spatial correlation, we construct a projection in which the spatial correlation of temperature-predicted agricultural productivities is fixed at its 2013 value and a projection in which we allow the spatial correlation of productivities to be affected by climate change (see Appendix D.2 and D.3 for details).

The projected change in the variance of welfare over the 21st century is shown in the right panel of Figure 15. The gray line shows the projection that omits changes in spatial correlation and the red line shows the projection that include such changes. The solid and dashed lines show the projected change in welfare variance under a one-sector (agriculture) and two-sector model (agriculture and non-agriculture), respectively. In a model with only the agricultural sector, projections that incorporate changes in the spatial correlation of agricultural productivity due to climate change predict a 34% greater increase in welfare inequality between 2013-2099 compared to a projection that holds spatial correlation fixed. In a two-sector model where there is adjustment in the non-agricultural sector, we predict a 29% greater increase in welfare inequality.

How do the projections differ across countries? High-productivity countries have higher welfare in the projection that includes changes in spatial structure than in the projection that omits such changes. This is due to the role of spatial correlation in mediating the relationship between productivity and gains from trade. Including an increase in the spatial correlation of productivity causes the gains from trade to be higher in more productive countries and lower in less productive countries than in a projection that holds spatial correlation fixed. Figure 16 maps the difference

Figure 16: Differences in projected welfare changes due to change in spatial correlation (2013-2099)



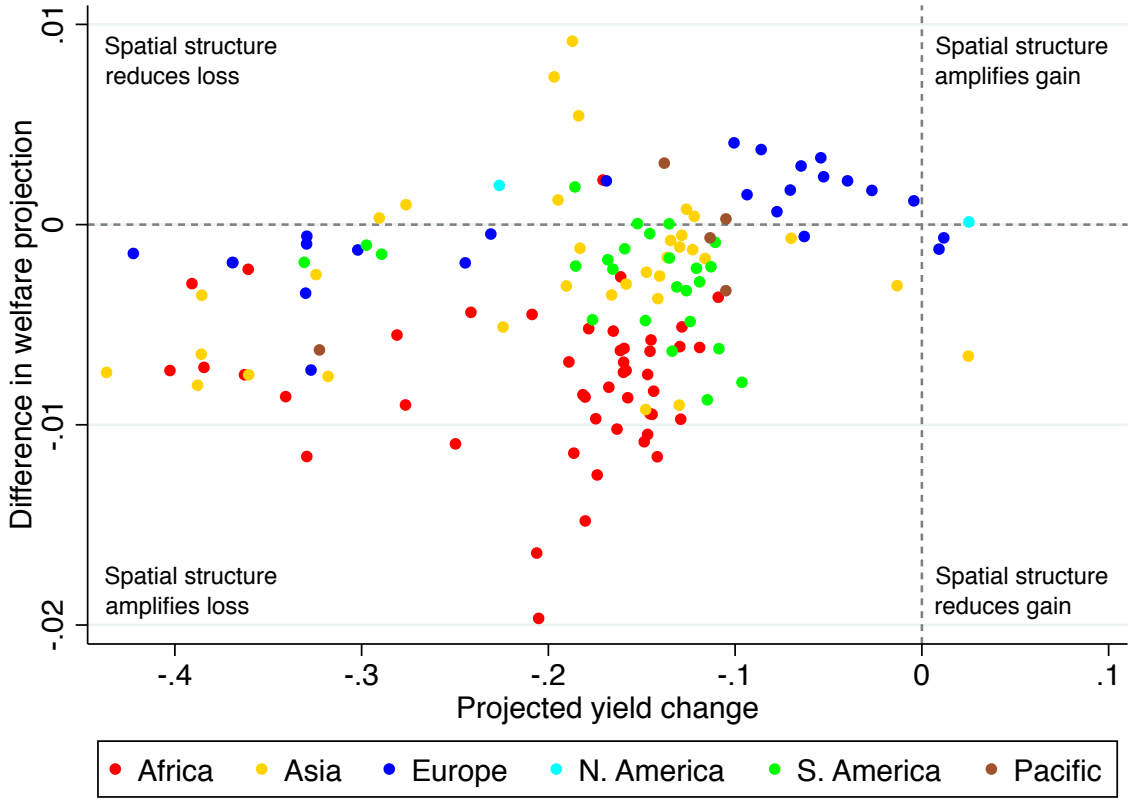
NOTES: Map shows the difference in projected country-level welfare change over 2013-2099 between projections that include (Figure D.2) and omit (Figure D.1) changes in spatial correlation. Climate projections from CMIP5 ensemble mean under a business-as-usual (RCP 8.5) scenario.

between the two projections for the one-sector model.[24] Most countries in Africa, South America, and many in Asia 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 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, which further lowers gains from trade compared to if each location were to warm independently. By the same logic, parts of Europe and North American have higher gains from trade when the projection includes changes in spatial correlation. The relatively milder temperatures experienced by these countries is accompanied by similar temperatures over neighboring locations.

Figure 17 depicts climate-change forecasts for each country in terms of the predicted change in agricultural productivity from Figure 14 and the difference in projected welfare from omitting the change in spatial correlation shown in Figure 16. The vast majority of countries suffer a decrease in agricultural productivity as a result of increased temperature. As in Figure 16, the strongest contrast in Figure 17 is between outcomes for African and European economies.[25] While there is substantial heterogeneity in the productivity declines across countries within each continent, most economies in Africa, South America, and many in Asia experience productivity losses that would be considerably amplified by changes in spatial correlation. By contrast, the welfare projections for most European economies are altered modestly by incorporating the increase in spatial correlation of productivity, and most have reduced 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.

[24] See equation (D.18) at the end of Appendix D.4.
[25] See Figure E.4 for the same plot with country identifiers.

Figure 17: 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 16) plotted against change in log cereal yields (from Figure 14) over 2013-2099 under climate change. Countries color-coded by continent.

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 arbitraged 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.

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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 ϑ.

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

$$\lambda_{ij} = \frac{\chi_i \left(\tau_{ij} w_i\right)^{-\epsilon}}{\sum_{l=1}^{N} \chi_l \left(\tau_{lj} w_l\right)^{-\epsilon}}$$

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 $\{A_i\}_i$ and trade elasticity ϵ 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 $-\frac{1}{\epsilon} \ln \lambda_{jj}$. In our theoretical environment, autarky welfare is equal to $\ln A_j + \gamma$, as implied by equation (1). γ is a function of structural parameters. In the Armington model with symmetric preferences, γ is zero. In the Eaton and Kortum (2002) model, $\gamma = \left[\Gamma\left(1 + \frac{1-\sigma}{\theta}\right)\right]^{1/(1-\sigma)}$ where Γ 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, $\epsilon = \sigma - 1$, $n_i = L_i/\left(\sigma f_i\right)$, and $\chi_i = n_i c_i^{-\epsilon}$.

Welfare. In this setting, real per capita consumption is

$$\ln\left(C_j/L_j\right) = \frac{1}{\epsilon}\ln n_j - \ln c_j + \ln\left(\frac{\sigma-1}{\sigma}\right) - \frac{1}{\epsilon}\ln\lambda_{jj}$$

If population size L_j and fixed costs f_j are country-invariant ($n_j = n\ \forall j$) and we interpret productivity as shifting marginal costs, $A_j = c_j^{-1}$, 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_j and marginal costs c_j are country-invariant and we interpret productivity as shifting fixed costs, $A_j = f_j^{-1/\epsilon}$, then this is equivalent to equation (1) with $\gamma = \frac{1}{\epsilon}\ln\left(L/\sigma\right) + \ln\left(\frac{\sigma-1}{\sigma c}\right)$.

In the case of countries with heterogeneous population sizes, equation (1) must be extended to replace γ with a location-specific γ_j that depends on structural parameters other than productivity. For example, if productivity shifts marginal costs, $A_j = c_j^{-1}$, then we obtain

$$\ln\left(\frac{C_j}{L_j}\right) = \ln A_j + \gamma_j - \frac{1}{\epsilon}\ln\lambda_{jj}, \tag{1'}$$

where $\gamma_j = \frac{1}{\epsilon}\ln n_j + \ln\left(\frac{\sigma-1}{\sigma}\right)$. If we assume that $cov(\ln A_i^u, \gamma_i) = cov(\ln A_i^c, \gamma_i)$, we obtain an extension of equation (3):

$$\begin{aligned} var\left(\ln C_i^c/L_i\right) - var\left(\ln C_i^u/L_i\right) = &-\frac{2}{\epsilon}\left[cov\left(\ln A_i^c, \ln\lambda_{ii}^c\right) - cov\left(\ln A_i^u, \ln\lambda_{ii}^u\right)\right] \\ &-\frac{2}{\epsilon}\left[cov\left(\gamma_i, \ln\lambda_{ii}^c\right) - cov\left(\gamma_i, \ln\lambda_{ii}^u\right)\right] \\ &+\frac{1}{\epsilon^2}\left[var\left(\ln\lambda_{ii}^c\right) - var\left(\ln\lambda_{ii}^u\right)\right]. \end{aligned} \tag{3'}$$

A.1.3 The case of symmetric trade costs

Starting from the equilibrium system of equations and using the assumption of symmetric trade costs ($\tau_{ij} = \tau_{ji}$):

$$\begin{aligned} Y_i = w_i L_i &= \sum_j \left(\frac{w_i}{A_i}\right)^{-\epsilon} \tau_{ij}^{-\epsilon}\frac{w_j L_j}{\Phi_j} = \left(\frac{w_i}{A_i}\right)^{-\epsilon}\Omega_i \\ \Rightarrow \frac{w_i}{A_i} &= \left(\frac{\Omega_i}{A_i L_i}\right)^{\frac{1}{\epsilon+1}} \\ \Rightarrow \Phi_i &= \sum_j \tau_{ji}^{-\epsilon}\left(\frac{w_j}{A_j}\right)^{-\epsilon} = \sum_j \tau_{ji}^{-\epsilon}\left(A_j L_j/\Omega_j\right)^{\frac{\epsilon}{\epsilon+1}} \\ &= \sum_j \tau_{ji}^{-\epsilon}\left(A_j L_j/\Phi_j\right)^{\frac{\epsilon}{\epsilon+1}} \end{aligned}$$

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 $\lambda_{ii} = \frac{(w_i/A_i)^{-\epsilon}}{\Phi_i}$, the above expression for w_i/A_i and the assumption of symmetric trade costs yield the result that

$$\lambda_{ii} = \frac{(\Omega_i/(A_i L_i))^{\frac{-\epsilon}{\epsilon+1}}}{\Phi_i} = (A_i L_i)^{\frac{\epsilon}{\epsilon+1}} \Phi_i^{-\frac{2\epsilon+1}{\epsilon+1}}$$

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

A.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.

A.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:

$$I(\ln A, W) = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \left(\ln A_i - \overline{\ln A}\right) \sum_j w_{ij} \left(\ln A_j - \overline{\ln A}\right)}{\sum_i \left(\ln A_i - \overline{\ln A}\right)^2}$$

where w_{ij} are spatial weights. Define the spatial weight matrix

$$W = \begin{bmatrix} w_0 & w_1 & w_2 & w_1 \\ w_1 & w_0 & w_1 & w_2 \\ w_2 & w_1 & w_0 & w_1 \\ w_1 & w_2 & w_1 & w_0 \end{bmatrix}$$

Thus, there is a one-to-one mapping between w_{ij} and τ_{ij}. w_1 is the spatial weight associated with trade cost d_1; w_2 is the spatial weight associated with trade cost d_2.

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

$\ln A^c$ is more spatially correlated than $\ln A^u$ if and only if $I(\ln A^c, W) > I(\ln A^u, W) \iff \sum_i \widehat{\ln A_i^c} \sum_j w_{ij} \widehat{\ln A_j^c} > \sum_i \widehat{\ln A_i^u} \sum_j w_{ij} \widehat{\ln A_j^u}$.

The relevant terms are as follows:

$$\sum_j w_{ij}\widehat{\ln A_j^c} = \begin{cases} \frac{1}{2}(w_0 - w_2)\ln\tilde{a} & \text{for } i = 1,2 \\ -\frac{1}{2}(w_0 - w_2)\ln\tilde{a} & \text{for } i = 3,4 \end{cases}$$

$$\sum_i \widehat{\ln A_i^c}\sum_j w_{ij}\widehat{\ln A_j^c} = (w_0 - w_2)(\ln\tilde{a})^2$$

$$\sum_j w_{ij}\widehat{\ln A_j^u} = \begin{cases} \frac{1}{2}(w_0 - 2w_1 + w_2)\ln\tilde{a} & \text{for } i = 1,3 \\ -\frac{1}{2}(w_0 - 2w_1 + w_2)\ln\tilde{a} & \text{for } i = 2,4 \end{cases}$$

$$\sum_i \widehat{\ln A_i^u}\sum_j w_{ij}\widehat{\ln A_j^u} = (w_0 - 2w_1 + w_2)(\ln\tilde{a})^2$$

$I(\ln A^c, W) > I(\ln A^u, W) \iff w_0 - w_2 > w_0 - 2w_1 + w_2 \iff w_1 > w_2.$ □

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

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 $\lambda_{ij} = A_i^\epsilon Y_i^{-\epsilon}\tau_{ij}^{-\epsilon}/\Phi_j$. Thus $\lambda_{ij}A_i^{-\epsilon}Y_i^\epsilon = \tau_{ij}^{-\epsilon}/\Phi_j$ and

$$x = \frac{\tau_{13}^{-\epsilon}/\Phi_3 + \tau_{14}^{-\epsilon}/\Phi_4}{\tilde{a}^{-\epsilon}Y_1^\epsilon - \tau_{11}^{-\epsilon}/\Phi_1 - \tau_{12}^{-\epsilon}/\Phi_2}.$$

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

$$x^{2\epsilon+1} + \underbrace{\frac{d_2^{-\epsilon} + d_1^{-\epsilon}}{1 + d_1^{-\epsilon}}}_{\equiv r^c}\tilde{a}^\epsilon\left(x^{\epsilon+1} - x^\epsilon\right) - \tilde{a}^{2\epsilon} = 0. \tag{A.1}$$

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

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

$$x^{2\epsilon+1} + \underbrace{\frac{d_1^{-\epsilon} + d_1^{-\epsilon}}{1 + d_2^{-\epsilon}}}_{\equiv r^u}\tilde{a}^\epsilon\left(x^{\epsilon+1} - x^\epsilon\right) - \tilde{a}^{2\epsilon} = 0. \tag{A.2}$$

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

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

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).[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 $F(x) = R(x;r_2) - R(x;r_1) = (r_2 - r_1)\tilde{a}^{\epsilon}x^{\epsilon}(x-1)$. 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.

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

Proof. Equilibrium domestic shares of expenditure can be expressed as $\lambda_{ii} = A_i^{\epsilon}Y_i^{-\epsilon}/\Phi_i$. 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

$$\lambda_{11} = \lambda_{22} = A_1^{\epsilon}Y_1^{-\epsilon}/\Phi_1 = \frac{1}{1 + d_1^{-\epsilon} + \tilde{a}^{-\epsilon}x_c^{\epsilon}(d_2^{-\epsilon} + d_1^{-\epsilon})} = \frac{1}{(1 + d_1^{-\epsilon})(1 + \tilde{a}^{-\epsilon}x_c^{\epsilon}r^c)}$$
$$\lambda_{33} = \lambda_{44} = A_3^{\epsilon}Y_3^{-\epsilon}/\Phi_3 = \frac{1}{1 + d_1^{-\epsilon} + \tilde{a}^{\epsilon}x_c^{-\epsilon}(d_2^{-\epsilon} + d_1^{-\epsilon})} = \frac{1}{(1 + d_1^{-\epsilon})(1 + \tilde{a}^{\epsilon}x_c^{-\epsilon}r^c)}$$

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.

$d_2^{-\epsilon}) + 2Y_1^{-\epsilon}\tilde{a}^{\epsilon}d_1^{-\epsilon}$, so

$$\lambda_{11} = \lambda_{33} = A_1^{\epsilon}Y_1^{-\epsilon}/\Phi_1 = \frac{1}{1 + d_2^{-\epsilon} + 2\tilde{a}^{-\epsilon}x_u^{\epsilon}d_1^{-\epsilon}} = \frac{1}{(1 + d_2^{-\epsilon})(1 + \tilde{a}^{-\epsilon}x_u^{\epsilon}r^u)}$$
$$\lambda_{22} = \lambda_{44} = A_2^{\epsilon}Y_2^{-\epsilon}/\Phi_2 = \frac{1}{1 + d_2^{-\epsilon} + 2\tilde{a}^{\epsilon}x_u^{-\epsilon}d_1^{-\epsilon}} = \frac{1}{(1 + d_2^{-\epsilon})(1 + \tilde{a}^{\epsilon}x_u^{-\epsilon}r^u)}$$

Thus, we obtain the following demeaned values of the log domestic shares of expenditure

$$\begin{aligned}\widehat{\ln \lambda_{11}} &= -\tfrac{1}{2}\left[\ln\left(1 + x^{\epsilon}\tilde{a}^{-\epsilon}r\right) - \ln\left(1 + \tilde{a}^{\epsilon}x^{-\epsilon}r\right)\right] \\ \widehat{\ln \lambda_{44}} &= -\widehat{\ln \lambda_{11}}\end{aligned}$$

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 ϵ and $\tilde{a}$ are fixed parameters while x is a function of r. This covariance is positive because $\tilde{a} > x$.[27]

It can be shown that $cov(\ln A_i, \ln \lambda_{ii})$ is increasing in r.

$$\frac{\mathrm{d}cov(\ln A_i, \ln \lambda_{ii})}{\mathrm{d}r} \propto -\frac{\mathrm{d}\ln\left(\frac{1+x^{\epsilon}\tilde{a}^{-\epsilon}r}{1+\tilde{a}^{\epsilon}x^{-\epsilon}r}\right)}{\mathrm{d}r} \propto \underbrace{\left(\frac{\tilde{a}}{x}\right)^{\epsilon} - \left(\frac{x}{\tilde{a}}\right)^{\epsilon}}_{>0} - \underbrace{\frac{r\epsilon}{x}\left[2 + x^{\epsilon}\tilde{a}^{-\epsilon} + x^{-\epsilon}\tilde{a}^{\epsilon}\right]}_{>0}\underbrace{\frac{\mathrm{d}x}{\mathrm{d}r}}_{<0} > 0$$

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.

□

$var(\ln(C_i/L))$ is greater in the spatially correlated case

Proof. In both equilibria,

$$var(\ln \lambda_{ii}) = \frac{2}{4}\left(\widehat{\ln \lambda_{11}}\right)^2 + \frac{2}{4}\left(\widehat{\ln \lambda_{44}}\right)^2 = \left(\widehat{\ln \lambda_{11}}\right)^2 = \frac{4\epsilon^2}{(\ln \tilde{a})^2}\left(cov(\ln A_i, -\frac{1}{\epsilon}\ln \lambda_{ii})\right)^2.$$

Therefore

$$\begin{aligned}var(\ln(C_i/L)) &= var(A_i) + 2cov(\ln A_i, \frac{-1}{\epsilon}\ln \lambda_{ii}) + \frac{1}{\epsilon^2}var(\ln \lambda_{ii}) \\ &= var(A_i) + 2cov(\ln A_i, \frac{-1}{\epsilon}\ln \lambda_{ii}) + \frac{4}{(\ln \tilde{a})^2}\left(cov(\ln A_i, -\frac{1}{\epsilon}\ln \lambda_{ii})\right)^2\end{aligned}$$

[27] $\tilde{a} > x$ because x is the largest positive zero of $R(x; r)$, $R(x'; r) < 0\ \forall x' \in (0, x)$, and $R(\tilde{a}; r) = (1+r)(\tilde{a}-1)\tilde{a}^{2\epsilon} > 0$.

This is increasing in $cov(\ln A_i, \frac{-1}{\epsilon}\ln\lambda_{ii})$ if and only if

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

This inequality is true. The triangle inequality for trade costs, $d_2 < d_1^2$, implies that $r^u < 1$. If $r<1$ and $\epsilon \geq 1$, then $R(\sqrt{\tilde{a}};r)\leq 0$.[28] Thus, $x^*(r)\geq\sqrt{\tilde{a}}\ \forall r\in(0,1)$. That implies the following inequality:

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

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

□

A.2.2 Circular geography

Figures 1 and 2 present an illustrative example in which we parameterize A_i and τ_{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 θ.[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 1 and 2 depict demeaned distributions. Table A.1 reports the means and variances of countries' welfare per capita under autarky and trade.

Table A.1: Outcomes for one-sector sine-wave economy

Frequency of $\ln A$ sine wave (θ)	1	2	3	4
Autarky welfare ($\ln A$) mean	10	10	10	10
Autarky welfare ($\ln A$) variance	0.510204	0.510204	0.510204	0.510204
Trading-equilbrium welfare ($\ln C/L$) mean	12.2654	12.2769	12.2807	12.2836
Trading-equilbrium welfare ($\ln C/L$) variance	0.298203	0.226274	0.203006	0.184882

Figure 3 introduces heterogeneous sizes to the parameterization used in figures 1 and 2. Size $\ln L_i$ is the sum of a sinewave with mean value 10, amplitude 1, and frequency $\theta_L=1$ and Gaussian noise $\sim\mathcal{N}(0,1)$.

[28]

$$R(\sqrt{\tilde{a}};r)=\tilde{a}^{\frac{2\epsilon+1}{2}}+r\tilde{a}^{\epsilon}(\tilde{a}^{\frac{\epsilon+1}{2}}-\tilde{a}^{\frac{\epsilon}{2}})-\tilde{a}^{2\epsilon}=\tilde{a}^{\epsilon}\left(\tilde{a}^{\frac{1}{2}}+r\tilde{a}^{\frac{\epsilon}{2}}(\tilde{a}^{\frac{1}{2}}-1)-\tilde{a}^{\epsilon}\right)$$
$$\leq\tilde{a}^{\epsilon}\left(\tilde{a}^{\frac{1}{2}}+\tilde{a}^{\frac{\epsilon}{2}}(\tilde{a}^{\frac{1}{2}}-1)-\tilde{a}^{\epsilon}\right)=-\tilde{a}^{\epsilon}\left(\tilde{a}^{\frac{\epsilon}{2}}-\tilde{a}^{\frac{1}{2}}\right)\left(1+\tilde{a}^{\frac{\epsilon}{2}}\right)\leq 0$$

[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.

Table A.2: Outcomes for two-sector sine-wave economy

Frequency of $\ln A_1$ sine wave (θ_1)	1	2	3	4
Autarky welfare ($\frac{1}{2}\ln A_1 + \frac{1}{2}\ln A_2$) mean	10	10	10	10
Autarky welfare ($\frac{1}{2}\ln A_1 + \frac{1}{2}\ln A_2$) variance	0.255102	0.255102	0.255102	0.255102
Trading-equilbrium welfare ($\ln C/L$) mean	12.3610	12.3699	12.3721	12.3736
Trading-equilbrium welfare ($\ln C/L$) variance	0.114255	0.097649	0.092189	0.087935

Figure 4 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 $\ln A_0 \sim N(0,1)$.

Figure 6 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 of welfare in the trading equilibrium, but our main prediction still obtains in this multi-sector setting with orthogonal productivities.

A.2.3 Randomly generated geography

In Figure 5, 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 τ is a positive scaling factor. Countries are of equal size, $L_j = 1\ \forall j$. The trade elasticity $\epsilon = 4$. The spatial weight matrix W we use to compute Moran's I is constructed using inverse distances, $w_{ij} = \frac{1}{d_{ij}}$ with $w_{ii} = 0$ by convention.

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 $J = ee^\intercal$, 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: $\lambda_{max}\frac{N}{W_0}$ and $\lambda_{min}\frac{N}{W_0}$ where λ_{max} and λ_{min} denote the largest and the smallest eigenvalues of Π 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 ith eigenvector. It can also be shown that the non-constant eigenvectors of Π are centered and have identical second moments.

With these eigenvectors in hand, we apply a translation $T_c : v \to v + c$ with $c \in \mathbb{R}^2_+$ to the non-constant eigenvectors of Π. 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 j 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

$$P_j = \prod_{s=1}^{S} P_{js}^{\alpha_{js}} \text{ and } P_{js} = \left(\int_{\omega_s \in \Omega_s} p_j(\omega_s)^{1-\sigma_s} d\omega_s \right)^{1/(1-\sigma_s)},$$

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

Production. Productivity in country j in sector s is A_{js}.

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} and j's total expenditure by $X_j \equiv \sum_{i=1}^{N} \sum_{s=1}^{S} X_{ijs}$. Across sectors, Cobb-Douglas preferences cause optimizing consumers to spend α_{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:

$$\lambda_{ijs} = \frac{X_{ijs}}{X_{js}} = \frac{\chi_{ijs} \left(\tau_{ijs} w_i\right)^{-\epsilon_s}}{\sum_{l=1}^{N} \chi_{ljs} \left(\tau_{ljs} w_l\right)^{-\epsilon_s}} = \frac{\chi_{ijs} \left(\tau_{ijs} w_i\right)^{-\epsilon_s}}{\Phi_{js}}.$$

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

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

In this environment, real consumption per capita is

$$\ln\left(\frac{C_j}{L_j}\right) = \sum_{s=1}^{S} \alpha_{js} \left(\ln A_{js} + \gamma_s - \frac{1}{\epsilon_s} \ln \lambda_{jjs} \right).$$

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

Dispersion in per capita welfare across countries thus depends on the exogenous variation in productivities A_{js} and the endogenous variation in domestic shares of expenditure λ_{jjs}. For the sake of expositional brevity, assume that $\sum_{s=1}^{S} \alpha_{js}\gamma_s$ is a constant. In that case, the variance of per capita welfare is

$$var\left(\ln\left(\frac{C_j}{L_j}\right)\right) = var\left(\sum_{s=1}^{S}\alpha_{js}\ln A_{js}\right) + var\left(\sum_{s=1}^{S}\frac{\alpha_{js}}{\epsilon_s}\ln\lambda_{jjs}\right) - 2\sum_{s=1}^{S}\sum_{s'=1}^{S}\frac{\alpha_s\alpha_{s'}}{\epsilon_{s'}}cov\left(\ln A_{js}, \ln\lambda_{jjs'}\right)$$

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, $var\left(\sum_{s=1}^{S}\alpha_{js}\ln A_{js}^{c}\right) = var\left(\sum_{s=1}^{S}\alpha_{js}\ln A_{js}^{u}\right)$. 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.

$$\begin{aligned} var\left(\ln\left(C_j^c/L_j\right)\right) - var\left(\ln\left(C_j^u/L_j\right)\right) = {} & 2\sum_{s=1}^{S}\sum_{s'=1}^{S}\frac{\alpha_s\alpha_{s'}}{\epsilon_{s'}}\left\{cov\left(\ln A_{js}^u, \ln\lambda_{jjs'}^u\right) - cov\left(\ln A_{js}^c, \ln\lambda_{jjs'}^c\right)\right\} \\ & - \sum_{s=1}^{S}\sum_{s'=1}^{S}\frac{\alpha_s\alpha_{s'}}{\epsilon_s\epsilon_{s'}}\left\{cov\left(\ln\lambda_{jjs}^u, \ln\lambda_{jjs'}^u\right) - cov\left(\ln\lambda_{jjs}^c, \ln\lambda_{jjs'}^c\right)\right\} \end{aligned}$$

Just as in the single-sector case, for typical values of the sectoral trade elasticities, $2\frac{\alpha_s\alpha_{s'}}{\epsilon_{s'}}$ is an order of magnitude larger than $\frac{\alpha_s\alpha_{s'}}{\epsilon_s\epsilon_{s'}}$. Thus, the difference in welfare dispersion is governed by the $cov\left(\ln A_{js}, \ln\lambda_{jjs'}\right)$ terms, provided that the block of $cov\left(\ln A_{js}, \ln\lambda_{jjs'}\right)$ terms is the same order of magnitude as the block of $cov\left(\ln\lambda_{jjs}, \ln\lambda_{jjs'}\right)$ terms.

B Data sources

Agricultural data Country-year cereal[30] output (in metric tons), yield (in metric tons per hectare), export quantity (in metric tons), export unit value (in current USD), and change in storage for 1961-2013 obtained from FAOstat.[31] Agriculture domestic share of expenditure constructed as the ratio of domestic expenditure over total expenditure. Agriculture domestic expenditure is the product of consumption of domestic good (i.e. output less export quantity) and export unit value. Agriculture total expenditure is the sum of domestic expenditure and import value (i.e. product of import quantity and import unit value). Bilateral value of cereal trade flows (exporter-importer-year value in current USD) for 1986-2013 obtained from FAOstat.

Non-agricultural data Country-year total output (obtained in current local currency and converted to current USD) for 1970-2013 from U.N. National Accounts Official Country Data.[32] Non-

[30] Aggregated across 8 major cereals: barley, maize, millet, oats, rice, rye, sorghum, and wheat.
[31] Available at http://www.fao.org/faostat/en/#data
[32] Available at http://data.un.org/Data.aspx?d=SNA&f=group_code%3a206

agriculture output value is the difference between total output value and agriculture output value. Country-year total import and export values (in current USD) for 1970-2013 from the World Bank's World Development Indicators (WDI).[33] Non-agriculture trade values is the difference between total trade values and agriculture trade values. Non-agriculture domestic share of expenditure constructed as the ratio of domestic expenditure over total expenditure. Non-agriculture domestic expenditure is the difference between non-agriculture output value and non-agriculture export value. Non-agriculture total expenditure is the sum of non-agriculture domestic expenditure and non-agriculture import value.

ENSO index Annual ENSO variations can be detected using different indices, with the most commonly used being equatorial Pacific sea surface temperature (SST) anomalies. Because ENSO activity peaks during December, we utilize 1960-2013 December values of the monthly Kaplan NINO3.4 index which averages SST over the area 5°N - 5°S, 170°W - 120°W (Kaplan et al., 1998).[34]

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, 1990*a*,*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).[35] 2014-2099 monthly data was first spatially aggregated from pixel to country-level using cross-sectional crop area weights from Ramankutty et al. (2008). 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.

Global oil prices Monthly West Texas Intermediate crude oil spot price obtained from the St. Louis Federal Reserve.[36] 1961-2013 annual values constructed by averaging January-December monthly values.

[33] Available at http://data.worldbank.org/data-catalog/world-development-indicators
[34] Available at http://iridl.ldeo.columbia.edu/SOURCES/.Indices/.nino/.EXTENDED/
[35] Available at https://climexp.knmi.nl/selectfield_cmip5.cgi
[36] Available at https://fred.stlouisfed.org/series/WTISPLC

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:

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

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.

Table C.1: Gravity regression for international trade in cereals

Outcome is log import value	
	(1)
$\ln \text{distance}_{ij}$	-1.519***
	(0.100)
R-squared	0.545
Country-level intra-industry trade share	0.614
Bilateral intra-industry trade share	0.236
Observations	59,927

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<0.01, ** p<0.05, * p<0.1.

C.2 Non-agriculture domestic share of expenditure

In order to perform welfare projections under climate change in a multi-sector setting (see Appendix D.3), we estimate how the non-agriculture domestic share of expenditure responds to local agricultural productivity and the global spatial correlation of agricultural productivity. Specifically, we conduct the same IV procedure detailed in Section 4.2, but replace the outcome variable in equation (8) with the domestic share of non-agricultural expenditure:

$$\ln \lambda_{iimt} = \phi_0 \ln A_{it} + \phi_1 \ln A_{it} I_t + \mathbb{Z}_{it} \Pi_m + \mu_{imt}$$

Table C.2 shows estimates of ϕ_0 and ϕ_1 corresponding to the domestic share of agricultural expenditure benchmark result in column 5, panel A of Table 2.

Table C.2: Domestic share of non-agricultural expenditure and spatial correlation in productivity

Outcome is log domestic share of expenditure	
	(1)
$\ln A_{it}$	-0.030
	(0.134)
$\ln A_{it} \times I_t$	0.053
	(0.562)
Cragg-Donald F-stat	23.83
Kleibergen-Paap F-stat	6.641
Anderson-Rubin weak-id robust p-value	0.784
Observations	2028

NOTES: IV estimates of equation (8) with the domestic share of non-agricultural expenditure. Quadratic ENSO functional form used for predicting instruments. Model incorporates country fixed effects, year fixed effects, and country-specific linear trends as included instruments. Standard errors clustered at country and continent-year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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):

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

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, $\bar{I} = .215$, by one standard deviation, $\sigma_I = .0192$. 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:

$$var(\ln A_{iu}) \equiv E_t[var_i(\ln A_{it}|t)] \tag{D.1}$$

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

$$cov(\ln A_{iu}, \ln \lambda_{iiu}) \equiv E_t[cov_i(\ln A_{it}, \ln \lambda_{iit}|t)] \tag{D.2}$$

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

$$var(\ln \lambda_{iiu}) \equiv E_t[var_i(\ln \lambda_{iit}|t)] \tag{D.3}$$

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

For the correlated state c, $var(\ln A_{ic})$ is also given by definitions (D.1) since we assume productivity variance is unaltered by changes in spatial correlation. $cov(\ln A_{ic}, \ln \lambda_{iic})$ and $var(\lambda_{iic})$, 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 $\ln \lambda_{it}$ from equation (8):

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

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:

$$\begin{aligned} cov(\ln A_{ic}, \ln \lambda_{iic}) \equiv (\widehat{\beta}_0 + \widehat{\beta}_1(\bar{I} + \sigma_I))E_t[var_i(\ln A_{it}|t)] \\ + E_t[cov_i(\ln A_{it}, \mathbb{Z}_{it}\widehat{\Pi}|t)] + E_t[cov_i(\ln A_{it}, \widehat{\mu}_{it}|t)] \end{aligned} \tag{D.4}$$

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

$$\begin{aligned} var(\ln \lambda_{iic}) \equiv (\widehat{\beta}_0^2 + 2\widehat{\beta}_0\widehat{\beta}_1(\bar{I} + \sigma_I) + \widehat{\beta}_1^2(\bar{I} + \sigma_I)^2)E_t[var_i(\ln A_{it}|t)] \\ + E_t[var_i(\mathbb{Z}_{it}\widehat{\Pi}|t)] + E_t[var_i(\widehat{\mu}_{it}|t)] \\ + 2(\widehat{\beta}_0 + \widehat{\beta}_1(\bar{I} + \sigma_I))E_t[cov_i(\ln A_{it}, \mathbb{Z}_{it}\widehat{\Pi}|t)] \\ + 2(\widehat{\beta}_0 + \widehat{\beta}_1(\bar{I} + \sigma_I))E_t[cov_i(\ln A_{it}, \widehat{\mu}_{it}|t)] \\ + 2E_t[cov_i(\mathbb{Z}_{it}\widehat{\Pi}, \widehat{\mu}_{it}|t)] \end{aligned} \tag{D.5}$$

Each term in equations (D.4) and (D.5) is either directly observable or can be obtained by estimating equation (8). For example, for the model estimated in column 5 of panel A in Table 2, with $\widehat{\beta}_0 = 2.219$ and $\widehat{\beta}_1 = -7.783$, we have:

$$\begin{aligned} E_t[var_i(\ln A_{it}|t)] &= .454 \\ E_t[var_i(\mathbb{Z}_{it}\widehat{\Pi}|t)] &= .816 \\ E_t[var_i(\widehat{\mu}_{it}|t)] &= .100 \\ E_t[cov_i(\ln A_{it}, \mathbb{Z}_{it}\widehat{\Pi}|t)] &= -.234 \\ E_t[cov_i(\ln A_{it}, \widehat{\mu}_{it}|t)] &= .000784 \\ E_t[cov_i(\mathbb{Z}_{it}\widehat{\Pi}, \widehat{\mu}_{it}|t)] &= -.00151 \end{aligned}$$

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

$$\frac{var\left(\ln \frac{C_{ic}}{L_{ic}}\right) - var\left(\ln \frac{C_{iu}}{L_{iu}}\right)}{var(\ln(C_{iu}/L_{iu}))} = \frac{var\left(\ln A_{ic}\right) - \frac{2}{\epsilon}cov\left(\ln A_{ic}, \ln \lambda_{iic}\right) + \frac{1}{\epsilon^2}var\left(\ln \lambda_{iic}\right)}{var\left(\ln A_{iu}\right) - \frac{2}{\epsilon}cov\left(\ln A_{iu}, \ln \lambda_{iiu}\right) + \frac{1}{\epsilon^2}var\left(\ln \lambda_{iiu}\right)} - 1 \tag{D.6}$$

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, $\mathcal{T} = 2099$, 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 (15) for $\ln A_{it}$ during the estimation period, $t \in [\underline{t}, \bar{t}]$:

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

Using equation (15) 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 $t \in [\bar{t}+1, \mathcal{T}]$:

$$\widehat{\ln A}_{it} = \widehat{k}(T_{it}) + \mathbb{X}_{i\bar{t}}\widehat{\Psi} + \widehat{\nu}_{i\bar{t}} \tag{D.7}$$

Figure 13 shows $\widehat{k}()$ for our benchmark specification. Figure 14 shows the associated change in log agricultural productivity, $\widehat{\ln A}_{i,2099} - \ln A_{i,2013}$, for each country. In the left panel of Figure 15, the gray line shows $var(\widehat{\ln A}_{it})$ while the blue line shows $\widehat{I}_t$ computed using $\widehat{\ln A}_{it}$ for each projection year.

To compute the change in variance of welfare from the end of the estimation period, $\bar{t}$, to any year during the projection period, $t \in [\bar{t}+1, \mathcal{T}]$, we difference equation (2):

$$\begin{aligned} var\left(\ln(C_{it}/L_{it})\right) - var\left(\ln(C_{i\bar{t}}/L_{i\bar{t}})\right) = & [var(\widehat{\ln A}_{it} - var(lnA_{i\bar{t}})] \\ & - (2/\epsilon)[cov(\widehat{\ln A}_{it}), \widehat{\ln \lambda}_{iit}) - cov(\ln A_{i\bar{t}}, \ln \lambda_{ii\bar{t}})] \\ & + (1/\epsilon^2)[var(\widehat{\ln \lambda}_{iit}) - var(\ln \lambda_{ii\bar{t}})] \end{aligned} \tag{D.8}$$

We consider two scenarios for obtaining future domestic share of expenditure, $\widehat{\ln \lambda}_{iit}$. 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, $t \in [\bar{t}+1, \mathcal{T}]$, is computed using our benchmark estimate of equation (8):

$$\widehat{\ln \lambda}^{n}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}})\widehat{\ln A}_{it} + \mathbb{Z}_{i\bar{t}}\widehat{\Pi} + \widehat{\mu}_{i\bar{t}} \tag{D.9}$$

Equations (D.7) and (D.9) allows construction of $var(\widehat{\ln \lambda}^{n}_{iit})$ and $cov(\widehat{\ln A}_{it}, \widehat{\ln \lambda}^{n}_{iit})$ 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 15.

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, $t \in [\bar{t}+1, \mathcal{T}]$, is computed using our benchmark estimate of equation (8):

$$\widehat{\ln \lambda}^{s}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 \widehat{I}_t)\widehat{\ln A}_{it} + \mathbb{Z}_{i\bar{t}}\widehat{\Pi} + \widehat{\mu}_{i\bar{t}} \tag{D.10}$$

Equations (D.7) and (D.10) allows construction of $var(\widehat{\ln \lambda}^{s}_{iit})$ and $cov(\widehat{\ln A}_{it}, \widehat{\ln \lambda}^{s}_{iit})$ 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 15.

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:

$$\frac{var\left(\ln\left(C^{s}_{i,2099}/L^{s}_{i,2099}\right)\right) - var\left(\ln\left(C_{i,2013}/L_{i,2013}\right)\right)}{var\left(\ln\left((C^{n}_{i,2099}/L^{n}_{i,2099}\right)\right) - var\left(\ln\left((C_{i,2013}/L_{i,2013}\right)\right)} - 1 \tag{D.11}$$

In our 1-sector model with baseline parameters, allowing climate change to alter the spatial correlation of productivities predicts a 61% greater increase in welfare variance than when spatial correlation is held fixed.

D.3 Calculating change in variance of welfare under climate change: 2-sector

This section calculates welfare projection implications in a multi-sector setting. We consider two simplifications to the multi-sector variance of welfare expression in equation (7). First, there are two sectors, agriculture and non-agriculture, $s \in \{a, m\}$. The global variance of welfare in any period t is:

$$\begin{aligned} var\left(\ln\left(\frac{C_{it}}{L_{it}}\right)\right) = {} & \alpha_a^2 var(\ln A_{iat}) + \alpha_m^2 var(\ln A_{imt}) + 2\alpha_a\alpha_m cov(\ln A_{iat}, \ln A_{imt}) \\ & - \frac{2\alpha_a^2}{\epsilon_a} cov\left(\ln A_{iat}, \ln \lambda_{iiat}\right) - \frac{2\alpha_a\alpha_m}{\epsilon_m} cov(\ln A_{iat}, \ln \lambda_{iimt}) \\ & - \frac{2\alpha_m^2}{\epsilon_m} cov\left(\ln A_{imt}, \ln \lambda_{iimt}\right) - \frac{2\alpha_n\alpha_a}{\epsilon_a} cov(\ln A_{imt}, \ln \lambda_{iiat}) \\ & + \frac{\alpha_a^2}{\epsilon_a^2} var(\ln \lambda_{iiat}) + \frac{\alpha_m^2}{\epsilon_m^2} var(\ln \lambda_{iimt}) + \frac{2\alpha_a\alpha_m}{\epsilon_a\epsilon_m} cov\left(\ln \lambda_{iiat}, \ln \lambda_{iimt}\right) \end{aligned} \tag{D.12}$$

where now $\epsilon_a = 8.59$ and we add $\epsilon_m = 4.14$ (Simonovska and Waugh, 2014). The average agricultural expenditure share in our data is $\alpha_a = 0.17$ and $\alpha_m = 1 - \alpha_a = .83$.

Second, we assume that climate change does not affect the variance of non-agricultural produc-

tivity, $var(\ln A_{imt})$, or the spatial correlation of non-agricultural productivity, I_{mt}.[37] This implies that any variance or covariance term in equation (D.12) containing $\ln A_{imt}$ will be differenced away under climate change. Thus, the difference in the variance of welfare from the end of the estimation period, $\bar{t}$, to any year in the projection period, $t \in [\bar{t}+1, \mathcal{T}]$ is:

$$\begin{aligned} var\left(\ln\left(\frac{C_{it}}{L_{it}}\right)\right) - var\left(\ln\left(\frac{C_{i\bar{t}}}{L_{i\bar{t}}}\right)\right) = \alpha_a^2 \left(var(\widehat{\ln A}_{iat}) - var(\ln A_{ia\bar{t}})\right) \\ - \frac{2\alpha_a^2}{\epsilon_a}\left(cov\left(\widehat{\ln A}_{iat}, \widehat{\ln \lambda}_{iiat}\right) - cov\left(\ln A_{ia\bar{t}}, \ln \lambda_{iia\bar{t}}\right)\right) \\ - \frac{2\alpha_a\alpha_m}{\epsilon_m}\left(cov(\widehat{\ln A}_{iat}, \widehat{\ln \lambda}_{iimt}) - cov(\ln A_{ia\bar{t}}, \ln \lambda_{iim\bar{t}})\right) \\ + \frac{\alpha_a^2}{\epsilon_a^2}\left(var(\widehat{\ln \lambda}_{iiat}) - var(\ln \lambda_{iia\bar{t}})\right) \\ + \frac{\alpha_n^2}{\epsilon_m^2}\left(var(\widehat{\ln \lambda}_{iimt}) - var(\ln \lambda_{iim,\bar{t}})\right) \\ + \frac{2\alpha_a\alpha_m}{\epsilon_a\epsilon_m}\left(cov\left(\widehat{\ln \lambda}_{iiat}, \widehat{\ln \lambda}_{iimt}\right) - cov\left(\ln \lambda_{iia\bar{t}}, \ln \lambda_{iim\bar{t}}\right)\right) \end{aligned} \tag{D.13}$$

The first, second, and fourth terms in equation (D.13) are agricultural terms identical to those used in the single-sector welfare calculations. Computing the remaining three terms in equation (D.13) requires one additional estimate: the causal effect of local agricultural yield and the global spatial correlation in yield on the domestic share of expenditure for non-agricultural goods. Those additional effects, discussed in Appendix C.2, are ϕ_0 and ϕ_1 in equation (C.2) and estimated in Table C.2. Each of the non-agricultural terms in equation (D.13) depends on spatial correlation, so they will differ between projections that omit and include changes in spatial structure.

Variance projection omitting changes in spatial structure Holding the spatial correlation of productivity fixed, the non-agriculture domestic share of expenditure during the projection period, $t \in [\bar{t}+1, \mathcal{T}]$, is computed using our benchmark estimate of equation (C.2):

$$\widehat{\ln \lambda}^n_{iimt} = (\widehat{\phi}_0 + \widehat{\phi}_1 I_{\bar{t}})\widehat{\ln A}_{it} + \mathbb{Z}_{i\bar{t}}\widehat{\Pi}_m + \widehat{\mu}_{im\bar{t}} \tag{D.14}$$

Equation (D.14) also facilitates construction of $cov(\widehat{\ln A}_{it}, \widehat{\ln \lambda}^n_{iimt})$, $var(\widehat{\ln \lambda}^n_{iimt})$, and $cov(\widehat{\ln \lambda}^n_{iiat}, \widehat{\ln \lambda}^n_{iimt})$ for each year in the projection period. These are then fed into equation (D.13) 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 dashed gray line in the right panel of Figure 15.

[37] This assumption is partly necessitated by data limitations: we are not aware of a source of plausibly exogenous variation in the spatial correlation of non-agricultural productivity that could be employed to estimate the relevant parameters. This is why our paper focuses on agricultural trade.

Variance projection including changes in spatial structure Allowing the spatial correlation of productivity to vary under climate change, the non-agriculture domestic share of expenditure during the projection period, $t \in [\bar{t}+1, \mathcal{T}]$, is computed using our benchmark estimate of equation (C.2):

$$\widehat{\ln \lambda}^{s}_{iimt} = (\widehat{\phi}_0 + \widehat{\phi}_1 \widehat{I}_t)\widehat{\ln A}_{it} + \mathbb{Z}_{i\bar{t}}\widehat{\Pi}_m + \widehat{\mu}_{im\bar{t}} \tag{D.15}$$

Equation (D.15) also facilitates construction of $cov(\widehat{\ln A}_{it}, \widehat{\ln \lambda}^{s}_{iimt})$, $var(\widehat{\ln \lambda}^{s}_{iimt})$, and $cov(\widehat{\ln \lambda}^{s}_{iiat}, \widehat{\ln \lambda}^{s}_{iimt})$ for each year in the projection period. These are then fed into equation (D.13) 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 dashed red line in the right panel of Figure 15.

Difference across projections For the period 2013-2099, we again apply equation (D.11) to calculate the percentage difference in the change in welfare variance between projections that include and omit changes in spatial correlation. In our 2-sector model with baseline parameters, allowing climate change to alter the spatial correlation of productivities predicts a 50% greater increase in welfare variance than when spatial correlation is held fixed.

D.4 Calculating change in country-level welfare under climate change

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

$$\ln (C_{it}/L_{it}) = \ln A_{it} + \gamma - \frac{1}{\epsilon} \ln \lambda_{iit}.$$

For the projection period, the productivity of country i, $\widehat{\ln A}_{it}$ 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, $t \in [\bar{t}+1, \mathcal{T}]$, is:

$$\widehat{\ln \lambda}^{n}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}})\widehat{\ln A}_{it} + \widehat{\kappa} I_{\bar{t}} + \mathbb{Z}_{i,\bar{t}}\widehat{\Pi} + \widehat{\mu}_{i\bar{t}} \tag{D.16}$$

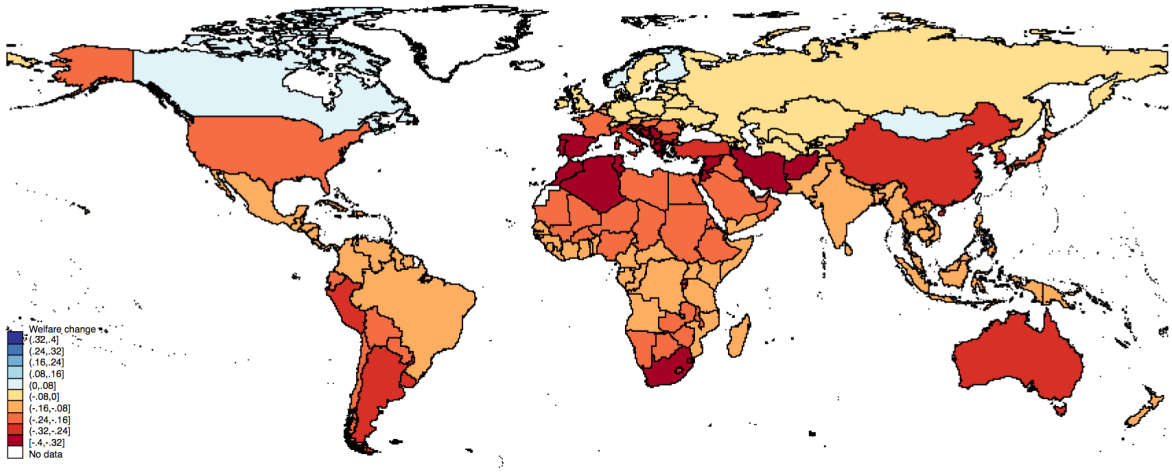
where spatial correlation affects both the average domestic share of expenditure (κ) and its relationship to domestic productivity (β_1).[38] The difference in country i welfare between end of the estimation period and the end of the projection period is:

$$\ln(C^{n}_{i\mathcal{T}}/L^{n}_{i\mathcal{T}}) - \ln(C_{i\bar{t}}/L_{i\bar{t}}) = [\widehat{\ln A}_{i\mathcal{T}} - \ln A_{i\bar{t}}] - (1/\epsilon)\left[(\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}})(\widehat{\ln A}_{i\mathcal{T}} - \ln A_{i\bar{t}})\right] \tag{D.17}$$

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

[38] To obtain κ, we first recover year fixed effects from equation (8). $\widehat{\kappa} = 11.17$ is the coefficient from a linear regression of year fixed effects on I_t.

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.

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, $t \in [\bar{t}+1, \mathcal{T}]$ is:

$$\widehat{\ln \lambda}^{s}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 \widehat{I}_t)\widehat{\ln A}_{it} + \widehat{\kappa}\widehat{I}_t + \mathbb{Z}_{i,\bar{t}}\widehat{\Pi} + \widehat{\mu}_{i,\bar{t}}$$

Similarly, the difference in country i welfare between end of the estimation period and the end of the projection period is:

$$\ln(C^s_{i\mathcal{T}}/L^s_{i\mathcal{T}}) - \ln(C_{i\bar{t}}/L_{i\bar{t}}) = [\widehat{\ln A}_{i\mathcal{T}} - \ln A_{i\bar{t}}] - (1/\epsilon)\left[(\widehat{\beta}_0 + \widehat{\beta}_1 \widehat{I}_{\mathcal{T}})\widehat{\ln A}_{i\mathcal{T}} - (\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}}) \ln A_{i\bar{t}} + \widehat{\kappa}(\widehat{I}_{\mathcal{T}} - I_{\bar{t}})\right]$$

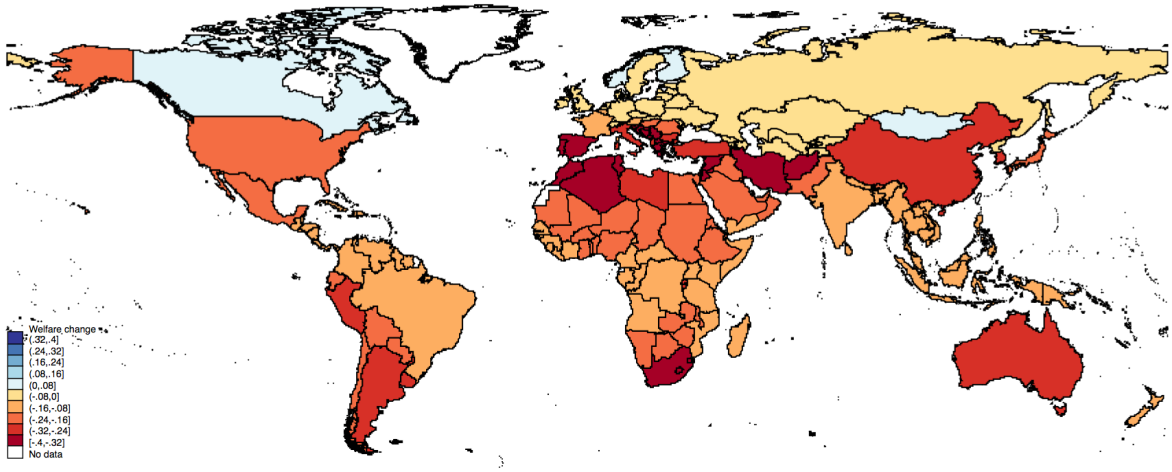
Figure D.2 shows the change in welfare for each country under this projection.

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

$$[\ln(C^s_{i\mathcal{T}}/L^s_{i\mathcal{T}}) - \ln(C_{i\bar{t}}/L_{i\bar{t}})] - [\ln(C^n_{i\mathcal{T}}/L^n_{i\mathcal{T}}) - \ln(C_{i\bar{t}}/L_{i\bar{t}})] = -(1/\epsilon)[(\widehat{\beta}_1 \widehat{\ln A}_{i\mathcal{T}} + \widehat{\kappa})(\widehat{I}_{\mathcal{T}} - I_{\bar{t}})] \quad \text{(D.18)}$$

Figure 16 shows the country-level difference across projections.

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.

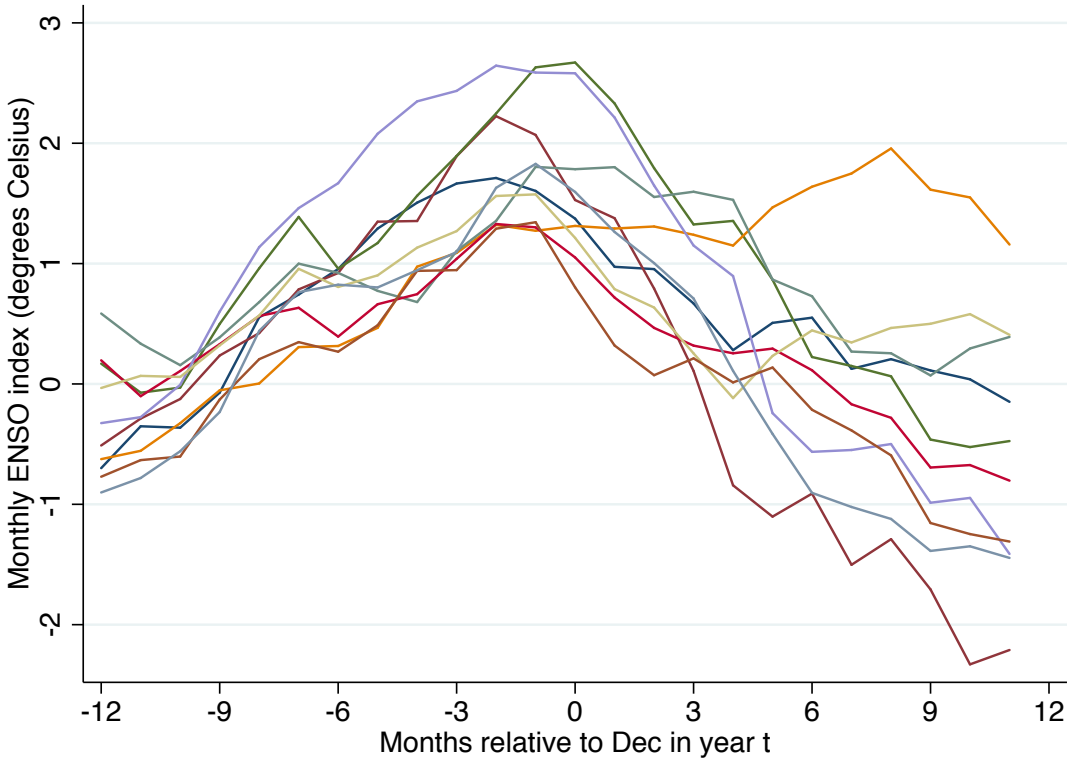
E Appendix figures

Figure E.1: Location of NINO3.4 sea-surface temperature measurements



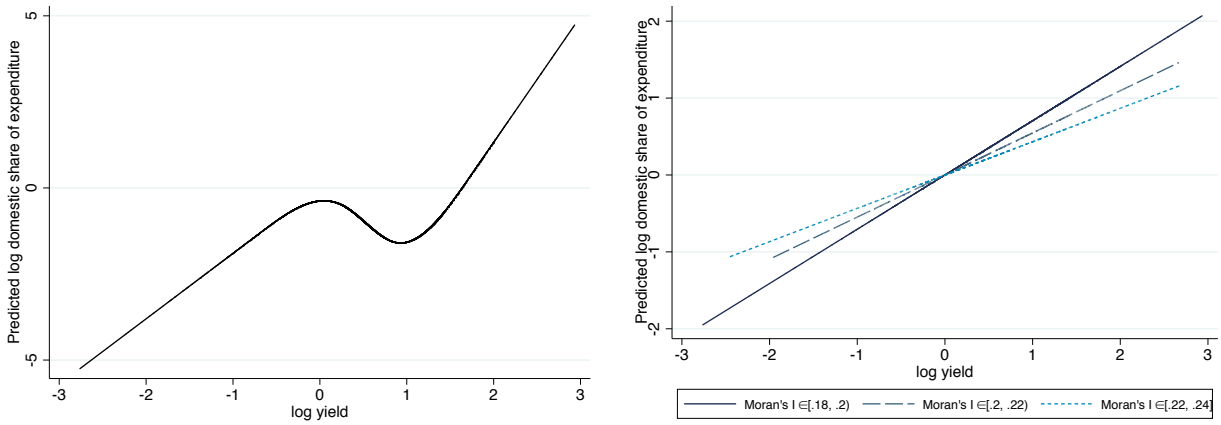
NOTES: Dark grey rectangle spanning 5°N-5°S and 170°W-120°W is the NINO3.4 region over which sea surface temperatures are averaged to compute the NINO3.4 index.

Figure E.2: Monthly ENSO index for top 10 positive events



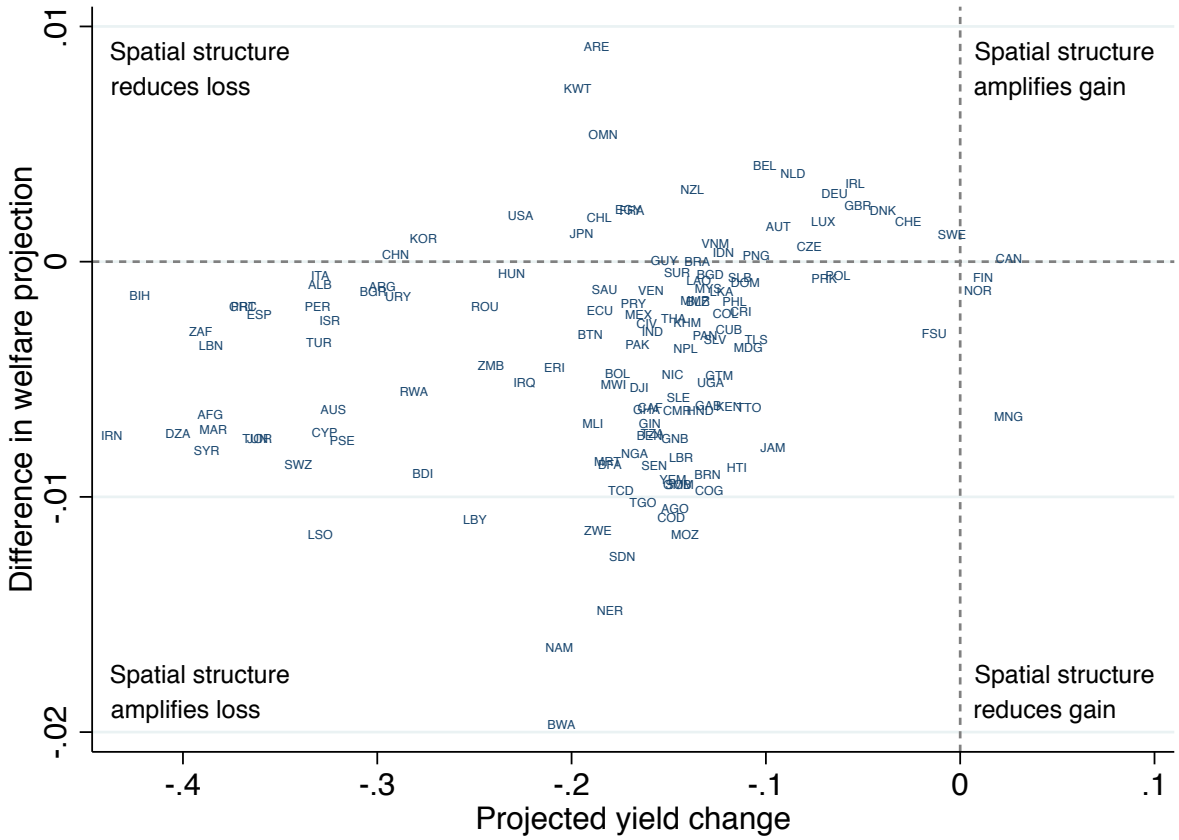
NOTES: Monthly evolution of ENSO index 12 months before and after the 10 most positive ENSO events over 1961-2013. ENSO events occur during the winters of 1965, 1972, 1982, 1986, 1991, 1994, 1997, 2002, 2006, and 2009.

Figure E.3: Robustness: Nonlinearities in second-stage functional form



NOTES: Left panel fits a restricted cubic spline function to log yield. Spline functions for endogenous yield and exogenous ENSO-predicted yield have four knots placed along the support according to Harrell (2001). Right panel assumes log yield function is linear and discretizes Moran's I into three evenly-spaced bins with similarly discretized instruments. All models based on IV estimator corresponding to column 5, panel A of Table 2.

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 16) plotted against change in log cereal yields (from Figure 14) over 2013-2099 under climate change. Countries labeled by ISO3 identifier.

F Appendix tables

Table F.1: Robustness: country and year clustered standard errors

Outcome is log domestic share of expenditure					
	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV
			Panel A: Linear trends		
$\ln A_{it}$ (β_0)	0.363**	3.754***	3.785***	2.133***	2.219***
	(0.163)	(1.229)	(1.043)	(0.660)	(0.605)
$\ln A_{it} \times I_t$ (β_1)	0.645	-14.333**	-14.471***	-7.382**	-7.783***
	(0.747)	(5.743)	(5.018)	(2.935)	(2.655)
Pct. change in welfare variance from 1 s.d. increase in I_t	-0.300	6.510**	6.571***	3.389**	3.571***
	(0.348)	(2.558)	(2.162)	(1.372)	(1.251)
ENSO poly. order for predicting $\ln A_{it}$		1	1	2	2
ENSO poly. order for predicting I_t		1	2	1	2
Cragg-Donald F-stat		22.95	24.78	64.52	67.84
Kleibergen-Paap F-stat		30.55	10.03	11.16	10.23
Anderson-Rubin weak-id robust p-value		1.62e-09	0	0	0
Observations	5681	5681	5681	5681	5681
			Panel A: Linear trends		
$\ln A_{it}$ (β_0)	0.406*	3.473***	3.575***	3.100***	3.091***
	(0.204)	(1.240)	(0.980)	(1.063)	(0.777)
$\ln A_{it} \times I_t$ (β_1)	0.501	-13.471**	-13.952***	-12.073**	-12.028***
	(0.870)	(5.959)	(4.747)	(4.967)	(3.537)
Pct. change in welfare variance from 1 s.d. increase in I_t	-0.233	6.127**	6.341***	5.503**	5.483***
	(0.404)	(2.585)	(2.036)	(2.228)	(1.626)
ENSO poly. order for predicting $\ln A_{it}$		1	1	2	2
ENSO poly. order for predicting I_t		1	2	1	2
Cragg-Donald F-stat		17.25	21	24.86	26.02
Kleibergen-Paap F-stat		8.783	10.06	5.453	10.70
Observations	5681	5681	5681	5681	5681

NOTES: Estimates of equation (8). Column 1 shows OLS estimates. Columns 2-5 show IV estimates. Columns 2-5 differ in the ENSO functional form used for predicting instruments. All models incorporate country and year fixed effects as included instruments. Panel A (B) includes global or country-specific linear (quadratic) trends in equations (8)-(12). 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 country and year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.2: Robustness: log cereal yield and local temperature

Outcome is log cereal yields						
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature 1st term	0.004	0.004	0.005	0.005	0.007	0.005
	(0.010)	(0.010)	(0.011)	(0.010)	(0.013)	(0.012)
Temperature 2nd term	-0.183***	-0.165***	-0.222***	-0.203**	-0.126*	-0.100
	(0.047)	(0.043)	(0.085)	(0.082)	(0.075)	(0.072)
Temperature 3rd term	0.650***	0.599***	0.418*	0.393*	0.020	-0.031
	(0.201)	(0.189)	(0.245)	(0.237)	(0.255)	(0.242)
Temperature 4th term	-1.162*	-1.100*	0.356	0.248	1.320*	1.394*
	(0.663)	(0.641)	(0.807)	(0.765)	(0.784)	(0.740)
Temperature 5th term			-2.204	-1.801	-2.895	-3.370
			(2.199)	(2.104)	(2.437)	(2.341)
Temperature 6th term					1.830	3.213
					(5.077)	(4.929)
Precipitation		0.003***		0.003***		0.003***
		(0.001)		(0.001)		(0.001)
Precipitation squared		-0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)
Number of knots	5	5	6	6	7	7
Temp. joint p-value	0.0001	0.0003	0.0002	0.0006	0.0005	0.0013
Optimal temp.	8.81	8.91	8.87	8.94	7.80	7.70
Observations	7226	7226	7226	7226	7226	7226

NOTES: Estimates of cubic spline terms for $h()$ in equation (15). 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. Optimal temperature indicates temperature associated with highest predicted log cereal yield. Standard errors clustered at country and continent-year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.