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International Risk Sharing for Food Staples

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Abstract

The global output of food staples is far more stable than most individual nations' outputs, but does this lead to consumption risk sharing? This paper applies tools from the risk sharing literature to address this question for rice, wheat, and maize, using a multilateral risk sharing model that, unlike the canonical model, accounts for trade costs. While the data show that optimal risk sharing does not occur, the wheat market comes closest to the idealized model. Our analysis also implies that both trade and storage play significant roles in smoothing domestic output shocks. Further, we find that risk sharing tends to rise with a nation's income.

Keywords: food markets, risk sharing, international trade, supply shocks

JEL Classification: **F14, Q17, D52**

1. INTRODUCTION

1.1 Trade and Risk in Food Staples

Domestic food staple output variation imposes risk that nations would like to reduce. Such risk presents a particular challenge to poorer people by threatening their food security; for instance, rice, wheat, and maize account for about half of dietary energy intake and about a quarter of total spending for people in the bottom quintile of the income distribution (Dawe et al., 2015). Thus, output reductions and concomitant price rises for these key crops can especially harm vulnerable people. Fortunately, nations can mitigate risk across space through international trade, international investment with ownership claims across outputs, and foreign aid. Nations can also mitigate risk across time through such mechanisms as storage, borrowing and lending, and crop insurance.

While nations can mitigate risk in theory, to what extent do they do so in practice? In this paper, we analyze one aspect of this question: the role that international trade plays in consumption risk sharing. We do so by developing a novel international risk sharing model that accounts for bilateral trade costs and using it to estimate for the first time the extent of actual versus feasible risk sharing in the rice, wheat, and maize markets. We also explore two related issues of interest: how risk sharing differs across rich and poor nations, and the amount of risk sharing that occurs through trade versus storage.

Trade makes risk reduction possible because the world output of food staples varies only a little, with standard deviations (measured as the difference in the log values of output over successive time periods) of 0.044 for rice, 0.065 for wheat, and 0.046 for maize. Stable world output combined with trade enables nations to pool risks, since trade in effect merges all markets together. A nation in a trading world can access output from any other trading nation. Since global output fluctuates far less than domestic outputs, trading nations face lower risk. Thus, in theory, trade enables individual nations to achieve more consumption stability than if they were in autarky. This has led economists to advocate international trade as an effective mechanism for price and consumption stabilization (Valdes, 1981; Krishna et al., 1983; Srinivasan and Jha, 2001; Dorosh, 2001; Timmer, 2008; Gilbert, 2011).[1]

Determining how well international trade mitigates risk requires using theory and empirics, which we will do below. At this point, though, a simple data comparison provides a general sense for the state of the world. In addition to the world output variations mentioned above, consider output and consumption variation at the national level. Figure 1 plots national consumption variation (y-axis) and national output variation (x-axis). For all commodities, the bulk of the scatter lies below the 45 degree line indicating that consumption variability is lower than output variability in most

[1] World consumption is even more stable than world output: standard deviations of 0.023 for rice, 0.024 for wheat, and 0.031 for maize. This indicates that nations use other means, such as storage and safety nets, to reduce risk even lower than can be achieved through trade alone.

countries. Most of the scatter, though, is also above the horizontal line, which represents global output variation. Thus, few countries achieve a level of consumption variation as low as world output variation. Similar data comparisons (not reported here) show that low income countries have output variations similar to high income countries but substantially higher consumption variation, indicating less risk sharing among poorer nations.

Although suggestive, these data comparisons are not conclusive. Even with optimal risk sharing, significant trade costs can dampen trade, disconnecting local consumption from global production. The consumption smoothing that we see could arise from storage rather than trade. Further, even when trade works well, consumption can vary significantly due to idiosyncratic demand shocks.[2] We address these possibilities in our analysis and still find that risk sharing is incomplete. We also find that storage plays an important role in smoothing consumption against idiosyncratic risks.

1.2 Relevant Literature

Several studies have analyzed how nations or regions within nations use global or national markets to reduce risk. Canova and Ravn (1996), Lewis (1996), Sorensen and Yosha (1998), and Crucini (1999) apply the benchmark risk sharing modeling of

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[2] We thank an anonymous referee for pointing us to these mechanisms.

Cochrane (1991) and Mace (1991) to the international or national context to test for perfect risk sharing. While the others assume a single consumption good, Lewis (1996) breaks consumption down into traded versus non-traded goods, as well as durable versus non-durable goods, but does not consider such key commodities as rice, wheat, and maize. Asdrubali et al (1996), Sorensen and Yosha (1998), and Crucini (1999) not only test for risk sharing but estimate its extent as well.

These papers assume international transfers incur no transaction costs that would hinder trade and prevent perfect risk sharing. Assuming costless trade overstates *feasible* risk sharing and thus understates the extent to which nations share risks. This paper advances the literature by adding trade costs to an international risk sharing model to shed light on how feasible risk sharing differs from perfect risk sharing.[3] Our approach modifies the standard econometric specification used to test for feasible risk sharing by allowing heterogeneity in the time fixed effects.

Distinct from the risk sharing literature just discussed, a large literature analyzes world markets for basic staples. Two components of this literature have special relevance for this paper. One strand examines the connection between global prices and domestic markets. Studies find that world price shocks generally have limited effects on domestic prices (Baquedano and Liefert, 2014; Ceballos et al., 2017; Dawe et

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[3] A small literature has explored **household** risk sharing with trade costs—see Schulhofer-Wohl (2011) and Jack and Suri (2014)--but no papers known to us explore international risk sharing with trade costs.

al., 2015; De Janvry and Sadoulet, 2010; Gilbert, 2011; Minot, 2011; Mundlak and Larson, 1992; Robles et al., 2010). This property implies that risk sharing is limited, due to trade restrictions or other policies that drive wedges between domestic and global markets. We depart from this literature by focusing not on price variation but consumption variation, which connects readily to welfare.[4]

The second strand analyzes trade barriers that arise from market insulating behavior, in which nations use trade policies to shield their domestic markets from global price volatility. Nations try to protect against price spikes by restricting exports or reducing tariffs and doing the opposite for price collapses. If all nations insulate their domestic markets, global food markets become extremely thin, magnifying global food price volatility (Abbott, 2011; Martin and Anderson, 2011; Giordani et al., 2016; Gilbert and Morgan, 2010; Mitra and Josling, 2009; Headey, 2011; Slayton, 2009). A widely cited instance is the behavior of rice markets during 2007-2008 when government panic buying and export prohibitions contributed to price spikes (Dawe and Slayton, 2011; Timmer, 2008; Wright, 2011). Such unreliability in world food markets could be one reason that risk sharing falls short of the optimum. Gouel and Jean (2015) show that some degree of insulating behavior can be optimal for a small open economy. The nation has an incentive to use storage policies to smooth

[4] Jha et al. (2016) is one of the few papers to analyze consumption variability and how domestic and foreign output shocks affect it. Their paper's estimation and results, though, do not occur within a well-defined risk sharing framework.

consumption and reduce aggregate risk, but, since openness to trade can cause stored output to leak overseas, smoothing consumption using storage requires trade restrictions in some states of the world.

2. THEORETICAL FRAMEWORK

Section 2.1 reviews the standard risk sharing model with no costs and introduces notation. This canonical model predicts that optimal consumption of the basic economic unit (such as a household or a nation) varies only with aggregate output of the collection of units (such as a village or the world) and is uncorrelated with output of the basic unit (Townsend, 1987). A large literature has employed tests based on this principle. This implies that, conditional on world output, individual national consumption does not vary with that nation's output.

Sections 2.2 and 2.3 extend the model to account for trade costs. We find that individual national consumption does not vary with the nation's own output once we account for consumption covariation with an "aggregate risk function", which is a complicated function of national outputs rather than the simple sum total. Trade costs enter as parameters in the aggregate risk function. One can think of this as conditional or feasible risk sharing. Introducing trade costs limits risk sharing by creating the possibility that the benefits of risk reduction fall short of the costs of trading. After developing the model, we take the predictions to data using econometric methods appropriate for estimating the extent of feasible risk sharing.

2.1 Standard Model with No Trade Costs

The theoretical structure in this section follows Canova and Ravn (1996), Lewis (1996), and Sorensen and Yosha (1998) by adapting the framework in Cochrane (1991) and Mace (1991) to an international setting. Townsend (1987) provides a foundational analysis for these articles. They assume an infinite number of time periods, so that they can consider consumption smoothing over time. To focus on trade costs, our model uses a one-period framework and thus abstracts from consumption smoothing and storage. The empirical analysis in Section 6, though, considers how storage can play a role in risk sharing with trade costs and estimates the extent to which nations use storage.

Consider a world with N nations and a finite number of states. Each state denoted s occurs with exogenous probability π_s. With S as the number of states, $\sum_{s=1}^{S} \pi_s = 1$. For each of the three goods, each nation i has a risk averse representative consumer with utility function $U_i = u_i(c_{is})$, where c_{is} is the amount consumed of the good in state s, and $u_i(c_{is})$ is continuous, monotonically increasing, concave, and twice differentiable. Each nation thus has expected utility $\sum_{s=1}^{S} \pi_s \, u_i(c_{is})$.

The best possible outcome for the world results when a social planner maximizes a weighted sum of expected utilities: $\sum_{i=1}^{N} \alpha_i \sum_{s=1}^{S} \pi_s \, u_i(c_{is})$, where α_i is the fixed exogenous Pareto weight the social planner applies to country i. Each nation is endowed with y_{is} units in state s. In each state, the total resource endowment constrains total consumption:

(1) $$\sum_{i=1}^{N} c_{is} = \sum_{i=1}^{N} y_{is} \equiv Y_s.$$

As Cochrane (1991) points out, we would get the same results if we were to extend the model to include a production function that links the total amount of consumption available in different states. In this case, the planner could first allocate production aggregates across states and then determine optimal consumption, taking those previously allocated outputs as endowments.

Maximizing gives the following first order condition (FOC):

(2) $$\alpha_i \pi_s u_i'(c_{is}^*) = \lambda_s^*,$$

where λ_s^* is the Lagrange multiplier on the aggregate resource constraint of the commodity. This multiplier depends on the total worldwide endowment Y_s. Once we take account of this, the consumption of a nation does not depend on its own output. There is perfect risk sharing in any given state.

Each nation has a FOC analogous to (2). For any pair of nations, i and j, divide their FOCs to get

(3) $$\frac{\alpha_i u_i'(c_{is}^*)}{\alpha_j u_j'(c_{js}^*)} = 1.$$

For each state, the social planner allocates the good so all nations have the same weighted marginal utility.

Now consider the following definitions and proposition.

Definition 1: Nation i is linked to nation j if $u_i'(c_{is}^*) \propto u_j'(c_{js}^*)$.

Definition 2: A set of nations in which any two nations are linked is a network.

Thus, for any two nations i and j in a network, $u_i'(c_{is}^*) \propto u_j'(c_{js}^*)$. The number of nations in a network can range from 2 to N.

Definition 3: An aggregate risk function for a network is a function of the member nations' outputs such that, conditional on this function, the output of a member nation does not affect its optimal consumption.

Equations (2) and (3) imply that, with no trade costs, the marginal utilities of all nations are proportional. This gives the following:

Proposition 1: When there are no trade costs, all nations in the world comprise a single network whose aggregate risk function A is simply the sum of individual outputs: $A = \sum_{i=1}^{N} y_{is}$.

Trade costs alter this result, as the next section shows.

2.2 Model with Trade Costs

The global equilibrium in (2) depends on the social planner making costless transfers across nations. The planner freely allocates the given global endowment so that the expected marginal benefit equals the social marginal cost λ_s^* for each nation. If transfers are costly, though, with each one shrinking the good's global endowment, then (2) does not apply, and perfect risk sharing is lost. In this case, we have conditional risk sharing. Also, trade costs can cause the world to break up into different networks. Nations engaged in such costly trade still have aggregate risk functions that depend on the outputs of all nations in the same trading network, but these functions are not simple sums of nation outputs as in Proposition 1. These results shed light on how we need to adjust the estimation approach to take account of trade costs. Specifically, aggregate shocks captured by time dummies ought to vary across networks, rather than assuming a homogeneous shock for all nations.

Suppose moving one unit of the good to nation i from nation j requires shipping $d_{ij} > 1$ units of that good from j. Thus, $d_{ij} - 1$ is the per-unit trade cost: the extra resources required to ship each unit of the good from j to i. We assume that these costs are symmetric: $d_{ij} = d_{ji}$. We also invoke the triangle inequality: For any three nations, i, j, and k, $d_{ij} < d_{ik}d_{kj}$. This means that shipping goods directly between two nations always costs less than going through a third nation.

Without trade costs, the social planner could make any transfer needed to make each FOC hold and maximize utility. With trade costs, though, a marginal transfer from j to i raises welfare only if the benefit exceeds the cost: $\alpha_i u_i'(c_{is}^*) > d_{ij}\alpha_j u_j{}'\left(c_{js}^*\right)$. This inequality captures the fact that reaping the marginal gain $\alpha_i u_i'(c_{is}^*)$ in i requires giving up $d_{ij}\alpha_j u_j{}'\left(c_{js}^*\right)$ worth of benefits in j. Likewise, a transfer from i to j raises welfare only if $d_{ji}\alpha_i u_i'(c_{is}^*) < \alpha_j u_j{}'\left(c_{js}^*\right)$. Because of trade costs, these conditions may not be met: the marginal social gain of transfers may not outweigh the associated trade costs. Thus, possible trades may not occur, and marginal utilities may not equalize across nations, meaning that perfect risk sharing does not occur.

Definition 4: A nation is autarkic in the Pareto optimal risk sharing solution if that nation neither exports nor imports the good.

For an autarkic nation, the marginal costs of both exporting and importing outweigh the respective marginal gains. Such a nation's aggregate risk function is simply its own output.

Definition 5: A nation is connected if it is not autarkic.

Two nations i and j are connected to each other if one exports to the other.

Since, with trade costs, it is possible for nations to be autarkic in the Pareto optimal solution, there might not be a single network that spans all nations. Also, there could be multiple networks. In this paper, we do not seek to characterize all possible networks.

Since the triangle inequality rules out any nation acting as an entrepot, with a homogeneous good we have:

Proposition 2: A connected nation either exports or imports the good but not both.

This implies that importers are not connected to each other and that exporters are not connected to each other.

If nation i trades with nation j, then Pareto optimal risk sharing requires that

(4) $$\alpha_i u_i'(c_{is}^*) = d_{ij}\alpha_j u_j{}'\left(c_{js}^*\right).$$

The following is immediate.

Proposition 3: If two nations are connected, then they are linked. (See Definition 1.)

Definition 6: The trade group of a nation consists of itself and the set of nations connected to it.

Thus, nation i's trade group consists of the nations to which it exports or the nations from which it imports. Trade groups can overlap. For instance, suppose nations i and j both import only from k. In this case, i's trade group consists of itself and k, and j's trade group consists of itself and k. These two trade groups overlap, since each contains k.

Proposition 4: If the trade groups of two unconnected nations overlap, then those two nations are linked.

Proof: Since the trade groups overlap, nations i and j are connected to at least one common nation, denoted k. The marginal utilities of i and j are proportional to that of k. Thus, i's marginal utility is proportional to that of j's, and they are thereby linked.

Note that Proposition 4 implies the converse of Proposition 3 is not true: nations can be linked without being connected.

Proposition 4 and the definition of a network lead to the final two propositions:

Proposition 5: The union of all overlapping trade groups is a network.

Proposition 6: Within a network, each nation has an aggregate risk function.

Proof: Consider a network W. Each nation in W is linked to every other nation in W. Thus, within W, each nation's marginal utility is proportional to each of the other nations' marginal utilities. Thus, a change in any of the nation's outputs changes all the nations' consumptions. It follows that, within W, each nation's consumption depends only on a single function of all outputs. This means that each nation in W has an aggregate risk function.

This result is important because it means that trade costs do not undermine risk sharing. We get **modified** risk sharing. For instance, if a nation's output drops, that nation will not suffer the full brunt of the drop. The nation will import from others in the network, minimizing the cost of that drop, given trade costs.

2.3 Special Cases

To shed further light on how nations can share risk with trade costs, consider examples of the aggregate risk function for some special cases. First, consider the simplest case of two nations 1 and 2 with stochastic endowments y_1 and y_2. Suppose a constant relative risk aversion utility function where γ is the coefficient of relative risk aversion. Focus on the case where the stochastic shocks are such that it is always optimal for nation 2 to export to nation 1. The same argument applies to the reverse trade pattern. Appendix A.1 shows the social planner chooses consumption levels given by $c_1^* = \frac{d_{12}\eta}{1+d_{12}\eta}(y_1 + \frac{y_2}{d_{12}})$ and $c_2^* = \frac{d_{12}}{1+d_{12}\eta}(y_1 + \frac{y_2}{d_{12}})$, where d_{12} is the cost of shipping a unit from 2 to 1, and $\eta \equiv \left(\frac{1}{d_{12}}\frac{\alpha}{1-\alpha}\right)^{\frac{1}{\gamma}}$. We see that each nation has the same aggregate risk function $A = y_1 + \frac{y_2}{d_{12}}$ (Zero trade costs would give the standard result that consumption depends on total output, ie, that $A = y_1 + y_2$.). A is the aggregate output available for sharing after accounting for trade costs. Adjusting for them, everything follows as in the zero trade cost case. In particular, conditional on the adjusted aggregate output, consumption allocations do not depend on individual outputs. Because the aggregate shock is adjusted for trade costs, this is a case of feasible risk sharing.

Appendices A.2 and A.3 show this result generalizes to networks with one exporter and many importers or one importer and many exporters. In the former case, if nation N exports to all others, then $A = d_{1N}y_1 + d_2y_2 + \cdots + d_{N-1}y_{N-1} + y_N$. In the latter case, if nation 1 imports from all others, then $A = y_1 + \frac{y_2}{d_{12}} + \cdots + \frac{y_N}{d_{1N}}$. In each of these instances, we have just one trade group.

We examine one other scenario: a network with two exporters and two importers. Such a situation has three possible trading patterns: Each exporter trades with each importer; each exporter trades exclusively with one importer; and an imbalanced case in which one exporter trades with one importer, while the other exporter trades with both importers. Appendix A.4 shows that the first pattern is not viable, as fixed trade costs imply nations trade only with the single nation whose shipping cost is lowest. Both exporters trading with both importers is not optimal unless trade costs happen to be exactly equal. The second case just means that the four nations break up into two bilateral pairs, and we are back to the two-nation case for each. The third case is instructive. Suppose that nations 3 and 4 are the exporters, and that 3 exports only to 1, while 4 exports to both 1 and 2. In this instance, nations 3 and 4 are not connected because they both export; likewise, nations 1 and 2 are not connected because they both import. Yet, nations 3 and 4 are linked because 3 is linked to 1, and 1 is linked to 4. Further, 1 and 2 are linked because 1 is linked to 3, which we have just seen is linked to 4, which is linked to 2. So, all four nations are part of the same network and thus have the same aggregate risk function. In particular, Appendix A.4 shows that

$A = \frac{y_1}{d_{24}} + \frac{y_2}{d_{14}} + \frac{y_3}{d_{13}d_{24}} + \frac{y_4}{d_{14}d_{24}}$. So, even imbalanced trade with trade costs leads to conditional risk sharing for all nations in the network.

It is worth emphasizing that the world can have multiple networks of different types. As shown above, each network will have a common aggregate risk function, meaning that we can analyze empirically each network in a way similar to how researchers have analyzed international risk sharing under the assumption of zero trade costs. The differences across networks, though, require output shocks to be heterogeneous across networks in the empirical analysis.

3. EMPIRICAL GROUNDWORK

This section begins the process of using the theoretical framework to assess empirically the amount of risk sharing among trading nations. The major implication of trade costs is that aggregate shocks are not the same across nations, requiring, as we shall first see, time fixed effects to vary across nations in a panel data framework. We then discuss our data sources, descriptive statistics, and key correlations before moving on to estimation in Section 4.

3.1 From Theoretical Model to Empirical Model

In each of the special modeling cases considered in Section 2.2, optimal consumption in a fully risk sharing nation depends on a nation-specific constant and an aggregate risk function: $c_{it}^* = \beta_i A_t$. As shown in the examples above, this β_i is a function of Pareto weights, taste parameters, and trade costs. Assuming that the parameters that determine β_i stay constant through time, the relationship holds for all t. This implies that $\frac{c_{i,t+1}^*}{c_{it}^*} = \frac{\beta_i A_{t+1}}{\beta_i A_t} = \frac{A_{t+1}}{A_t} \Rightarrow \ln \frac{c_{i,t+1}^*}{c_{it}^*} = \ln \frac{A_{t+1}}{A_t} \Rightarrow \Delta \ln c_{it}^* = \Delta \ln A_t$. So, the risk sharing model says that the log change of consumption should only depend on the log change in the aggregate risk function: Only trade-cost-adjusted aggregate output shocks should change consumption.

We can test this by then specifying the following regression equation:

$$(5) \qquad \Delta \ln c_{it}^* = \delta_i + \mu_t + \theta \Delta \ln \tilde{y}_{it} + \epsilon_{it},$$

where $\Delta \ln A_t$ is replaced by a time fixed effect μ_t. The nation dummy δ_i captures any time-invariant nation-specific consumption influences outside the model, and ϵ_{it} is an error term. The domestic output term, $\Delta \ln \tilde{y}_{it}$, captures violations of risk sharing; θ is its regression coefficient.[5] From theory, for all nations within the same network, full risk sharing requires θ to be zero; with no trade costs, this zero applies to all nations,

[5] If there are idiosyncratic demand shocks, the parameters that determine β_i may shift over time. In such a case, $\Delta \ln c_{it}^* = \Delta \ln \beta_{it} + \Delta \ln A_t$. In transitioning to (5), the demand shock merges into the time dummies and error term. The risk sharing parameter is identified if demand shocks are uncorrelated with output shocks. If demand shocks are correlated with output shocks, then we need an instrumental variable strategy to estimate θ. In section 4.2, we employ such a strategy to examine the robustness to errors in measurement. This also serves to examine the robustness to correlated demand shocks.

since no trade costs imply one global network. We test whether θ is between 0 and 1, with 0 implying full risk sharing, and 1, no risk sharing. Equation (5) is thus the standard specification to test risk sharing in a world with zero trade costs.

A world with trade costs likely contains multiple networks, each likely with a different aggregate risk function. This means we should modify (5) to allow the time fixed effects to vary across nations. Furthermore, while (5) assumes constant θ, the theory does not impose such a restriction. Accordingly, we explore both of these types of heterogeneity in the empirical analysis below.

3.2 Data

The Food and Agriculture Organization's (FAO) `Food Balance Sheets' dataset (FAOSTAT, 2014) provides nation-level time series (1961-2013) for output, domestic supply, food consumption, stock variations, and trade of major agricultural commodities. This allows construction of large panels, which are unbalanced due to missing data for some years for some small nations. We focus on three important staple food commodities: rice, wheat, and maize. Our consumption measure includes food, feed, and other uses.[6] We calculate consumption as follows: Consumption = Output +

[6] The alternative is to include consumption as food only. This is not appropriate for maize as its primary use is as livestock feed and as feedstock in biofuel output. Second, as pointed out by an anonymous referee, the arbitrages are likely to be the same for food and feed crops, so what happens to the feed market should be as interesting and informative as what happens to the food market.

Imports – Exports - Stock Variation.

We convert the consumption and output quantities into per capita terms using the population figures from the World Bank World Development Indicators (WDI) database. To match the regression equations specified above, we take logs and first differences of per capita consumption and output to get year-on-year growth rates. To guard against the possibility that small nations may drive the results, we weight our summary statistics and regressions,[7] using population shares as weights, since they are highly correlated with consumption shares, and since population is not directly used in the regressions other than to normalize consumption and output.

Figure 2 plots the trends in trade of rice, wheat, and maize as a proportion of their outputs. The volume of rice trade was almost stagnant until the 1990s when it started showing a significant rising trend. Export liberalization in India in 1993 and the rise of Vietnam as a major rice exporter drove this increase (Jha et al., 2016). Wheat trade volume varies a lot with no visible trend. Maize trade increased in the 1970s and peaked in 1980 before showing a declining trend. Over the period, 1961-2013, wheat is the most traded commodity, with about 18% of output traded on average, followed by maize at 12% and rice at 4%. This suggests that consumption risk sharing is likely the greatest for wheat markets.

[7] We owe this insight to an anonymous referee.

3.3 Correlations

As a step towards testing the predictions of the efficient risk sharing hypothesis, we examine the correlation of the growth in domestic consumption with the growth in domestic output and with the growth in world output for rice, wheat, and maize. Figure 3 summarizes these correlations. The solid lines show the trend in the median decadal moving average correlations of domestic consumption and world output growth, and the dashed lines show the trend in the corresponding correlations of domestic consumption with domestic output. The estimated correlation coefficients between domestic consumption and world output are well below unity, while domestic consumption is correlated with domestic output for the entire period. The first result indicates that markets are not fully open, and the second that risk sharing is imperfect. These results imply that it will be worthwhile to explore how much risk sharing nations achieve in a world with trade costs, which we do in Section 4.

We break down these correlations by national income levels. Following the World Bank classification, we consider four groups: low income, lower middle income, upper middle income, and high income. For the sake of brevity, Figure 4 displays these results only for low- and high-income nations. For all three goods, poor nations have slightly higher correlations between domestic consumption and output growth (red dotted lines), implying lower risk sharing. The domestic consumption and world output correlations (blue solid lines) have dropped over time in poorer nations for rice and maize, indicating diminishing international integration, with an especially steep initial drop in rice and a small recovery thereafter. For rich nations, though, the correlations do not show much of a trend.

4. TESTS OF RISK SHARING WITHOUT TRADE COSTS

4.1 Benchmark Specification

We first consider the benchmark case with no trade costs and thus estimate (5). For notational convenience, rewrite (5) as

$$c_{it} = \delta_i + \mu_t + \theta y_{it} + \epsilon_{it}, \tag{6}$$

where $c_{it} \equiv \Delta \ln c_{it}^{*}$ and $y_{it} \equiv \Delta \ln \tilde{y}_{it}$. As discussed above, controlling for aggregate shocks, optimal risk sharing implies consumption should be independent of idiosyncratic shocks: $\theta = 0$. Rejection implies nations cannot fully insure themselves from idiosyncratic supply shocks; hence consumption will be correlated with output. In that case, $1 - \theta$ is a measure of the degree of insurance or risk sharing achieved.

Several studies (Asdrubali et al., 1996; Lewis, 1996; Sørensen and Yosha, 1998; Sørensen et al., 2007; Kose et al., 2009) have conducted tests of risk sharing based on a version of (6). The idea is that time dummies will remove the common component in both consumption and output growth, meaning that we can interpret θ as the effect of idiosyncratic output growth on idiosyncratic consumption growth. Thus, a two-way fixed effects specification provides a simple way to control for unobserved heterogeneity at the nation level and common time effects for all nations.[8]

Non-stationarity of the variables in (6) may lead to spurious estimates of θ. We thus conduct panel unit root tests and report the results in Appendix B (Table B1). We see that, while the variables are non-stationary in levels, the null of unit roots are rejected for log first differences, meaning that we need not worry about non-stationarity in our regressions. We also test for serial correlation and heteroscedasticity. The F statistic is significant at the 1% level for the rice market, indicating serial correlation. For wheat and maize, the F statistic is significant at the 10% level. The χ^2 statistic is significant at 1% level for all three commodities, indicating heteroscedasticity (Appendix B, Table B2). Nation-clustered standard errors address these issues.

The first column of Table 1 shows the results of regressing consumption growth on domestic output growth (y_{it}) without nation and time dummies for each of the three food staples. The second column adds the nation dummies, while the third column—the preferred specification—includes time dummies as well. The addition of time dummies in the third specification leads to a minor increase in R^2 but leaves the

[8] A straightforward extension of the model in Section 2.1 to multiple commodities would deliver the prediction that the allocation of a good depends not only on aggregate endowments of the same good but also on aggregate endowments of all the other goods in the utility function. The time fixed effects covers this possibility.

coefficient unchanged. This is because these regressions are estimated on first differences (of logs), removing aggregate trends in the data.[9] These results are robust across specifications. The fourth column omits time dummies and instead adds the growth rate of global consumption as a control for aggregate shocks. The estimates are robust to this specification as well.

The estimates of θ differ significantly from zero for the three grains, rejecting the optimal risk sharing hypothesis. These results reinforce our earlier observation that nations seem unable to insulate domestic consumption from idiosyncratic output shocks. Comparing the degree of risk sharing across food markets in Table 1, the wheat market performs best, providing 88% insurance against domestic output shocks, compared to 75% for rice and 67% for maize.

Table 2 presents the estimates of θ for large and small consumers and producers of the three commodities separately.[10] We define large consumer or producer nations as those whose consumption or output exceeds 5% of the world's total. Table 2 shows large consumers and producers share risk less than small ones. Thus, both large consumers and large producers rely less on international food markets for consumption smoothing. In theory, large consuming nations should share risk as much as small

[9] We estimated these regressions in (log) levels and found that the coefficient on log output does decrease with the addition of time dummies.
[10] We thank an anonymous referee for proposing this analysis.

ones. As noted in Table 2, though, large consumers are also large producers[11], which are more likely to engage in market insulating policies and thus less likely to risk share. Table 3 shows evidence that large consumers risk share less. This table shows results using inverse population shares as weights. This means that smaller consumers are given a larger weight than larger ones. With this inverse population share weighting scheme, estimates of θ are smaller, indicating more risk sharing as a whole. Since giving more weight to smaller nations raises the overall estimate of risk sharing, we conclude that large nations share risk less.

4.2 Robustness

We test the robustness of our results using additional controls: shocks to per capita gross domestic product (GDP) at constant prices, fluctuations in the national GDP deflator, fluctuations in the nominal exchange rate, and an indicator variable for when the nation joined the World Trade Organization (WTO). Table 4 has these results. The control variables are for the most part statistically insignificant and do not influence the magnitude of the coefficient on output shocks y_{it}. We also test for time trends by interacting y_{it} with a linear trend in (6). The coefficient on the interaction term (Column 6) is statistically significant and negative for rice and maize, indicating that risk sharing

[11] The correlations between average consumption and output shares across nations for rice, wheat, and maize are 0.88, 0.73, and 0.90, respectively.

in the rice and maize markets has improved over time.

Appendix C reports two additional robustness tests. C.1 shows tests for the lagged and lead effects of output shocks on consumption growth: The estimates of θ are robust to these additional variables. C.1 also adds lagged consumption growth as a regressor to test for serially correlated measurement error in consumption aggregates, resulting from different conventions on the reporting time periods across countries. These estimates for θ remain significant but are lower: 0.19 for rice, 0.065 for wheat, and 0.20 for maize.

In C.2, we address the concern that measurement errors in output may bias the estimates by implementing the Lewbel (2012) instrumental variable estimator. These results are comparable to the estimates from the benchmark specification.

We also checked for the robustness of our results using the alternative `Production, Supply and Distribution' database of the United States Department of Agriculture (Table C.3 in Appendix C). The estimated θ coefficients remain highly statistically significant and are comparable with the results from the FAO database.

4.3 Heterogeneity in the Risk Sharing Coefficient

Equation (6) assumes that the coefficient of the individual output shock, θ, is the same across nations, the typical assumption in risk sharing tests. The theoretical framework imposes no such restriction. Let us, therefore, drop it and posit a more general version of (6):

(7) $c_{it} = \delta_i + \mu_t + \theta_i y_{it} + \epsilon_{it}$,

where $\theta_i = \theta + \nu_{it}$, and ν_{it} is a mean zero random variable. Substituting for θ_i,

(8) $c_{it} = \delta_i + \mu_t + \theta y_{it} + \nu_{it} y_{it} + \epsilon_{it}$.

A fixed effects estimation of (8) is inconsistent whenever the deviation ν_{it} is correlated with the sample variance of y_{it} (Wooldridge, 2005). A consistent estimator for θ is the mean group estimator (Pesaran and Smith, 1995), obtained by estimating (8) for each nation and then taking the average of the estimated θ coefficients across all regressions.

The first row of Table 5 displays the mean group estimates of θ for the three food staple markets. Compared to the Table 1 benchmark results, allowing for heterogeneity leads to a decrease in the magnitude of the wheat estimates, while the estimates for other commodities do not change much. Since the mean group estimator provides an estimate of θ for each nation separately, Table 5 also presents the averages of these θ's for large and small consumers. Here again, large consumers show a higher average θ, or lower risk sharing.

4.4 Heterogeneity in Risk Sharing by Income

As observed in Figure 4, risk sharing could vary with per capita income. Here we extend the benchmark specification to examine this possibility. This also provides the opportunity to see across nation groups the change in risk sharing over time. To do this, we allow θ to vary across income groups of nations with a nation-group specific linear time trend, specified as $\phi_1 + \psi_1 t + \sum_{g=2}^{4}(\phi_g + \psi_g t)INC_g$, where INC_g is a dummy variable for each of the four income groups, denoted g. Substituting for θ in the benchmark specification (6), we obtain $c_{it} = \delta_i + \mu_t + [\phi_1 + \psi_1 t + \sum_{g=2}^{4}\big(\phi_g + \psi_g t\big)INC_g]y_{it} + \epsilon_{it}$. Table 6 has the results. Low-income nations have the lowest degree of risk sharing, which rises with income. For example, rice consumption in low-income nations is insured against only 38% of the shocks to output, while domestic consumption is almost completely insured from output shocks in high-income nations (Column 1). Wheat has a similar situation. For maize, high-income nations fall short of complete insurance but come close. The difference in the degree of risk sharing between low- and high-income nations for all three goods is statistically significant. We also see from Table 6 that θ declines and risk sharing improves over time in low-income nations for all three commodities, more so for rice and maize.

The difference in the extent of risk sharing can also be seen graphically in Figure 5, which displays the marginal impacts of idiosyncratic output shocks on consumption growth rates for the different nation groups. These marginal impacts are evaluated in 1987, the mid-point of the 1961-2013 period.

5. TESTS OF FEASIBLE RISK SHARING WITH TRADE COSTS

As discussed at the end of Section 3.1, trade costs could lead to multiple networks, each with a different aggregate risk function. This calls for allowing the time fixed effect to vary across nations.[12] In this section, we model heterogeneous time effects in three ways. The first method follows Pesaran (2006) in assuming random coefficients. The other two methods allow the time effect to vary across networks but neglect variation within networks. The second method assumes networks are determined entirely by distance, partitions the world into K clusters, and determines network-time fixed effects accordingly. The third method assumes a fixed number of networks but allows network membership to be estimated from the data (Bonhomme and Manresa, 2015) and thus allows networks to depend on more than just distance.

5.1 Heterogeneity in Aggregate Shocks: A Random Coefficient Model

We maintain heterogeneity in the risk sharing coefficient but allow for a random coefficient, ζ_i, on the time fixed effect, to capture the fact that trade costs can cause aggregate shocks to affect different nations differently. Modifying (8), we get

[12] Divergent preferences could also be another reason for heterogeneity. For instance, as consumption patterns differ across nations, a global supply shock in rice matters more to some nations than others.

(9) $$c_{it} = \delta_i + \zeta_i \mu_t + \theta y_{it} + \nu_{it} y_{it} + \epsilon_{it}.$$

Because a nation is the cross-sectional unit in the panel, we cannot estimate this model with nation-time fixed effects. We thus use the Pesaran (2006) common correlated effects framework to model the unobserved heterogeneity in aggregate shocks. Average (9) across the cross-section units to get $\frac{1}{N}\sum_{i=1}^{N} c_{it} = \frac{1}{N}\sum_{i=1}^{N} \delta_i + \frac{1}{N}\mu_t \sum_{i=1}^{N} \zeta_i + \frac{1}{N}\theta \sum_{i=1}^{N} y_{it} + \frac{1}{N}\sum_{i=1}^{N} \nu_{it} y_{it} + \frac{1}{N}\sum_{i=1}^{N} \epsilon_{it}$, which can be expressed as $\bar{c}_t = \bar{\delta} + \mu_t \bar{\zeta} + \theta \bar{y}_t + \bar{\epsilon}_t + \frac{1}{N}\sum_{i=1}^{N} \nu_{it} y_{it}$, where bars indicate cross-section averages. For large N, the averages converge to the population magnitudes, causing the last two terms to vanish. Hence, we can consistently estimate θ by a linear combination of the nation fixed effect and the cross-sectional averages of consumption and output. Pesaran (2006) uses this insight to show that the following equation estimates θ_i for each nation:

(10) $$c_{it} = \delta_i + \theta_i y_{it} + \alpha_i \bar{c}_t + \beta_i \bar{y}_t + \varepsilon_{it}.$$

The average estimate of these $\theta_i{}'s$ is a consistent estimator of θ. This is the common correlated effect mean group (CCEMG) estimator. Table 5 displays the CCEMG estimates, which do not differ much from the mean group estimates. We reject Pareto optimal risk sharing for all three food staples. As with the previous results, these estimates imply that wheat has more risk sharing than rice and maize.

5.2 Distance-based Networks

For this second method, we group nations into networks according to distance with the K-means clustering algorithm, a method of partitioning N elements into K clusters. Each observation is assigned a cluster with the closest mean where the number of clusters is fixed exogenously. We use the latitude and longitude of each nation's centroid for clustering, which groups nations based on bilateral distances.

Figure 6 shows the average bilateral distance among nations in a group, with the number of groups ranging from 1 to 50. Naturally, as the number of groups rises, the average distance among group members drops. These clusters mimic the trade linkages that may form between countries if bilateral distance is the only variable impeding trade. If trade happens only within these groups, then the weighted average output of all group members is the relevant aggregate shock for each country. Consider therefore the following version of the group fixed effect regression,

$$(11) \quad c_{it} = \delta_i + \mu_{g(d)t} + \theta y_{it} + \epsilon_{it},$$

where the time fixed effects, $\mu_{g(d)t}$, are group specific, and group membership depends on bilateral distances. Since we have no basis for fixing the number of groups, we run the above regression on all values of K, from 1 to 50. The idea is to see whether there is some value for the number of networks for which θ would be insignificant.

Figure 7 plots the estimated θ's from the regressions, with the number of groups on the horizontal axis. Although the estimated θ's decline somewhat for wheat and maize as the number of groups increases, they are still bounded away from zero for all three commodities. The results indicate that the wheat market could approach full risk sharing as distance-based trade costs decline. For rice and maize, it appears that something other than trade costs prevents full risk sharing.

5.3 Clustered Aggregate Shocks with Endogenous Group Membership

While distance-based group partitions are a reasonable way to capture trade relationships, distance does not always drive trade patterns. For instance, the US trades more with China than with Mexico. So, we can gain more confidence in the estimates by allowing group membership to flow from the data. Bonhomme and Manresa (2015) provide an approach for capturing unobserved group membership. Their group fixed effects (GFE) estimator allows for clustered time patterns of unobserved heterogeneity that are common within groups of countries. Rather than ad hoc assignment of units to groups, the group-specific time patterns and individual group membership are left unrestricted and estimated from the data. Thus, this estimator allows for networks based considerations other than distance.

In this framework, we can write the estimating equation as

$$(12) \quad c_{it} = \delta_i + \mu_{gt} + \theta y_{it} + \epsilon_{it},$$

where μ_{gt} is the time fixed effect specific to countries belonging to group g. Minimizing a least squares sum of residuals over all possible country groupings leads to group assignments that are functions of the given parameters. The group fixed effects estimator searches over the parameter space to minimize a least squares criterion given the group assignment function from the first step. The estimator is consistent for large N and T. The researcher chooses the number of groups beforehand.

We vary the number of groups from 2 to 7. Figure 8 shows the GFE estimates to be robust across these specifications. The last row of Table 5 reports the GFE estimates with five groups. Note that the estimates from the GFE are unweighted and hence not strictly comparable to the benchmark estimates. Allowing for these clustered aggregate shocks, though, does not change the basic narrative of incomplete risk sharing and how it varies across food staples.

6. RELATIVE CONTRIBUTIONS OF TRADE AND STORAGE

In a world without trade frictions, international trade in staple foods can achieve full insurance against idiosyncratic shocks (Gouel, 2014, 2016). The social planner can then choose storage to optimally smooth consumption over time, achieving maximum insurance against aggregate shocks.[13] When there are trade costs, especially large ones, it may make sense to store in order to insure against idiosyncratic risks as well (Gouel, 2014). In this section, we adapt the framework of Asdrubali et al. (1996) to quantify the contribution of trade and stocks to such risk sharing in the face of idiosyncratic risk. For the sake of exposition, we first assume homogeneous time fixed effects. The method generalizes to network-time fixed effects, and we present those results as well.

Consider the following identity,

$$(13) \qquad Y_{it} = \frac{Y_{it}}{Y_{it}^{NX}} \frac{Y_{it}^{NX}}{C_{it}} C_{it},$$

where Y_{it} and C_{it} are per capita output and consumption in nation i at time period t. Y_{it}^{NX} is output left after net exports. Mathematically, $Y_{it}^{NX} \equiv Y_{it} - NX_{it}$, where NX_{it} is net exports. Thus, we can express net exports as $NX_{it} = Y_{it} - Y_{it}^{NX}$. Consumption is the output left after net exports minus the change in stocks: $C_{it} = Y_{it}^{NX} - \Delta B_{it}$, where ΔB_{it} is the change in stocks. Thus, $\Delta B_{it} = Y_{it}^{NX} - C_{it}$. Note also that Y_{it}^{NX} is consumption plus change in stocks.

[13] Private sector storage might carry less stocks than optimal if consumers are risk averse and risk markets are missing (Gouel, 2013; Newbery, 1989). In this case, too, though, storage reduces volatility caused by aggregate shocks.

As shown in Appendix D1, the variance in demeaned per capita output can be decomposed as

$$(14) \quad Var(\ddot{y}_{it}) = Cov(\ddot{y}_{it}, \ddot{y}_{it} - \ddot{y}_{it}^{NX}) + Cov(\ddot{y}_{it}, \ddot{y}_{it}^{NX} - \ddot{c}_{it}) + Cov(\ddot{y}_{it}, \ddot{c}_{it}),$$

where $\ddot{y}_{it} = \Delta \ln \ddot{Y}_{it}$, $\ddot{y}_{it}^{NX} = \Delta \ln \ddot{Y}_{it}^{NX}$, and $\ddot{c}_{it} = \Delta \ln \ddot{C}_{it}$. Double dots over variables denote demeaning with respect to both nations and time periods. Thus, the variance in output is comprised of its covariance with three variables: net exports, the change in stocks, and consumption.

Dividing through by $Var(\ddot{y}_{it})$, we get

$$(15) \quad 1 = \frac{Cov(\ddot{y}_{it}, \ddot{y}_{it} - \ddot{y}_{it}^{NX})}{Var(\ddot{y}_{it})} + \frac{Cov(\ddot{y}_{it}, \ddot{y}_{it}^{NX} - \ddot{c}_{it})}{Var(\ddot{y}_{it})} + \frac{Cov(\ddot{y}_{it}, \ddot{c}_{it})}{Var(\ddot{y}_{it})}.$$

The right-side variables are regression coefficients. The last term on the right is the θ coefficient with nation and time fixed effects that we have been examining all along. Denoting the first two coefficients by θ^T and θ^S—for trade and storage—we have $1 = \theta^T + \theta^S + \theta \Rightarrow 1 - \theta = \theta^T + \theta^S$. As discussed in Section 4.1 above, $1 - \theta$ measures the amount of risk sharing for a given commodity. Thus, we have decomposed risk sharing into the two mechanisms that accomplish it: trade and storage. By estimating θ^T and θ^S, we can quantify the fraction of risk sharing that results from these two mechanisms.

We thus run the following regressions:

$$(16) \quad y_{it} - y_{it}^{NX} = \delta_i^T + \mu_t^T + \theta^T y_{it} + \epsilon_{it}^T$$

$$(17) \quad y_{it}^{NX} - c_{it} = \delta_i^S + \mu_t^S + \theta^S y_{it} + \epsilon_{it}^S$$

In these regressions, we revert to the benchmark specification in which the time dummies do not vary by network group.

Table 7 reports the results. For reference, in Column 3, we show the estimates of θ from the corresponding benchmark regression, (6). Theory says that the three thetas from (16), (17), and (6) should add to 1, and they do. In the case of wheat, trade contributes more to risk sharing than storage ($\theta^T = 0.53 > \theta^S = 0.35$). For rice, domestic stocks play the dominant role ($\theta^T = 0.26 < \theta^S = 0.49$). For maize, trade and domestic stocks contribute about equally to risk sharing. Of the risk sharing that is achieved (measured by $1 - \theta$), trade is responsible for 35% ($\frac{0.26}{0.26+0.49}$) in rice, 60% ($\frac{0.53}{0.53+0.35}$) in wheat, and 53% ($\frac{0.36}{0.36+0.32}$) in maize.

In absolute terms, trade contributes more to smoothing domestic output shocks in wheat (53%) than in maize (36%) and rice (26%). We expect this, as wheat is one of the most traded food commodities in the global market and has fewer trade distortions than rice. In the case of maize, insurance through trade is lower than for wheat and closer to rice. This is contrary to our expectation as the total volume of maize exports far exceeds that for rice. The different varieties of maize traded could help to explain this. Dawe et al. (2015) study the price behavior of staple food commodities in low- and middle-income countries and find that domestic maize prices are more volatile than rice and wheat prices, because of the thin global market for white maize, which is mostly used for human consumption, especially in sub-Saharan Africa. (Maize in sub-Saharan Africa accounts for $30 - 50\%$ of total household consumption expenditure.)

We can generalize the regressions in (16), (17), and (6) to include heterogeneous time fixed effects as in the previous section. In Appendix D.2, Figures D1 and D2 plot the estimated trade and storage components of risk sharing using the K-means cluster estimator outlined in Section 5.2. These figures show that the qualitative results of the importance of trade in relation to storage follow the same pattern as in Table 7.

7. CONCLUSION

Greater stability in the growth of global food output than in national or regional output theoretically implies tremendous potential for trade to enable risk sharing across nations. No previous paper, though, has formally tested for risk sharing in world food markets. The present paper fills this gap in the literature by using the efficient risk sharing hypothesis as a benchmark to examine the extent to which trade insulates domestic consumption against domestic output shocks. We do this after suitably extending the existing theoretical and econometric methods to account for trade costs. We also compare the importance of trade relative to storage in risk sharing.

The rejection of the efficient risk sharing hypothesis likely does not surprise observers of world food markets. The superior performance of the wheat market in providing insurance also matches expectations. The finding, though, that the maize market performs just as poorly as the rice market is unexpected. One possible reason is that these markets have significant product differentiation, making it harder for the market to provide insurance. Another noteworthy finding is that both trade and storage provide insurance for all three markets. In the ideal frictionless world, trade would smooth all shocks. With trade costs, though, trade cannot smooth all shocks; so storage also plays an important role in smoothing consumption.

Limited risk sharing, especially in the maize and rice markets, is cause for concern. An additional concern is that such risk sharing is even lower for poorer nations. In rice, for example, low-income nations achieve only 38% of full insurance relative to almost complete insurance achieved by high-income nations. We see similar results in the wheat and maize markets. Improving risk sharing for poor nations can play a vital role in achieving food security. This paper provides grounds for such a discussion.

REFERENCES

Abbott, P. C. (2011) Export restrictions as stabilization responses to food crisis. *American Journal of Agricultural Economics*, 94(2):428–434.

Asdrubali, P., Sørensen, B. E., and Yosha, O. (1996) Channels of interstate risk sharing: United States 1963–1990. *The Quarterly Journal of Economics*, 111(4):1081–1110.

Baquedano, F. G. and Liefert,W. M. (2014) Market integration and price transmission in consumer markets of developing countries. *Food Policy*, 44:103–114.

Bonhomme, S. and Manresa, E. (2015) Grouped patterns of heterogeneity in panel data. *Econometrica*, 83(3):1147–1184.

Canova, F. and Ravn, M. O. (1996) International consumption risk sharing. *International Economic Review*, 573–601.

Ceballos, F., Hernandez, M. A., Minot, N., and Robles, M. (2017) Grain price and volatility transmission from international to domestic markets in developing countries. *World Development*, 94:305–320.

Cochrane, J. H. (1991) A simple test of consumption insurance. *Journal of Political Economy*, 99 (5):957–976.

Crucini, M. J. (1999) On international and national dimensions of risk sharing. *Review of Economics and Statistics*, 81(1):73–84.

Dawe, D. and Slayton, T. (2011) The world rice market in 2007-08. In Prakash, A., editor, *Safeguarding Food Security in Volatile Global Markets*, Chapter 9, pages 164–82. Food and Agriculture Organization of the United Nations, Rome.

Dawe, D., Morales-Opazo, C., Balie, J., and Pierre, G. (2015) How much have domestic food prices increased in the new era of higher food prices? *Global Food Security*, 5:1–10.

De Janvry, A. and Sadoulet, E. (2010) The global food crisis and Guatemala: What crisis and for whom? *World Development*, 38(9):1328–1339.

Dorosh, P. A. (2001) Trade liberalization and national food security: Rice trade between Bangladesh and India. *World Development*, 29(4):673–689.

FAOSTAT. (2014) *Food Balance Sheets*. URL http://www.fao.org/faostat.

Gilbert, C. L. (2011) Grains price pass-through, 2005-09. In Prakash, A., editor, *Safeguarding Food Security in Volatile Global Markets*, Chapter 7, pages 127–148. Food and Agriculture Organization of the United Nations, Rome.

Gilbert, C. L. and Morgan, C. W. (2010) Food price volatility. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 365(1554):3023–3034.

Giordani, P. E., Rocha, N., and Ruta, M. (2016) Food prices and the multiplier effect of trade policy. *Journal of International Economics*, 101:102–122.

Gouel, C. (2013) Optimal food price stabilisation policy. *European Economic Review*, 57:118–134.

Gouel, C. (2014) *Food Price Volatility and Domestic Stabilization Policies in Developing Countries*, in Chavas J.-P., Hummels D. and Wright B. (ed.) The Economics of Food Price Volatility. Chapter 7 (pp. 261-306). Chicago: University of Chicago Press.

Gouel, C. (2016) Trade policy coordination and food price volatility. *American Journal of Agricultural Economics*, 98(4):1018–1037.

Gouel, C., and Jean, S. (2015). Optimal food price stabilization in a small open developing country. *The World Bank Economic Review*, *29*(1), 72-101.

Headey, D. (2011) Rethinking the global food crisis: The role of trade shocks. *Food Policy*, 36 (2):136–146.

Jack, W. and Suri, T. (2014) Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review*, 104(1):183–223.

Jha, S., Kubo, K., and Ramaswami, B. (2016) International trade and risk sharing in the global rice market: The impact of foreign and domestic supply shocks. *Asian Development Review*, 33(1):162–182.

Kose, M. A., Prasad, E. S., and Terrones, M. E. (2009) Does financial globalization promote risk sharing? *Journal of Development Economics*, 89(2):258–270.

Krishna, R., Haykin, S., and Chhibber, A. (1983) *Policy modeling of a dual grain market: The case of wheat in India*. International Food Policy Research Institute.

Lewbel, A. (2012) Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1):67–80.

Lewis, K. K. (1996) What can explain the apparent lack of international consumption risk sharing? *Journal of Political Economy*, 104(2):267–297.

Mace, B. J. (1991) Full insurance in the presence of aggregate uncertainty. *Journal of Political Economy*, 99(5):928–956.

Martin, W. and Anderson, K. (2011) Export restrictions and price insulation during commodity price booms. *American Journal of Agricultural Economics*, 94(2):422–427.

Minot, N. (2011) *Transmission of world food price changes to markets in Sub-Saharan Africa*. International Food Policy Research Institute.

Mitra, S. and Josling, T. (2009) Agricultural export restrictions: Welfare implications and trade disciplines. *International Food & Agricultural Trade Policy Council (IPC)*, pages 1–37.

Mundlak, Y. and Larson, D. F. (1992) On the transmission of world agricultural prices. *The World Bank Economic Review*, 6(3):399–422.

Newbery, D. M. (1989) The theory of food price stabilisation. *The Economic Journal*, 99(398): 1065–1082.

Pesaran, M. H. (2006) Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4):967–1012.

Pesaran, M. H. and Smith, R. (1995) Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1):79–113.

Robles, M., Torero, M., and Cuesta, J. (2010) Understanding the impact of high food prices in Latin America. *Economia*, 10(2):117–164.

Schulhofer-Wohl, S. (2011) Heterogeneity and tests of risk sharing. *Journal of Political Economy*, 119(5):925–958.

Slayton, T. (2009) *Rice crisis forensics: How Asian governments carelessly set the world rice market on fire*. Center for Global Development working paper.

Sørensen, B. E. and Yosha, O. (1998) International risk sharing and European monetary unification. *Journal of International Economics*, 45(2):211–238

Sørensen, B. E., Wu, Y.-T., Yosha, O., and Zhu, Y. (2007) Home bias and international risk sharing: Twin puzzles separated at birth. *Journal of International Money and Finance*, 26(4):587–605.

Srinivasan, P. V. and Jha, S. (2001). Liberalized Trade and Domestic Price Stability. The Case of Rice and Wheat in India. *Journal of Development Economics*, 65(2), 417–441.

Timmer, C. P. (2008) *Causes of high food prices*. Technical report, ADB Economics Working Paper Series.

Townsend, R. M. (1987) Arrow-debreu programs as microfoundations of macroeconomics. In *Advances in Economic Theory: Fifth World Congress*, volume 2, pages 379–428. Cambridge University Press Cambridge, MA.

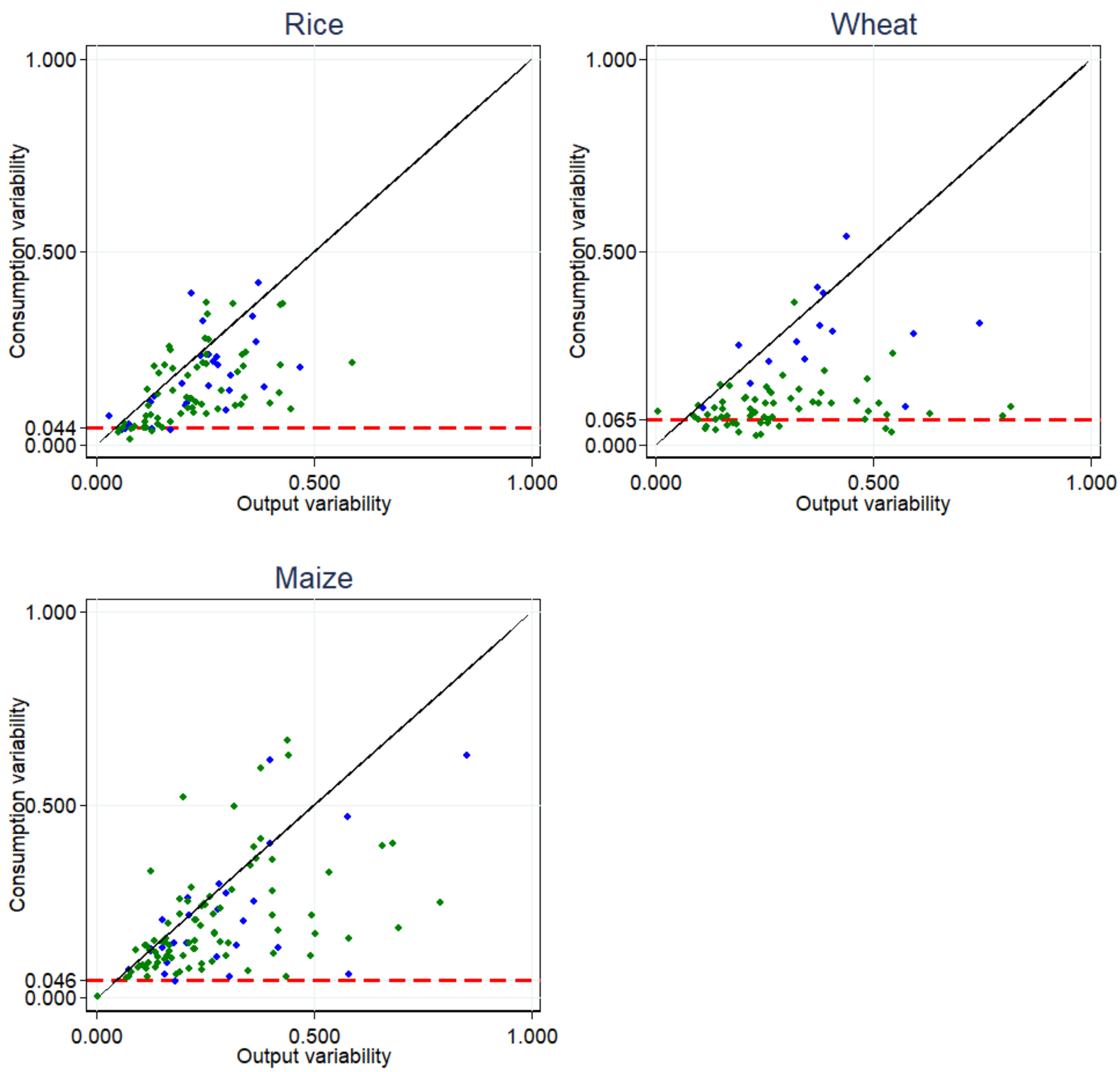
Valdes, A. (1981) *Food Security for Developing Countries*. Westview Press.

Wooldridge, J. M. (2005) Fixed-effects and related estimators for correlated random-coefficient and treatment-effect panel data models, *The Review of Economics and Statistics*, 87(2), 385-390.

Wright, B. D. (2011) The economics of grain price volatility. *Applied Economic Perspectives and Policy*, 33(1):32–58.

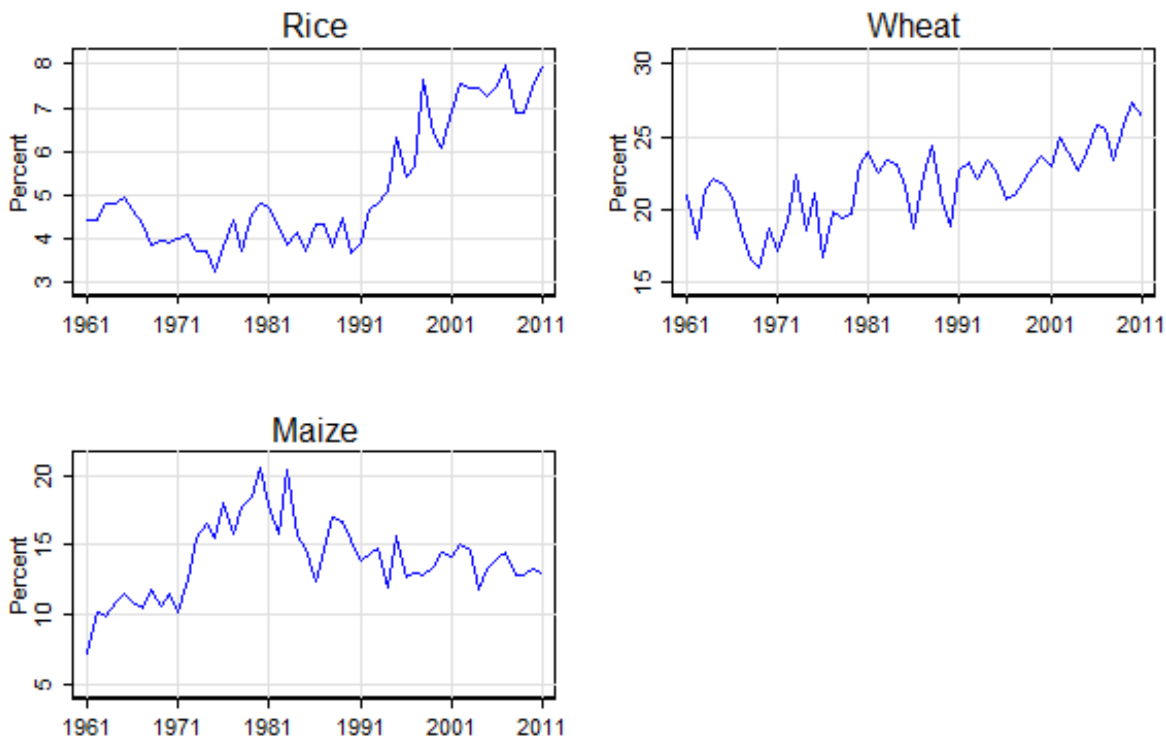
FIGURES

Figure 1: Volatility in Output and Consumption: Domestic and World Aggregates



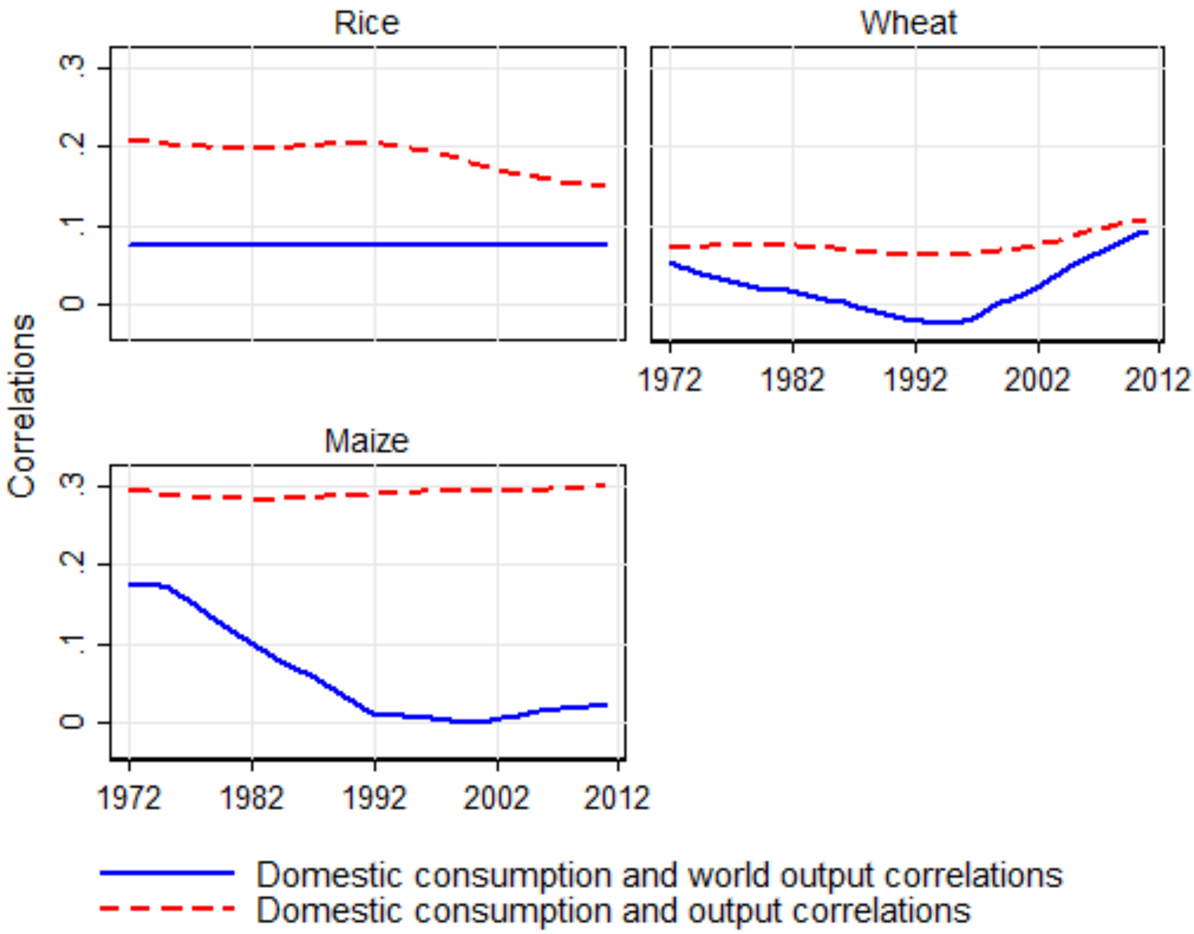
Notes: The figures show the scatter between the standard deviation of log first differenced per capita consumption (y-axis) and output (x-axis) across countries for the three commodities. The horizontal dashed red lines show the global output variation measured as the standard deviation of the log first differenced world per capita output for the three commodities. The blue color dots are for low income countries based on the classification followed by the World Bank. The standard deviations are calculated over the time period 1961-2013 and are based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database.

Figure 2: Trends in World Exports as a Share of World Production: 1961-2013



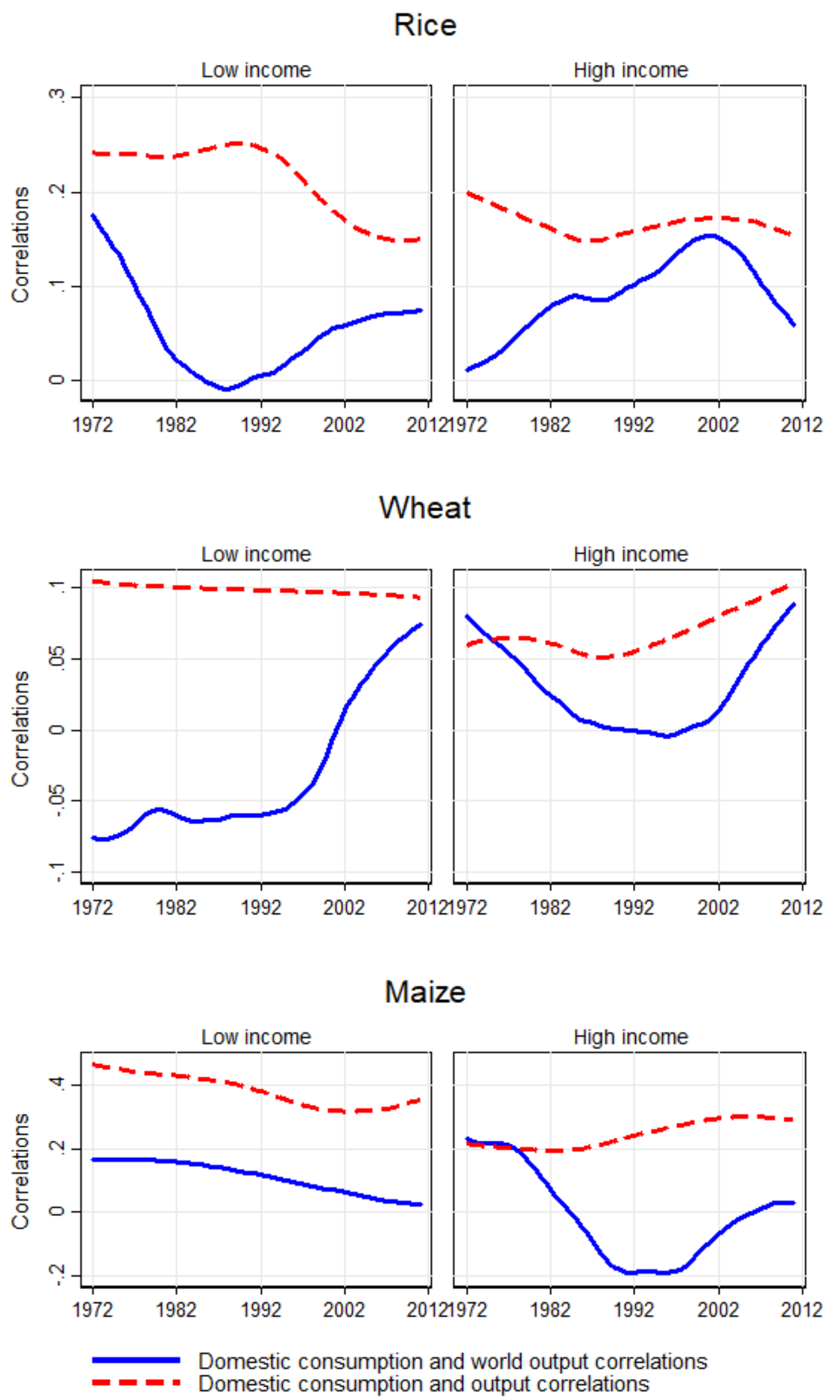
Notes: Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database.

Figure 3: Average 10 Year Rolling Correlations: 1961-2013



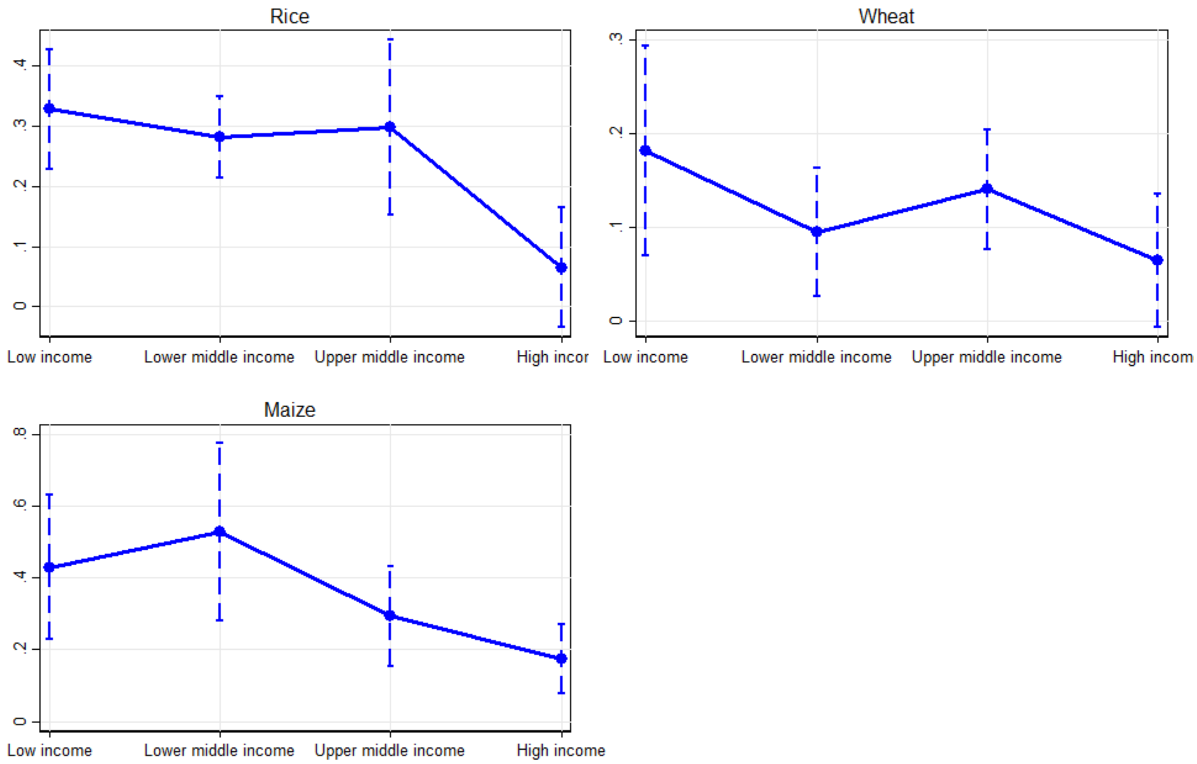
Notes: Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database. Moving average correlations were calculated for each country. The figures plot the non-parametrically fitted regression line to country level moving average correlations.

Figure 4: Average 10 Year Rolling Correlations by Income: 1961-2013



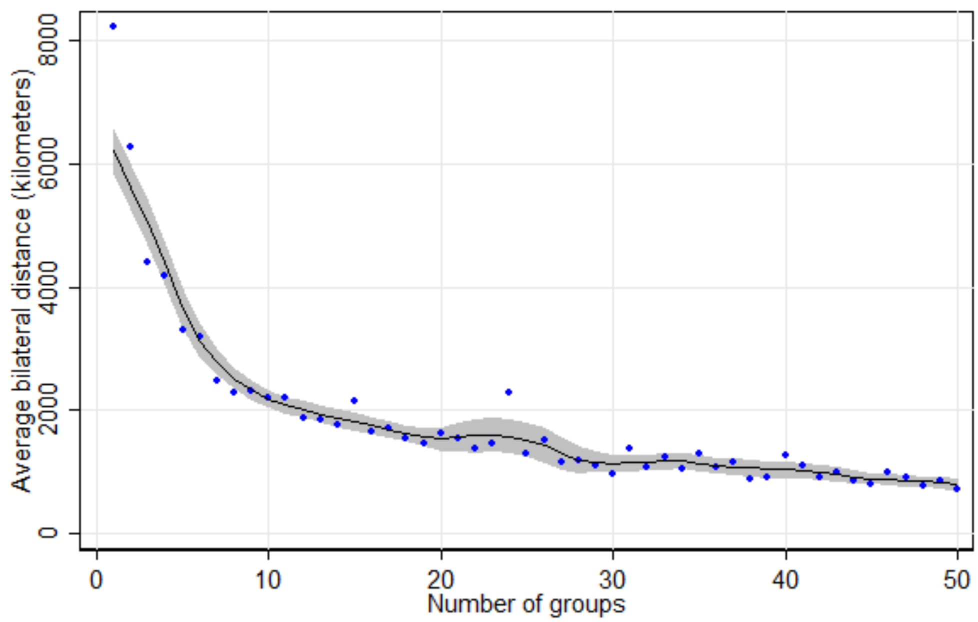
Notes: Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database. Moving average correlations were calculated for each country. The figures plot the non-parametrically fitted regression line to country level moving average correlations. Low and high income countries are based on the classification followed by the World Bank. The world bank classification of income groups used is time-invariant and corresponds to the year 2014.

Figure 5: Risk Sharing and Income



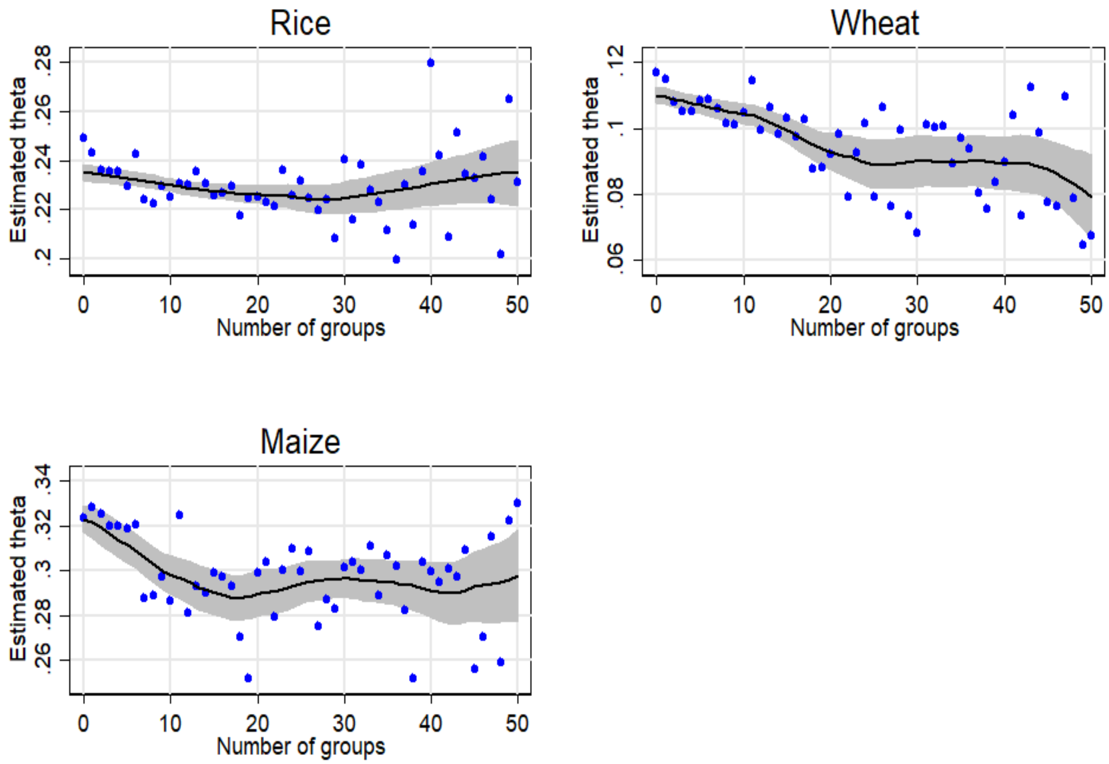
Notes: The figure displays the estimated θ's, along with 95% interval estimates, for low income, lower middle income, upper middle income, and high income countries. The average marginal effects have been estimated for the year 1987, which is the midpoint of the time period in our dataset. Country groups are based on the classification followed by the World Bank. The world bank classification of income groups used is time-invariant and corresponds to the year 2014.

Figure 6: Average Bilateral Distance Between Group Members



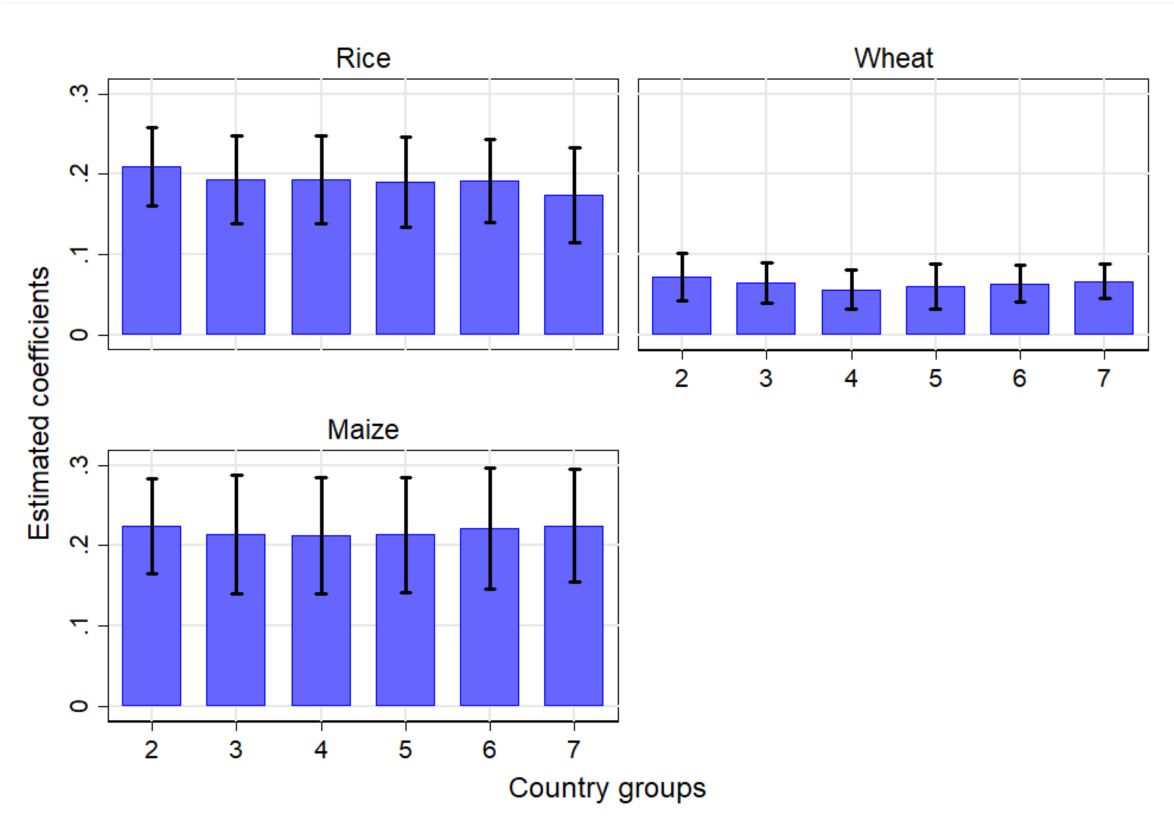
Notes: The figure displays the average bilateral distance between the group members as the number of groups increases. These groups age generated using the K-means clustering algorithm. As the number of groups or clusters increases, the average bilateral distance between countries within each group goes down. The black line shows the non-parametrically estimated relationship between the average distance among group members and the number of country groups; the shading shows 95% interval estimates.

Figure 7: Estimates of θ Conditional on Group Specific Time Fixed Effects



Notes: The figure displays the estimated θ's from separate regressions conditional on the number of groups displayed on the y-axis, interacted with time fixed effects. All regressions are population share weighted. The black line shows the non-parametrically estimated relationship between the estimated θ's and the number of country groups; the shading shows 95% interval estimates.

Figure 8: Risk Sharing and Endogenous Group Membership: Estimates of θ from the Group Fixed Effects Estimator



Notes: The figure displays the estimated θ's from the group fixed effects estimator with the 95% interval estimates. Each bar represents the estimate of θ from a separate regression. The number on the horizontal axis is the number of country groups specific time fixed effects that were included in the regression.

TABLES

Table 1: Test of Risk Sharing: Benchmark Specification

	(1)	(2)	(3)	(4)
Dependent variable: per capita consumption growth				
(a) Rice				
y_{it}	0.255***	0.251***	0.249***	0.250***
	(0.032)	(0.031)	(0.031)	(0.031)
$\bar{c}_t$				0.219**
				(0.105)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	5018	5018	5018	5018
R-squared	0.133	0.145	0.167	0.147
F-statistic	64.896	63.984	63.232	39.390
(b) Wheat				
y_{it}	0.118***	0.117***	0.117***	0.118***
	(0.023)	(0.023)	(0.022)	(0.023)
$\bar{c}_t$				0.682***
				(0.164)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	4753	4753	4753	4753
R-squared	0.039	0.046	0.105	0.062
F-statistic	25.426	25.682	28.119	19.616
(c) Maize				
y_{it}	0.333***	0.336***	0.324***	0.333***
	(0.062)	(0.062)	(0.049)	(0.062)
$\bar{c}_t$				0.451***
				(0.101)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	6342	6342	6342	6342
R-squared	0.169	0.184	0.219	0.190
F-statistic	28.500	29.215	42.797	53.502

Notes: The table presents the estimates of θ as defined in Equation (6). Variable y_{it} denotes the per capita output growth rate and $\bar{c}_t$ denotes the cross sectional average of per capita consumption growth. All regressions are weighted by the country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2: Risk Sharing for Large and Small Consumers and Producers

	(1)	(2)	(3)	(4)
	Consumption share		Output share	
	≥ 5%	< 5%	≥ 5%	< 5%
	Large nations	Small nations	Large nations	Small nations
Dependent variable: per capita consumption growth				
(a) Rice				
y_{it}	0.244***	0.211***	0.244***	0.211***
	(0.033)	(0.027)	(0.033)	(0.027)
$\bar{c}_t$	-0.136	0.613***	-0.136	0.613***
	(0.112)	(0.165)	(0.112)	(0.165)
N	208	4810	208	4810
R-squared	0.229	0.112	0.229	0.112
F-statistic	26.949	37.385	26.949	37.385
(b) Wheat				
y_{it}	0.188***	0.072***	0.186***	0.072***
	(0.046)	(0.014)	(0.038)	(0.014)
$\bar{c}_t$	0.601**	0.634***	0.488**	0.640***
	(0.259)	(0.126)	(0.220)	(0.128)
N	184	4569	234	4519
R-squared	0.111	0.045	0.114	0.045
F-statistic	10.407	21.789	13.909	21.603
(c) Maize				
y_{it}	0.370***	0.223***	0.370***	0.223***
	(0.031)	(0.036)	(0.031)	(0.036)
$\bar{c}_t$	0.106	0.689***	0.106	0.689***
	(0.152)	(0.122)	(0.152)	(0.122)
N	154	6188	154	6188
R-squared	0.504	0.121	0.504	0.121
F-statistic	73.767	39.186	73.767	39.186

Notes: Variable y_{it} denotes the per capita output growth rate and $\bar{c}_t$ denotes the cross sectional average of per capita consumption growth. For both consumption and output, rice large countries are Bangladesh, China, India, and Indonesia; wheat large countries are China, India, Russia, and USA; and maize large countries are Brazil, China, and USA. In addition, France is a large wheat producer. All other countries are taken as small consumer/producer countries. All regressions include country fixed effects and are unweighted. The correlation between average consumption and output shares across countries for rice, wheat and maize are 0.88, 0.73 and 0.90. Figures in parentheses are standard errors robust to heteroscedasticity and within-country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3: Test of Risk Sharing: Inverse Population Share Weights

	(1)	(2)	(3)	(4)
Dependent variable: per capita consumption growth				
(a) Rice				
y_{it}	0.191***	0.192***	0.186***	0.192***
	(0.051)	(0.052)	(0.049)	(0.052)
$\bar{c}_t$				0.087
				(0.499)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	5018	5018	5018	5018
R-squared	0.095	0.103	0.160	0.103
F-statistic	13.978	13.458	14.329	7.021
(b) Wheat				
y_{it}	0.063***	0.063***	0.062***	0.063***
	(0.017)	(0.017)	(0.017)	(0.016)
$\bar{c}_t$				0.728**
				(0.346)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	4753	4753	4753	4753
R-squared	0.018	0.051	0.107	0.059
F-statistic	13.349	13.052	13.575	8.428
(c) Maize				
y_{it}	0.247***	0.247***	0.243***	0.247***
	(0.073)	(0.073)	(0.069)	(0.073)
$\bar{c}_t$				0.028
				(0.363)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	6342	6342	6342	6342
R-squared	0.096	0.110	0.156	0.110
F-statistic	11.505	11.308	12.439	5.669

Notes: The table presents the estimates of θ as defined in Equation (6). Variable y_{it} denotes the per capita output growth rate and $\bar{c}_t$ denotes the cross sectional average of per capita consumption growth. All regressions are weighted by the inverse of a country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4: Robustness to Additional Controls and Trends in Risk Sharing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: per capita consumption growth						
(a) Rice						
y_{it}	0.251***	0.248***	0.248***	0.248***	0.248***	0.387***
	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.095)
GDP shocks		0.095	0.090	0.098	0.096	
		(0.064)	(0.064)	(0.065)	(0.066)	
Inflation shocks			-0.008	-0.023	-0.023	
			(0.010)	(0.019)	(0.019)	
Exchange rate shocks				0.016	0.016	
				(0.014)	(0.014)	
WTO					-0.011	
					(0.009)	
$y_{it} \times T$						-0.005*
						(0.003)
N	4000	4000	4000	4000	4000	4000
R-squared	0.174	0.175	0.175	0.176	0.176	0.183
F-statistic	57.041	35.828	23.946	19.639	17.883	35.797
(b) Wheat						
y_{it}	0.100***	0.097***	0.098***	0.098***	0.098***	0.115**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.057)
GDP shocks		0.159	0.164	0.159	0.161	
		(0.119)	(0.117)	(0.112)	(0.113)	
Inflation shocks			0.009	0.018	0.018	
			(0.008)	(0.023)	(0.023)	
Exchange rate shocks				-0.009	-0.009	
				(0.021)	(0.021)	
WTO					0.025***	
					(0.007)	
$y_{it} \times T$						-0.001
						(0.002)
N	3599	3599	3599	3599	3599	3599
R-squared	0.115	0.118	0.118	0.118	0.120	0.115
F-statistic	21.291	14.095	9.975	7.564	7.748	11.574

(c) Maize						
y_{it}	0.332***	0.326***	0.326***	0.326***	0.326***	0.532***
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.118)
GDP shocks		0.278***	0.274**	0.281***	0.283***	
		(0.106)	(0.109)	(0.107)	(0.106)	
Inflation shocks			-0.006	-0.017	-0.016	
			(0.012)	(0.018)	(0.018)	
Exchange rate shocks				0.011	0.011	
				(0.013)	(0.013)	
WTO					0.025	
					(0.017)	
$y_{it} \times T$						-0.007***
						(0.002)
N	4854	4854	4854	4854	4854	4854
R-squared	0.259	0.263	0.263	0.263	0.264	0.270
F-statistic	35.341	24.727	16.864	13.769	11.722	23.941

Notes: The table presents the estimates of θ as defined in Equation (6). Variable y_{it} denotes the per capita output growth rate and T denotes linear time trend. All specifications include country fixed effects and year dummies. All regressions are weighted by the country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within-country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: SomeAdditional Models: Heterogeneity in the Slope Coefficient and in Aggregate Shocks

	(1)	(2)	(3)
	Rice	Wheat	Maize
Dependent variable: per capita consumption growth			
Mean group (MG) estimator	0.242***	0.096***	0.354***
	(0.024)	(0.019)	(0.030)
MG: Large consumers (Consumption Share ≥ 5%)	0.261	0.323	0.468
	(0.141)	(0.065)	(0.122)
MG: Small consumers (Consumption Share < 5%)	0.244	0.085	0.373
	(0.025)	(0.021)	(0.032)
Common correlated effects			
mean group (CCEMG) estimator	0.244***	0.095***	0.359***
	(0.025)	(0.019)	(0.031)
Group fixed effects (GFE) estimator	0.191***	0.061***	0.213***
	(0.029)	(0.014)	(0.037)

Notes: The table presents the estimates of θ from estimators which are robust to heterogeneity in idiosyncratic and aggregate shocks. All regressions are unweighted. The number of country groups in the group fixed effect estimator is five. Standard errors for group fixed effects (GFE) estimator are bootstrapped with 100 replications. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Heterogeneity in Risk Sharing by Income

	(1) Rice	(2) Wheat	(3) Maize
Dependent variable: per capita consumption growth			
y_{it}	0.616***	0.286***	0.778**
	(0.108)	(0.0875)	(0.302)
y_{it} × Lower middle income	-0.238	-0.284***	-0.063
	(0.180)	(0.101)	(0.357)
y_{it} × Upper middle income	-0.0985	0.0164	-0.372
	(0.171)	(0.125)	(0.340)
y_{it} × High income	-0.663***	-0.279***	-0.636**
	(0.140)	(0.093)	(0.317)
y_{it} × T	-0.011***	-0.004**	-0.013*
	(0.002)	(0.002)	(0.007)
y_{it} × T × Lower middle income	0.007	0.007***	0.006
	(0.005)	(0.003)	(0.009)
y_{it} × T × Upper middle income	0.003	-0.002	0.008
	(0.004)	(0.003)	(0.008)
y_{it} × T × High income	0.015***	0.006***	0.014*
	(0.005)	(0.002)	(0.008)
N	4816	4494	6033
R-squared	0.212	0.122	0.262
F-statistic	20.49	4.615	15.80

Notes: The table presents results from a specification where we allow θ to vary across country groups and have a linear time trend. The base category is low income countries. Variable y_{it} denotes the per capita output growth rate and T denotes a linear time trend. Country groups are low income, lower middle income, upper middle income and high income countries and are based on the classification followed by the World Bank. The world bank classification of income groups used is time-invariant and corresponds to the year 2014. All specifications include country fixed effects and year dummies and are weighted by the country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within-country serial correlation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Estimates of Contribution of Trade and Storage in Risk Sharing

	(1)	(2)	(3)
	Trade	Storage	Residual
Rice	0.263***	0.488***	0.249***
	(0.078)	(0.067)	(0.031)
Wheat	0.532***	0.350***	0.117***
	(0.070)	(0.062)	(0.022)
Maize	0.358***	0.319***	0.324***
	(0.076)	(0.063)	(0.050)

Notes: The table presents the estimates of trade (θ^T) and storage (θ^S). Column (3) shows the benchmark estimates of θ from Equation (6), reported in Table 1, Column 3. Theory implies that $\theta = 1 - \theta^T - \theta^S$. All specifications include country fixed effects and year dummies. All regressions are weighted by the country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within-country serial correlation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

APPENDIX

A. AGGREGATE RISK FUNCTIONS WITH TRADE COSTS: SPECIAL CASES

In each of these examples, to derive concrete results we assume that each nation has the same CRRA utility: $u(c_i) = \frac{c_i^{1-\gamma}}{1-\gamma}, \gamma > 0, \gamma \neq 1$. (When $\gamma = 1$, $u(c_i) = \log c_i$.)

A.1. Two Nations

Let d be the shipping cost, and α, the Pareto weight on Nation 1. Suppose that stochastic output shocks are such that 2 exports to 1, which means that 1's autarky weighted marginal utility exceeds 2's: $\alpha y_1^{-\gamma} > d(1-\alpha)y_2^{-\gamma} \Rightarrow \alpha y_2^{\gamma} > d(1-\alpha)y_1^{\gamma} \Rightarrow \left(\frac{y_2}{y_1}\right)^{\gamma} > d\frac{1-\alpha}{\alpha} \Rightarrow \frac{y_2}{y_1} > \left(d\frac{1-\alpha}{\alpha}\right)^{\frac{1}{\gamma}}$. This is more likely to hold, the smaller are y_1 and d, and the larger are y_2 and α.

The planner thus chooses c_1 and c_2 to maximize $\frac{1}{1-\gamma}\left[\alpha c_1^{1-\gamma} + (1-\alpha)c_2^{1-\gamma}\right]$ such that $y_1 + y_2 \equiv Y = c_1 + c_2 + \frac{d-1}{d}(y_2 - c_2) = c_1 + \frac{c_2}{d} + \frac{(d-1)y_2}{d}$. The constraint captures the fact that output must be used for shipping costs as well as consumption. $y_2 - c_2$ is the amount traded, and $\frac{d-1}{d}$ is the fraction of the exported product that is lost due to shipping costs, so that the product of the two is the output lost due to trade.

The Lagrangian is $\mathcal{L} = \frac{1}{1-\gamma}\left[\alpha c_1^{1-\gamma} + (1-\alpha)c_2^{1-\gamma}\right] + \lambda(Y - c_1 - \frac{(d-1)y_2}{d} - \frac{c_2}{d})$, leading to the following first order conditions:

(A1) $\frac{\partial \mathcal{L}}{c_1} = \alpha(c_1^*)^{-\gamma} - \lambda = 0 \Rightarrow \alpha(c_1^*)^{-\gamma} = \lambda.$

(A2) $\frac{\partial \mathcal{L}}{c_2} = (1-\alpha)(c_2^*)^{-\gamma} - \frac{\lambda}{d} = 0 \Rightarrow (1-\alpha)(c_2^*)^{-\gamma} = \frac{\lambda}{d}.$

(A3) $\frac{\partial \mathcal{L}}{\lambda} = Y - c_1^* - \frac{c_2^*}{d} - \frac{(d-1)y_2}{d} = 0.$

Dividing (A1) by (A2), we get $\frac{\alpha(c_1^*)^{-\gamma}}{(1-\alpha)(c_2^*)^{-\gamma}} = d \Rightarrow \alpha(c_1^*)^{-\gamma} = d(1-\alpha)(c_2^*)^{-\gamma}$

$\Rightarrow (c_1^*)^{-\gamma} = d\frac{1-\alpha}{\alpha}(c_2^*)^{-\gamma} \Rightarrow c_1^* = \eta c_2^*$, where $\eta \equiv \left(d\frac{1-\alpha}{\alpha}\right)^{-\frac{1}{\gamma}} = \left(\frac{1}{d}\frac{\alpha}{1-\alpha}\right)^{\frac{1}{\gamma}}$. η, and thus 1's consumption, rises with 1's Pareto weight and falls with trade costs.

(A3)$\Rightarrow Y = c_1^* + \frac{(d-1)y_2}{d} + \frac{c_2^*}{d} \Rightarrow y_1 + y_2 = c_1^* + \frac{c_2^*}{d} + \frac{(d-1)y_2}{d}$

$\Rightarrow y_1 = c_1^* + \frac{c_2^*}{d} - \frac{y_2}{d} = c_1^* + \frac{c_1^*}{d\eta} - \frac{y_2}{d} \Rightarrow c_1^* + \frac{1}{d\eta}c_1^* = y_1 + \frac{y_2}{d}$

$\Rightarrow \left(1 + \frac{1}{d\eta}\right)c_1^* = \frac{1+d\eta}{d\eta}c_1^* = y_1 + \frac{y_2}{d} \Rightarrow c_1^* = \frac{d\eta}{1+d\eta}(y_1 + \frac{y_2}{d}) \Rightarrow c_2^* = \frac{d}{1+d\eta}(y_1 + \frac{y_2}{d})$. We see that the aggregate risk function is $A = y_1 + \frac{y_2}{d}$. Once we control for it, neither country's consumption depends on that country's output.

A.2. One Exporter and Multiple Importers

Suppose that there are N nations and that stochastic output shocks are such that nation N exports to all other nations. Now the planner chooses $c_1, \dots, c_N$ to maximize $\frac{1}{1-\gamma}\sum_{i=1}^{N}\alpha_i(c_i)^{1-\gamma}$ such that $\sum_{i=1}^{N} y_i \equiv Y = \sum_{i=1}^{N} c_i + \sum_{i=1}^{N-1}\frac{d_{iN}-1}{d_{iN}} d_{iN}(c_i - y_i)$ $= \sum_{i=1}^{N} c_i + \sum_{i=1}^{N-1}(d_{iN}-1)(c_i - y_i) = c_N + \sum_{i=1}^{N-1} d_{iN}(c_i - y_i) + \sum_{i=1}^{N-1} y_i$. As in the two-nation case, output is spread over consumption and trade costs. We can express trade costs from two perspectives: importers' or exporters'. In this case, it is easier to do it from the importers' perspectives because they only receive from one source, nation N. So, for a given importer i, we know that the amount it imports is $c_i - y_i$. For it to receive this amount, $d_{iN}(c_i - y_i)$ must be sent by the exporter. The trade cost for this shipment to i is thus $\frac{d_{iN}-1}{d_{iN}} d_{iN}(c_i - y_i) = (d_{iN}-1)(c_i - y_i)$.[14] Subtracting $\sum_{i=1}^{N-1} y_i$ from both sides, the constraint becomes $y_N = c_N + \sum_{i=1}^{N-1} d_{iN}(c_i - y_i)$, leading to the following Lagrangian: $\mathcal{L} = \frac{1}{1-\gamma}\sum_{i=1}^{N}\alpha_i(c_i)^{1-\gamma} + \lambda[y_N - c_N - \sum_{i=1}^{N-1} d_{iN}(c_i - y_i)]$. Maximizing gives the following first order conditions:

For $i = 1, \dots, N-1$, $\frac{\partial\mathcal{L}}{c_i} = \alpha_i(c_i^*)^{-\gamma} - \lambda d_{iN} = 0 \Rightarrow \alpha_i(c_i^*)^{-\gamma} = \lambda d_{iN}$.

$\frac{\partial\mathcal{L}}{c_N} = \alpha_N(c_N^*)^{-\gamma} - \lambda = 0 \Rightarrow \alpha_N(c_N^*)^{-\gamma} = \lambda$.

$\frac{\partial\mathcal{L}}{\lambda} = y_N - c_N^* - \sum_{i=1}^{N-1} d_{iN}(c_i^* - y_i) = 0 \Rightarrow$

(A4) $\quad y_N = c_N^* + \sum_{i=1}^{N-1} d_{iN}(c_i^* - y_i)$.

For $i = 1, \dots, N-1$, $\frac{\alpha_i(c_i^*)^{-\gamma}}{\alpha_N(c_N^*)^{-\gamma}} = d_{iN} \Rightarrow \alpha_i(c_i^*)^{-\gamma} = d_{iN}\alpha_N(c_N^*)^{-\gamma} \Rightarrow (c_i^*)^{-\gamma} = d_{iN}\frac{\alpha_N}{\alpha_i}(c_N^*)^{-\gamma}$ $\Rightarrow c_i^* = \left(d_{iN}\frac{\alpha_N}{\alpha_i}\right)^{-\frac{1}{\gamma}} c_N^* \Rightarrow c_i^* = \eta_{iN}c_N^*$, where $\eta_{iN} \equiv \left(\frac{1}{d_{iN}}\frac{\alpha_i}{\alpha_N}\right)^{\frac{1}{\gamma}}$. Substituting these expressions for the c_i^*s into (A4), we get $y_N = c_N^* + \sum_{i=1}^{N-1} d_{iN}(\eta_{iN}c_N^* - y_i)$ $\Rightarrow c_N^*\sum_{i=1}^{N} d_{iN}\eta_{iN} = \sum_{i=1}^{N} d_{iN}y_i$. Note that $d_{NN} = \eta_{NN} = 1$. Thus, equilibrium consumptions are $c_N^* = \frac{\sum_{i=1}^{N} d_{iN}y_i}{\sum_{i=1}^{N} d_{iN}\eta_{iN}}$ and $c_i^* = \frac{\eta_{iN}\sum_{i=1}^{N} d_{iN}y_i}{\sum_{i=1}^{N} d_{iN}\eta_{iN}}$, for $i = 1, \dots, N-1$. We see that the aggregate risk function is $A = \sum_{i=1}^{N} d_{iN}y_i$. Once we control for it, no country's consumption depends on that country's output.

[14] Since the exporter has multiple destinations, before solving, we do not know how much the exporter will send to each nation. We know that N's total exports are $y_N - c_N$, but do not know how those exports are allocated across the $N-1$ destinations, making it problematic to express the budget constraint in terms of N's exports. So, we use the formulation shown.

A.3. One Importer and Multiple Exporters

Suppose that there are N nations and that stochastic output shocks are such that 1 imports from all other nations. Now the planner chooses $c_1, \ldots, c_N$ to maximize $\frac{1}{1-\gamma}\sum_{i=1}^{N}\alpha_i(c_i)^{1-\gamma}$ such that $\sum_{i=1}^{N}y_i \equiv Y = \sum_{i=1}^{N}c_i + \sum_{i=2}^{N}\frac{d_{1i}-1}{d_{1i}}(y_i - c_i) =$ $\sum_{i=1}^{N}c_i + \sum_{i=2}^{N}\left(1-\frac{1}{d_{1i}}\right)(y_i - c_i) = c_1 + \sum_{i=2}^{N}(\frac{c_i}{d_{1i}} + \left(1-\frac{1}{d_{1i}}\right)y_i)$. Here we express trade costs from the exporters' perspectives because they only send to one destination, 1. Subtracting $\sum_{i=2}^{N}y_i$ from both sides, the constraint becomes $y_1 = c_1 + \sum_{i=2}^{N}\frac{c_i - y_i}{d_{1i}}$.

$\mathcal{L} = \frac{1}{1-\gamma}\sum_{i=1}^{N}\alpha_i(c_i)^{1-\gamma} + \lambda[y_1 - c_1 - \sum_{i=2}^{N}\frac{c_i - y_i}{d_{1i}}]$. Maximizing gives the following first order conditions:

$\frac{\partial\mathcal{L}}{c_1} = \alpha_1(c_1^*)^{-\gamma} - \lambda = 0 \Rightarrow \alpha_1(c_1^*)^{-\gamma} = \lambda.$

For $i = 2, \ldots, N$, $\frac{\partial\mathcal{L}}{c_i} = \alpha_i(c_i^*)^{-\gamma} - \frac{\lambda}{d_{1i}} = 0 \Rightarrow \alpha_i(c_i^*)^{-\gamma} = \frac{\lambda}{d_{1i}}$.

$\frac{\partial\mathcal{L}}{\lambda} = y_1 - c_1^* - \sum_{i=2}^{N}\frac{c_i^* - y_i}{d_{1i}} = 0 \Rightarrow$

(A5) $\quad y_1 = c_1^* + \sum_{i=2}^{N}\frac{c_i^* - y_i}{d_{1i}}$.

For $i = 2, \ldots, N$, $\frac{\alpha_1(c_1^*)^{-\gamma}}{\alpha_i(c_i^*)^{-\gamma}} = d_{1i} \Rightarrow \alpha_1(c_1^*)^{-\gamma} = d_{1i}\alpha_i(c_i^*)^{-\gamma} \Rightarrow (c_1^*)^{-\gamma} = d_{1i}\frac{\alpha_i}{\alpha_1}(c_i^*)^{-\gamma}$ $\Rightarrow c_1^* = \eta_{1i}c_i^* \Rightarrow c_i^* = \frac{1}{\eta_{1i}}c_1^*$. Plugging into (A5), we get $y_1 = c_1^* + \sum_{i=2}^{N}(\frac{c_1^*}{\eta_{1i}d_{1i}} - \frac{y_i}{d_{1i}}) \Rightarrow c_1^*\sum_{i=1}^{N}\frac{1}{\eta_{1i}d_{1i}} = \sum_{i=1}^{N}\frac{y_i}{d_{1i}}$. Thus, equilibrium consumptions are $c_1^* = \frac{\sum_{i=1}^{N}\frac{y_i}{d_{1i}}}{\sum_{i=1}^{N}\frac{1}{\eta_{1i}d_{1i}}}$ and $c_i^* = \frac{\sum_{i=1}^{N}\frac{y_i}{d_{1i}}}{\eta_{1i}\sum_{i=1}^{N}\frac{1}{\eta_{1i}d_{1i}}}$, for $i = 2, \ldots, N$. Now the aggregate risk function is $A = \sum_{i=1}^{N}\frac{y_i}{d_{1i}}$.

A.4. Four Nations

With four nations, there are three possible trading patterns: one exporter, one importer, and two of each. The first two are special cases of the two cases just analyzed. We analyze the last one in this section.

A.4.1. Two Exporters and Two Importers

This pattern has three possible trade patterns. The four countries break up into two bilateral pairs; both exporters export to both importers; or we have an "imbalanced case", in which one exporter sends to both importers, while the other exporter sends to just one importer. If they break up into bilateral pairs, we are back in the two-country case analyzed above. We will discuss the other two.

Both Exporters Export to Both Importers

Suppose that stochastic outputs are such that 1 and 2 import, and 3 and 4 export. If 1 and 2 both import from both, we would have $\frac{u_1'}{u_3'} = \frac{\alpha_3}{\alpha_1} d_{13}$, $\frac{u_1'}{u_4'} = \frac{\alpha_4}{\alpha_1} d_{14}$, $\frac{u_2'}{u_3'} = \frac{\alpha_3}{\alpha_2} d_{23}$, and $\frac{u_2'}{u_4'} = \frac{\alpha_4}{\alpha_2} d_{24}$. If all four of these hold, then the first two imply that $\frac{u_4'}{u_3'} = \frac{\alpha_3}{\alpha_4} \frac{d_{13}}{d_{14}}$, and the last two imply that $\frac{u_4'}{u_3'} = \frac{\alpha_3}{\alpha_4} \frac{d_{23}}{d_{24}}$. This only works if $\frac{d_{13}}{d_{14}} = \frac{d_{23}}{d_{24}}$, a knife-edge event with measure 0. The model is overdetermined. In general, both exporters will not export to both importers. This stems from fixed trade costs and social efficiency requiring using the low-cost route.

"Imbalanced Case"

Suppose that stochastic outputs in the four nations are such that 3 Exports to 1, and 4 Exports to both 1 and 2. These linkages imply the following first order conditions: $\frac{u_1'}{u_3'} = \frac{\alpha_3}{\alpha_1} d_{13}$, $\frac{u_1'}{u_4'} = \frac{\alpha_4}{\alpha_1} d_{14}$, and $\frac{u_2'}{u_4'} = \frac{\alpha_4}{\alpha_2} d_{24}$. Now, the model is not overdetermined, since we have three ratios and three equations. Let us solve this model to find the aggregate risk function.

We now have an importer (1) receiving from two countries, and an exporter (4) sending to two countries. This configuration complicates the budget constraint. We can solve without a constraint and reduce the problem's dimension from four to three in the process by optimizing with respect to the amounts transferred and then solving for the consumptions. Let Δ_{ij} be the amount shipped from j to i. We thus solve the following: $\underset{\Delta_{13},\Delta_{14},\Delta_{24}}{Max} \frac{1}{1-\gamma} [\alpha_1 \left(x_1 + \frac{\Delta_{13}}{d_{13}} + \frac{\Delta_{14}}{d_{14}}\right)^{1-\gamma} + \alpha_2 \left(x_2 + \frac{\Delta_{24}}{d_{24}}\right)^{1-\gamma} + \alpha_3 (x_3 - \Delta_{13})^{1-\gamma} + \alpha_4 (x_4 - \Delta_{14} - \Delta_{24})^{1-\gamma}]$. The quantities in parentheses are how much each nation consumes after trades take place. This expression captures 1 receiving from both 3 and 4, and 2 receiving from just 4.

Optimizing yields the following first order conditions:

$$\alpha_1\left(x_1+\frac{\Delta_{13}^*}{d_{13}}+\frac{\Delta_{14}^*}{d_{14}}\right)^{-\gamma}\frac{1}{d_{13}}=\alpha_3(x_3-\Delta_{13}^*)^{-\gamma}\Rightarrow x_1+\frac{\Delta_{13}^*}{d_{13}}+\frac{\Delta_{14}^*}{d_{14}}=\eta_{13}(x_3-\Delta_{13}^*).$$

$$\alpha_1\left(x_1+\frac{\Delta_{13}^*}{d_{13}}+\frac{\Delta_{14}^*}{d_{14}}\right)^{-\gamma}\frac{1}{d_{14}}=\alpha_4(x_4-\Delta_{14}^*-\Delta_{24}^*)^{-\gamma}\Rightarrow x_1+\frac{\Delta_{13}^*}{d_{13}}+\frac{\Delta_{14}^*}{d_{14}}=\eta_{14}(x_4-\Delta_{14}^*-\Delta_{24}^*).$$

$$\alpha_2\left(x_2+\frac{\Delta_{24}^*}{d_{24}}\right)^{-\gamma}\frac{1}{d_{24}}=\alpha_4(x_4-\Delta_{14}^*-\Delta_{24}^*)^{-\gamma}\Rightarrow x_2+\frac{\Delta_{24}^*}{d_{24}}=\eta_{24}(x_4-\Delta_{14}^*-\Delta_{24}^*).$$

We have a 3x3 system of equations:

$$\begin{aligned}(\tfrac{1}{d_{13}}+\eta_{13})\Delta_{13}^*+\tfrac{1}{d_{14}}\Delta_{14}^*&=-x_1+\eta_{13}x_3\\ \tfrac{1}{d_{13}}\Delta_{13}^*+(\tfrac{1}{d_{14}}+\eta_{14})\Delta_{14}^*+\eta_{14}\Delta_{24}^*&=-x_1+\eta_{14}x_4.\\ \eta_{24}\Delta_{14}^*+(\tfrac{1}{d_{24}}+\eta_{24})\Delta_{24}^*&=-x_2+\eta_{24}x_4\end{aligned}$$

$$\Rightarrow\begin{bmatrix}\frac{1}{d_{13}}+\eta_{13} & \frac{1}{d_{14}} & 0\\ \frac{1}{d_{13}} & \frac{1}{d_{14}}+\eta_{14} & \eta_{14}\\ 0 & \eta_{24} & \frac{1}{d_{24}}+\eta_{24}\end{bmatrix}\begin{bmatrix}\Delta_{13}^*\\ \Delta_{14}^*\\ \Delta_{24}^*\end{bmatrix}=\begin{bmatrix}-x_1+\eta_{13}x_3\\ -x_1+\eta_{14}x_4\\ -x_2+\eta_{24}x_4\end{bmatrix}.$$ Letting **A** be the coefficient matrix,

$$|\mathbf{A}|=\left(\frac{1}{d_{13}}+\eta_{13}\right)\left(\frac{1}{d_{14}}+\eta_{14}\right)\left(\frac{1}{d_{24}}+\eta_{24}\right)-\frac{1}{d_{13}}\frac{1}{d_{14}}\left(\frac{1}{d_{24}}+\eta_{24}\right)-\eta_{14}\eta_{24}\left(\frac{1}{d_{13}}+\eta_{13}\right)$$
$$=\left(\frac{1}{d_{13}}+\eta_{13}\right)\left(\frac{1}{d_{14}}\frac{1}{d_{24}}+\frac{1}{d_{14}}\eta_{24}+\frac{1}{d_{24}}\eta_{14}+\eta_{14}\eta_{24}\right)-\frac{1}{d_{13}}\frac{1}{d_{14}}\frac{1}{d_{24}}-\frac{1}{d_{13}}\frac{1}{d_{14}}\eta_{24}-\frac{1}{d_{13}}\eta_{14}\eta_{24}-\eta_{13}\eta_{14}\eta_{24}$$
$$=\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}+\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}+\frac{1}{d_{14}}\eta_{13}\eta_{24}+\frac{1}{d_{24}}\eta_{13}\eta_{14}.$$

Using Cramer's rule, we get

$$\Delta_{13}^*=\frac{1}{|\mathbf{A}|}\begin{vmatrix}-x_1+\eta_{13}x_3 & \frac{1}{d_{14}} & 0\\ -x_1+\eta_{14}x_4 & \frac{1}{d_{14}}+\eta_{14} & \eta_{14}\\ -x_2+\eta_{24}x_4 & \eta_{24} & \frac{1}{d_{24}}+\eta_{24}\end{vmatrix}$$
$$=\frac{1}{|\mathbf{A}|}[(-x_1+\eta_{13}x_3)\left(\frac{1}{d_{14}}+\eta_{14}\right)\left(\frac{1}{d_{24}}+\eta_{24}\right)+\frac{1}{d_{14}}\eta_{14}(-x_2+\eta_{24}x_4)-\eta_{14}\eta_{24}(-x_1+\eta_{13}x_3)-\frac{1}{d_{14}}\left(\frac{1}{d_{24}}+\eta_{24}\right)(-x_1+\eta_{14}x_4)]$$
$$=\frac{1}{|\mathbf{A}|}[(-x_1+\eta_{13}x_3)\left(\frac{1}{d_{14}}\frac{1}{d_{24}}+\frac{1}{d_{14}}\eta_{24}+\frac{1}{d_{24}}\eta_{14}+\eta_{14}\eta_{24}\right)-\frac{1}{d_{14}}\eta_{14}x_2+\frac{1}{d_{14}}\eta_{14}\eta_{24}x_4+\eta_{14}\eta_{24}x_1-\eta_{13}\eta_{14}\eta_{24}x_3+\frac{1}{d_{14}}\left(\frac{1}{d_{24}}x_1-\frac{1}{d_{24}}\eta_{14}x_4+\eta_{24}x_1-\eta_{14}\eta_{24}x_4\right)]$$
$$=\frac{1}{|\mathbf{A}|}(-\frac{1}{d_{24}}\eta_{14}x_1-\frac{1}{d_{14}}\eta_{14}x_2+\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_3+\frac{1}{d_{14}}\eta_{13}\eta_{24}x_3+\frac{1}{d_{24}}\eta_{13}\eta_{14}x_3-\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{14}x_4).$$

$$\Delta_{14}^*=\frac{1}{|\mathbf{A}|}\begin{vmatrix}\frac{1}{d_{13}}+\eta_{13} & -x_1+\eta_{13}x_3 & 0\\ \frac{1}{d_{13}} & -x_1+\eta_{14}x_4 & \eta_{14}\\ 0 & -x_2+\eta_{24}x_4 & \frac{1}{d_{24}}+\eta_{24}\end{vmatrix}$$

$= \frac{1}{|\mathbf{A}|}[(-x_1 + \eta_{14}x_4)\left(\frac{1}{d_{13}} + \eta_{13}\right)\left(\frac{1}{d_{24}} + \eta_{24}\right) - (-x_1 + \eta_{13}x_3)\frac{1}{d_{13}}\left(\frac{1}{d_{24}} + \eta_{24}\right) - (-x_2 +$
$\eta_{24}x_4)\eta_{14}(\frac{1}{d_{13}} + \eta_{13})]$
$= \frac{1}{|\mathbf{A}|}[(-x_1 + \eta_{14}x_4)\left(\frac{1}{d_{13}}\frac{1}{d_{24}} + \frac{1}{d_{13}}\eta_{24} + \frac{1}{d_{24}}\eta_{13} + \eta_{13}\eta_{24}\right) + \frac{1}{d_{13}}\frac{1}{d_{24}}x_1 + \frac{1}{d_{13}}\eta_{24}x_1 -$
$\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 - \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{13}}\eta_{14}x_2 + \eta_{13}\eta_{14}x_2 - \frac{1}{d_{13}}\eta_{14}\eta_{24}x_4 - \eta_{13}\eta_{14}\eta_{24}x_4]$
$= \frac{1}{|\mathbf{A}|}[-\frac{1}{d_{24}}\eta_{13}x_1 - \eta_{13}\eta_{24}x_1 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_4 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_4 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 - \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 +$
$\frac{1}{d_{13}}\eta_{14}x_2 + \eta_{13}\eta_{14}x_2]$
$= \frac{1}{|\mathbf{A}|}[-\frac{1}{d_{24}}\eta_{13}x_1 - \eta_{13}\eta_{24}x_1 + \frac{1}{d_{13}}\eta_{14}x_2 + \eta_{13}\eta_{14}x_2 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 - \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 +$
$\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_4 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_4].$

$$\Delta_{24}^* = \frac{1}{|\mathbf{A}|}\begin{vmatrix} \frac{1}{d_{13}} + \eta_{13} & \frac{1}{d_{14}} & -x_1 + \eta_{13}x_3 \\ \frac{1}{d_{13}} & \frac{1}{d_{14}} + \eta_{14} & -x_1 + \eta_{14}x_4 \\ 0 & \eta_{24} & -x_2 + \eta_{24}x_4 \end{vmatrix}$$
$= \frac{1}{|\mathbf{A}|}[(-x_2 + \eta_{24}x_4)\left(\frac{1}{d_{13}} + \eta_{13}\right)\left(\frac{1}{d_{14}} + \eta_{14}\right) + (-x_1 + \eta_{13}x_3)\frac{1}{d_{13}}\eta_{24} - \frac{1}{d_{13}}\frac{1}{d_{14}}(-x_2 +$
$\eta_{24}x_4) - \eta_{24}(\frac{1}{d_{13}} + \eta_{13})(-x_1 + \eta_{14}x_4)].$
$= \frac{1}{|\mathbf{A}|}[(-x_2 + \eta_{24}x_4)\left(\frac{1}{d_{13}}\frac{1}{d_{14}} + \frac{1}{d_{13}}\eta_{14} + \frac{1}{d_{14}}\eta_{13} + \eta_{13}\eta_{14}\right) - \frac{1}{d_{13}}\eta_{24}x_1 + \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 +$
$\frac{1}{d_{13}}\frac{1}{d_{14}}x_2 - \frac{1}{d_{13}}\frac{1}{d_{14}}\eta_{24}x_4 - \eta_{24}(-\frac{1}{d_{13}}x_1 + \frac{1}{d_{13}}\eta_{14}x_4 - \eta_{13}x_1 + \eta_{13}\eta_{14}x_4)]$
$= \frac{1}{|\mathbf{A}|}[-\frac{1}{d_{13}}\eta_{14}x_2 - \frac{1}{d_{14}}\eta_{13}x_2 - \eta_{13}\eta_{14}x_2 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_4 + \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \eta_{13}\eta_{24}x_1]$
$= \frac{1}{|\mathbf{A}|}[\eta_{13}\eta_{24}x_1 - \frac{1}{d_{13}}\eta_{14}x_2 - \frac{1}{d_{14}}\eta_{13}x_2 - \eta_{13}\eta_{14}x_2 + \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_4]$

Now, solving for consumptions, we get:
$c_1^* = x_1 + \frac{\Delta_{13}^*}{d_{13}} + \frac{\Delta_{14}^*}{d_{14}}$
$= x_1 + \frac{1}{|\mathbf{A}|}[\frac{1}{d_{13}}\left(-\frac{1}{d_{24}}\eta_{14}x_1 - \frac{1}{d_{14}}\eta_{14}x_2 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_3 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_3 -\right.$
$\left.\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{14}x_4\right) + \frac{1}{d_{14}}(-\frac{1}{d_{24}}\eta_{13}x_1 - \eta_{13}\eta_{24}x_1 + \frac{1}{d_{13}}\eta_{14}x_2 + \eta_{13}\eta_{14}x_2 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 -$
$\frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_4 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_4)]$
$= x_1 + \frac{1}{|\mathbf{A}|}[-\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_1 - \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_1 - \frac{1}{d_{14}}\eta_{13}\eta_{24}x_1 + \frac{1}{d_{14}}\eta_{13}\eta_{14}x_2 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}\eta_{14}x_3 +$
$\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}\eta_{14}x_4]$
$= \frac{1}{|\mathbf{A}|}[\left(\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14} + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13} + \frac{1}{d_{14}}\eta_{13}\eta_{24} + \frac{1}{d_{24}}\eta_{13}\eta_{14}\right)x_1 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_1 - \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_1 -$
$\frac{1}{d_{14}}\eta_{13}\eta_{24}x_1 + \frac{1}{d_{14}}\eta_{13}\eta_{14}x_2 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}\eta_{14}x_3 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}\eta_{14}x_4]$
$= \frac{1}{|\mathbf{A}|}[\frac{1}{d_{24}}\eta_{13}\eta_{14}x_1 + \frac{1}{d_{14}}\eta_{13}\eta_{14}x_2 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}\eta_{14}x_3 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}\eta_{14}x_4]$
$= \frac{\eta_{13}\eta_{14}}{|\mathbf{A}|}\left[\frac{x_1}{d_{24}} + \frac{x_2}{d_{14}} + \frac{x_3}{d_{13}d_{24}} + \frac{x_4}{d_{14}d_{24}}\right].$

$c_2^* = x_2 + \frac{\Delta_{24}^*}{d_{24}}$
$= x_2 + \frac{1}{|\mathbf{A}|}\frac{1}{d_{24}}[\eta_{13}\eta_{24}x_1 - \frac{1}{d_{13}}\eta_{14}x_2 - \frac{1}{d_{14}}\eta_{13}x_2 - \eta_{13}\eta_{14}x_2 + \frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_4]$
$= \frac{1}{|\mathbf{A}|}[\left(\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14} + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13} + \frac{1}{d_{14}}\eta_{13}\eta_{24} + \frac{1}{d_{24}}\eta_{13}\eta_{14}\right)x_2 + \frac{1}{d_{24}}\eta_{13}\eta_{24}x_1 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_2 -$
$\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_2 - \frac{1}{d_{24}}\eta_{13}\eta_{14}x_2 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}\eta_{24}x_4]$
$= \frac{1}{|\mathbf{A}|}[\frac{1}{d_{24}}\eta_{13}\eta_{24}x_1 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_2 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}\eta_{24}x_4]$
$= \frac{\eta_{13}\eta_{24}}{|\mathbf{A}|}[\frac{x_1}{d_{24}} + \frac{x_2}{d_{14}} + \frac{x_3}{d_{13}d_{24}} + \frac{x_4}{d_{14}d_{24}}].$

$c_3^* = x_3 - \Delta_{13}^*$
$= x_3 - \frac{1}{|\mathbf{A}|}(-\frac{1}{d_{24}}\eta_{14}x_1 - \frac{1}{d_{14}}\eta_{14}x_2 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_3 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_3 -$
$\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{14}x_4)$
$= \frac{1}{|\mathbf{A}|}[\left(\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14} + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13} + \frac{1}{d_{14}}\eta_{13}\eta_{24} + \frac{1}{d_{24}}\eta_{13}\eta_{14}\right)x_3 + \frac{1}{d_{24}}\eta_{14}x_1 + \frac{1}{d_{14}}\eta_{14}x_2 -$
$\frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13}x_3 - \frac{1}{d_{14}}\eta_{13}\eta_{24}x_3 - \frac{1}{d_{24}}\gamma_{13}\gamma_{14}x_3 + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{14}x_4]$
$= \frac{\eta_{14}}{|\mathbf{A}|}[\frac{x_1}{d_{24}} + \frac{x_2}{d_{14}} + \frac{x_3}{d_{13}d_{24}} + \frac{x_4}{d_{14}d_{24}}].$

$c_4^* = x_4 - \Delta_{14}^* - \Delta_{24}^*$
$= x_4 - \frac{1}{|\mathbf{A}|}\Big[-\frac{1}{d_{24}}\eta_{13}x_1 - \eta_{13}\eta_{24}x_1 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_4 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_4 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 -$
$\frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{13}}\eta_{14}x_2 + \eta_{13}\eta_{14}x_2 + \eta_{13}\eta_{24}x_1 - \frac{1}{d_{13}}\eta_{14}x_2 - \frac{1}{d_{14}}\eta_{13}x_2 - \eta_{13}\eta_{14}x_2 +$
$\frac{1}{d_{13}}\eta_{13}\eta_{24}x_3 + \frac{1}{d_{14}}\eta_{13}\eta_{24}x_4\Big]$
$= x_4 - \frac{1}{|\mathbf{A}|}\Big[-\frac{1}{d_{24}}\eta_{13}x_1 - \frac{1}{d_{14}}\eta_{13}x_2 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 + \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_4 + \frac{1}{d_{24}}\eta_{13}\eta_{14}x_4 +$
$\frac{1}{d_{14}}\eta_{13}\eta_{24}x_4\Big]$
$= \frac{1}{|\mathbf{A}|}\Big[\left(\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14} + \frac{1}{d_{14}}\frac{1}{d_{24}}\eta_{13} + \frac{1}{d_{14}}\eta_{13}\eta_{24} + \frac{1}{d_{24}}\eta_{13}\eta_{14}\right)x_4 + \frac{1}{d_{24}}\eta_{13}x_1 + \frac{1}{d_{14}}\eta_{13}x_2 +$
$\frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{13}x_3 - \frac{1}{d_{13}}\frac{1}{d_{24}}\eta_{14}x_4 - \frac{1}{d_{24}}\eta_{13}\eta_{14}x_4 - \frac{1}{d_{14}}\eta_{13}\eta_{24}x_4\Big]$
$= \frac{\eta_{13}}{|\mathbf{A}|}[\frac{x_1}{d_{24}} + \frac{x_2}{d_{14}} + \frac{x_3}{d_{13}d_{24}} + \frac{x_4}{d_{14}d_{24}}].$

Note that $c_1^* = \eta_{13}c_3^* = \eta_{14}c_4^*$ and $c_2^* = \eta_{24}c_4^*$. The aggregate risk function is
$A = \frac{x_1}{d_{24}} + \frac{x_2}{d_{14}} + \frac{x_3}{d_{13}d_{24}} + \frac{x_4}{d_{14}d_{24}}.$

B. TESTS OF UNIT ROOT, SERIAL CORRELATION AND HETEROSCEDASTICITY

Table B1: Unit Root Tests

	Inverse χ^2	Inverse logit	Inverse normal	Modified inverse χ^2	Inverse χ^2	Inverse logit	Inverse normal	Modified inverse χ^2
	Level				Differences			
				Rice				
Log per capita consumption	227.64	-0.10	-0.22	1.49	761.84	-20.42	-18.07	28.33
	(0.07)	(0.46)	(0.41)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita output	142.15	4.51	4.23	-2.81	621.34	-15.77	-14.38	21.27
	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)
				Wheat				
Log per capita consumption	144.50	2.03	2.13	-1.87	651.36	-18.07	-16.14	24.84
	(0.98)	(0.98)	(0.98)	(0.97)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita output	156.69	2.83	2.64	-1.23	824.45	-23.47	-19.69	33.97
	(0.89)	(1.00)	(1.00)	(0.89)	(0.00)	(0.00)	(0.00)	(0.00)
				Maize				
Log per capita consumption	228.77	1.71	1.78	0.04	728.84	-17.87	-16.56	23.45
	(0.47)	(0.96)	(0.96)	(0.49)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita output	220.52	0.77	0.71	-0.35	809.90	-19.88	-17.87	27.25
	(0.63)	(0.78)	(0.76)	(0.64)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Table presents results from the Fisher-type unit-root test, which works well with an unbalanced panel. The null hypothesis is that the series is I(1). Figures in parentheses are p-values.

Table B2: Tests of Serial Correlation and Heteroscedasticity

Tests	Statistic	Probability
Rice		
Wooldrige test for null of no serial correlation on panel data	F(1, 113) = 17.63	Prob. > F = 0.0001
Modified Wald test for group wise heteroscedasticity	Chi2(114) = 1.8e+05	Prob > Chi2 = 0.0000
Wheat		
Wooldrige test for null of no serial correlation on panel data	F(1, 121) = 3.630	Prob. > F = 0.0591
Modified Wald test for group wise heteroscedasticity	Chi2(122) = 1.7e+05	Prob > Chi2 = 0.0000
Maize		
Wooldrige test for null of no serial correlation on panel data	F(1, 143) = 2.853	Prob. > F = 0.0934
Modified Wald test for group wise heteroscedasticity	Chi2(150) = 7.0e+06	Prob > Chi2 = 0.0000

Note: All tests were conducted on the benchmark specification in Equation (6).

C. ROBUSTNESS CHECKS

C.1. Lagged and Lead Output Shocks and Lagged Dependence

In this section, we test the robustness of the risk sharing coefficient to lagged and lead output and lagged consumption shocks. Specification (1) to (4) of Table C1 presents the results from regressions with lagged and lead output shocks as additional regressors. In specification (5) we present results with lagged consumption shock as an additional regressor. Since, with a lagged dependent variable, the fixed effects estimator is biased, we use the Arellano and Bond (1991) estimator and treat both lagged consumption and output shocks as endogenous.

Table C1: Robustness of estimates to lagged and lead output growth and lagged dependence

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	Arellano-Bond
Dependent variable: per capita consumption growth					
(a) Rice					
y_{it}	0.238***	0.226***	0.254***	0.255***	0.194***
	(0.029)	(0.029)	(0.033)	(0.034)	(0.026)
y_{it-1}	-0.038	-0.044			
	(0.028)	(0.029)			
y_{it-2}		-0.014			
		(0.011)			
y_{it+1}			0.039***	0.041**	
			(0.014)	(0.016)	
y_{it+2}				0.003	
				(0.014)	
c_{it-1}					-0.255***
					(0.024)
N	4893	4771	4892	4769	4785

(b) Wheat					
y_{it}	0.112***	0.109***	0.123***	0.121***	0.065***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.014)
y_{it-1}	-0.025*	-0.032*			
	(0.014)	(0.019)			
y_{it-2}		-0.013			
		(0.026)			
y_{it+1}			0.023	0.018	
			(0.022)	(0.021)	
y_{it+2}				-0.015	
				(0.011)	
c_{it-1}					-0.233***
					(0.040)
N	4615	4479	4615	4479	4503
(c) Maize					
y_{it}	0.329***	0.336***	0.332***	0.342***	0.203***
	(0.049)	(0.050)	(0.051)	(0.052)	(0.034)
y_{it-1}	0.022	0.036**			
	(0.018)	(0.018)			
y_{it-2}		0.029			
		(0.018)			
y_{it+1}			0.024	0.040	
			(0.035)	(0.041)	
y_{it+2}				0.054	
				(0.044)	
c_{it-1}					-0.201***
					(0.030)
N	6169	6001	6169	6001	6023

Notes: Specifications 1 to 4 include country fixed effects and year dummies. All OLS regressions are weighted by the country's average share of the world population. Specification 4 has lagged dependent variable and is consistently estimated using Arellano and Bond (1991) GMM estimator. Figures in parentheses are standard errors robust to heteroscedasticity and within-country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

C.2. Measurement Errors in Output Aggregates

In this section, we address the issue that measurement errors in output aggregates may influence the estimates of risk sharing. To deal with the bias in estimated θ due to measurement error we use the Lewbel (2012) instrumental variable strategy. Lewbel (2012) shows that, in the absence of an instrumental variable correlated with the mismeasured regressor, θ can be identified just based on heteroscedasticity. The critical assumption for identification is that the errors in a linear projection of the mismeasured regressor on the other regressors be heteroscedastic. For details, see Lewbel (2012). Lewbel's approach is essentially implemented as a two-stage instrumental variable estimation where the instruments are constructed using a set of control variables and the estimated errors from the first stage regression. We use region dummies and average annual rainfall as control variables in our regressions. We formally test for heteroscedasticity using the Breusch-Pagan test and find the errors from first stage regressions for rice, wheat, and maize to be heteroscedastic. Table C2 presents the results from the Lewbel estimator. The estimated coefficients are comparable in magnitude to the estimates reported in Table 2. Also, we continue to find that the wheat market is closest to efficient risk sharing, while the maize market is furthest.

Table C2: Instrumental Variable Estimates

	(1)	(2)	(3)
Dependent variable: per capita consumption growth			
	Rice	Wheat	Maize
y_{it}	0.262***	0.123***	0.352***
	(0.035)	(0.039)	(0.078)
N	4748	4444	5968
Breusch-Pagan test $\chi^2(1)$	39.67	25.02	6.43
p-value	0.000	0.000	0.010

Notes: Table presents results from the Lewbel (2012) instrumental variable estimator where the exogenous variables are region dummies and average annual rainfall. All regressions are weighted by the country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within-country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

C.3. Estimates from Alternative Data Source

We estimate our benchmark specification on data from the `Production, Supply and Distribution' database of the United States Department of Agriculture's Foreign Agriculture Service (FAS) (USDA, 2014). Like the main dataset (FAO Food Balance Sheets) used in the paper, the FAS-USDA also collects data on country-level consumption, output, trade and storage aggregates for agricultural commodities.

In Table C3 we present the estimates of θ from the FAO and USDA databases. The estimated coefficients continue to be highly statistically significant and comparable across the two datasets.

Table C3: Robustness Check Using an Alternative Data Source

	(1)	(2)
	FAO	USDA
Dependent variable: per capita consumption growth		
(a) Rice		
y_{it}	0.249***	0.293***
	(0.031)	(0.035)
N	5018	4389
R-squared	0.167	0.192
F-statistic	63.232	69.677
(b) Wheat		
y_{it}	0.117***	0.107***
	(0.022)	(0.029)
N	4753	3486
R-squared	0.105	0.093
F-statistic	28.119	13.701
© Maize		
y_{it}	0.324***	0.390***
	(0.049)	(0.054)
N	6342	5012
R-squared	0.219	0.296
F-statistic	42.797	51.180

Notes: The table presents the estimates of θ from two different sources of data. FAO stands for the Food and Agriculture Organization and USDA stands for the United States Department of Agriculture. Variable y_{it} denotes the per capita output growth rate. All specifications include country fixed effects and year dummies. All regressions are weighted by the country's average share of the world population. Figures in parentheses are standard errors robust to heteroscedasticity and within country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

REFERENCES FOR APPENDIX C

Arellano, M. and Bond, S. (1991) Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297.

Lewbel, A. (2012) Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1):67–80.

USDA. (2014) *Production, Supply and Distribution Database*, URL https://apps.fas.usda.gov/psdonline.

D. TRADE AND STORAGE

D.1. Decomposition of Cross-Sectional Output Variance

Let Y_{it} be the output and C_{it} be the consumption in country *i* at time period *t*. Define

(D1) $Y_{it}^{NX} = Y_{it} - NX_{it}$,

where $NX_{it} = \text{Exports}_{\text{it}} - \text{Imports}_{\text{it}}$ is net exports. Define consumption as

(D2) $C_{it} = Y_{it}^{NX} - \Delta B_{it}$,

where ΔB_{it} is the change in stocks.
Output for country *i* at time period *t* can be expressed as

(D3) $Y_{it} = \frac{Y_{it}}{Y_{it}^{NX}} \frac{Y_{it}^{NX}}{C_{it}} C_{it}$.

Taking logs on both sides gives

(D4) $\ln Y_{it} = (\ln Y_{it} - \ln Y_{it}^{NX}) + (\ln Y_{it}^{NX} - \ln C_{it}) + \ln C_{it}$.

First differencing gives

(D5) $\Delta \ln Y_{it} = (\Delta \ln Y_{it} - \Delta \ln Y_{it}^{NX}) + (\Delta \ln Y_{it}^{NX} - \Delta \ln C_{it}) + \Delta \ln C_{it}$.

Averaging Equation (D5) over *i* on both sides gives

(D6) $\overline{\Delta \ln Y_t} = \left(\overline{\Delta \ln Y_t} - \overline{\Delta \ln Y_t^{NX}}\right) + \left(\overline{\Delta \ln Y_t^{NX}} - \overline{\Delta \ln C_t}\right) + \overline{\Delta \ln C_t}$.

Averaging Equation (D5) over *t* on both sides gives

(D7) $\overline{\Delta \ln Y_\iota} = \left(\overline{\Delta \ln Y_\iota} - \overline{\Delta \ln Y_\iota^{NX}}\right) + \left(\overline{\Delta \ln Y_\iota^{NX}} - \overline{\Delta \ln C_\iota}\right) + \overline{\Delta \ln C_\iota}$.

Averaging Equation (D5) over *i* and *t* on both sides gives

(D8) $\overline{\Delta \ln Y} = \left(\overline{\Delta \ln Y} - \overline{\Delta \ln Y^{NX}}\right) + \left(\overline{\Delta \ln Y^{NX}} - \overline{\Delta \ln C}\right) + \overline{\Delta \ln C}$.
To derive the contributions of trade and storage as coefficients from two-way fixed effects regressions, we subtract Equations (D6) and, (D7) and add Equation (D8) to Equation (D5). This gives

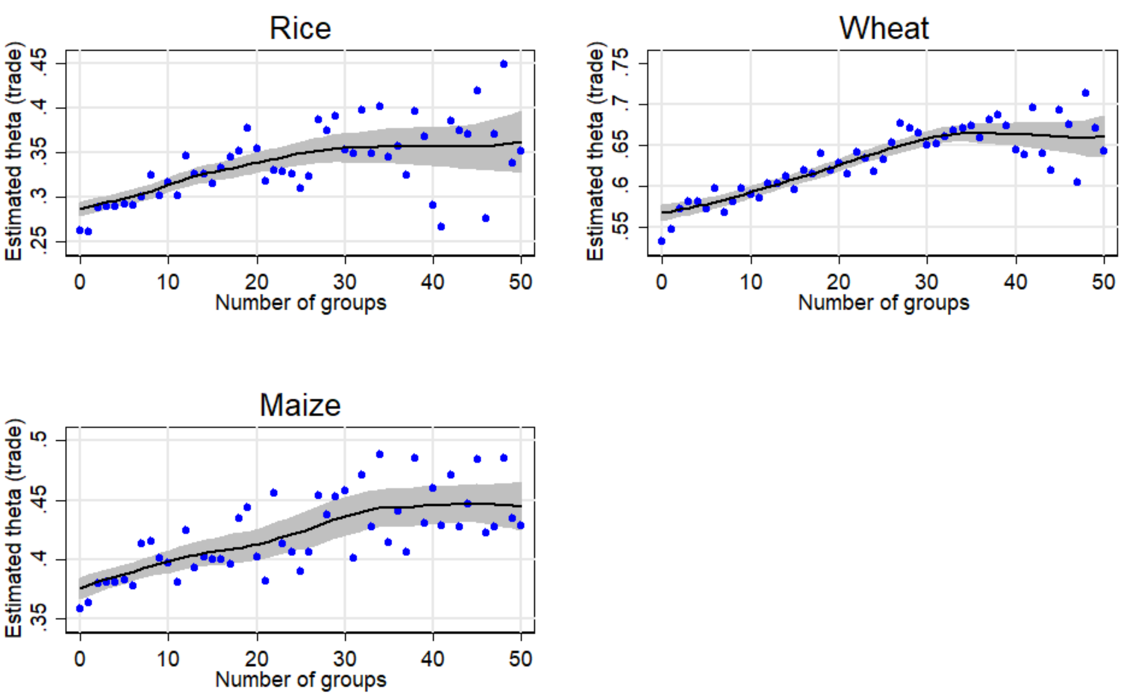
(D9) $\Delta \ln \ddot{Y}_{it} = \left(\Delta \ln \ddot{Y}_{it} - \Delta \ln \ddot{Y}_{it}^{NX}\right) + \left(\Delta \ln \ddot{Y}_{it}^{NX} - \Delta \ln \ddot{C}_{\iota t}\right) + \Delta \ln \ddot{C}_{\iota t}$,

where double dots over variables denote time and country demeaned variables, i.e., $\Delta \ln \ddot{Y}_{it} = \Delta \ln Y_{it} - \overline{\Delta \ln Y_t} - \overline{\Delta \ln Y_\iota} + \overline{\Delta \ln Y}$, $\Delta \ln \ddot{Y}_{it}^{NX} = \Delta \ln Y_{it}^{NX} - \overline{\Delta \ln Y_t^{NX}} - \overline{\Delta \ln Y_\iota^{NX}} + \overline{\Delta \ln Y^{NX}}$, and $\Delta \ln \ddot{C}_{it} = \Delta \ln C_{it} - \overline{\Delta \ln C_t} - \overline{\Delta \ln C_\iota} + \overline{\Delta \ln C}$.
Multiplying by $\ln \Delta \ddot{Y}_{\iota t}$ on both sides and taking expectations of Equation (D9), we get the following decomposition of cross-sectional variance of output:

(D10) $Var\left(\Delta \ln \ddot{Y}_{it}\right) = Cov\left(\Delta \ln \ddot{Y}_{it}, \Delta \ln \ddot{Y}_{it} - \Delta \ln \ddot{Y}_{it}^{NX}\right) + Cov\left(\Delta \ln \ddot{Y}_{it}, \Delta \ln \ddot{Y_{it}^{NX}} - \Delta \ln \ddot{C}_{\iota t}\right) + Var\left(\Delta \ln \ddot{Y}_{it}, \Delta \ln \ddot{C}_{\iota t}\right)$.

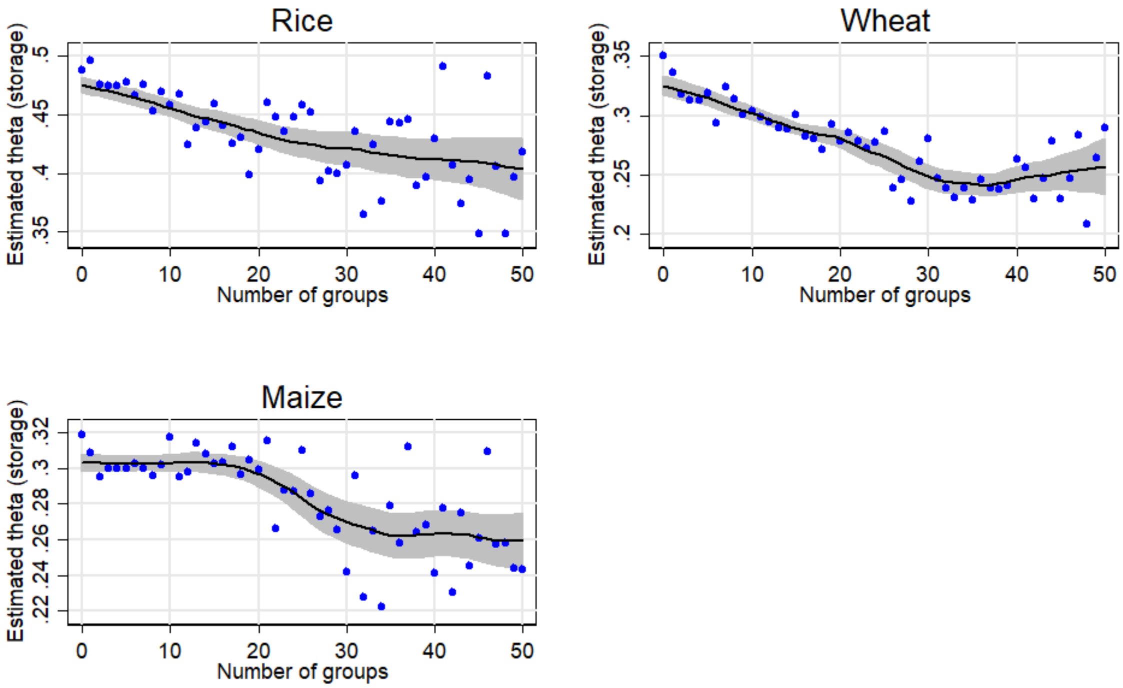
D.2 Distance Based Networks and the Contributions of Trade and Storage to Risk Sharing

Figure D1: Estimates of θ^T Conditional on Group Specific Time Fixed Effects



Notes: The figure displays the estimated trade components, θ^Ts, from separate regressions conditional on the number of groups, displayed on the y-axis, and group-specific time fixed effects. All estimates are from regressions weighted by the country's average share of the world population. The groups are defined such that the average bilateral distance between countries decreases as the number of groups increases. The black line shows the non-parametrically estimated relationship between and the number of country groups; shading shows 95% interval estimates.

Figure D2: Estimates of θ^S Conditional on Group Specific Time Fixed Effects



Notes: The figure displays the estimated storage components, θ^Ss, from separate regressions conditional on the number of groups, displayed on the y-axis, and group-specific time fixed effects. All estimates are from regressions weighted by the country's average share of the world population. The groups are defined such that the average bilateral distance between countries decreases as the number of groups increases. The black line shows the non-parametrically estimated relationship between and the number of country groups; shading shows 95% interval estimates.