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1 Introduction

World production of food staples is very stable. The standard deviation of world production shocks (measured as the difference in log values of production over successive time periods) is 0.03 for rice, 0.05 for wheat and 0.08 for maize. On the other hand, production at a country level is highly variable. Figure 1 compares the standard deviation of global shocks with the standard deviation of individual country output (averaged over 100 countries). Despite the country level instability, individual countries should be able to achieve stability in consumption of about the same order as that of world production, whether through ex-ante mechanisms or ex-post trade. Indeed, the stability of world food aggregates has frequently led economists to advocate international trade as an effective mechanism for price and, therefore, consumption stabilization.

Figure 2 adds the variability of individual country consumption to the global and individual country production variability plotted in Figure 1. It can be seen that while, on average, individual country staple food consumption variability is lower than production variability, it is, however, still higher than the global variability in food production. Figure 2 suggests, that while there is some consumption smoothing, global food markets fall short of the risk sharing ideal.

Figure 2 also points to heterogeneity across commodities. Despite, higher production variability, wheat and maize markets seem to achieve greater risk sharing than the rice market. Figure 3 illustrates heterogeneity across another dimension i.e., income. The gap between consumption variability and domestic production variability is much more pronounced for OECD countries than for countries in Sub-Saharan Africa. It is only in the case of maize that the African countries display substantial consumption smoothing.

Figures 2 and 3 are the motivation for this paper. First, it formally tests for risk sharing in the markets for maize, rice and wheat. Second, the paper estimates the extent of risk sharing and the contribution of trade and storage to it. The analysis is conducted separately for each of the staples to allow for heterogeneity across markets. Third, the paper examines whether consumption smoothing is different for rich and poor countries. Finally, we show the robustness of our results to macroeconomic shocks like price and income shocks, exchange rate fluctuations, membership to World Trade Organization and other regional trade blocks.

Maize, rice and wheat account for 50 per cent of dietary energy supply and 20-25 per cent of total expenditures for people in the bottom quintile of the income distribution (Dawe et al., 2015). Arguably, variability in this component of consumption is expensive for the poor. It is, natural therefore, to examine risk sharing in the markets for these staples.

There is a large literature on the functioning of world markets for the basic staples. Two components of this literature are particularly relevant to this paper. The first strand examines the transmission of prices from global markets to domestic markets. Typically, the finding is that the transmission is imperfect because of trade barriers. In the second and related literature, trade barriers are seen as instances of 'market insulating' behavior. Countries use trade policies to insulate their domestic markets from price volatility in the global market. During price spikes, use of trade-restrictive policies is common, and when all countries attempt to insulate their domestic markets simultaneously, these render global food markets extremely thin and can magnify volatility in global food prices.

The contribution of this paper to the food markets literature is several fold. First, although a lack of risk sharing is implicit in past literature, this is the first work to study and quantify it. Second, the focus on consumption variability directs attention to the variable that matters in economic models. Thin world markets and imperfect price transmission make it awkward to study price variability. Third, the paper provides a common metric to assess the relative performance of the markets for maize, rice and wheat. Fourth, the methodology allows us to address the consumption smoothing of poor countries vis-á-vis the rich countries.

Our study is also related to consumption risk sharing that has been analyzed for macro aggregates (regions, countries). A principal difference is that the macro literature considers consumption aggregates in value terms while it is both natural and feasible to measure food consumption and production in physical units. In that sense, the application in this paper is tethered more closely to the theory of risk sharing than the macro literature. As the preliminary evidence (for instance, Figure 3) suggests heterogeneity in risk sharing, the formal empirics pay a great deal of attention to unobserved heterogeneity in the coefficients of idiosyncratic and aggregate shocks.

2 Literature

Trade and storage are two principal means by which countries have sought to align unstable output with the need to smooth consumption. However, public stocks are considered to be a costly option, as they tie up scarce resources, are vulnerable to deterioration, corruption and theft; and may crowd out private sector from holding food stocks (Gilbert, 2011). Knudsen and Nash (1990), from a review of experiences on domestic price stabilization programs across the world, concluded that stabilization schemes should "avoid handling the commodity when possible".

On the other hand, several studies have indicated that in comparison to public stocks holdings, international trade is an economical means of stabilizing food supplies (Valdes, 1981; Krishna et al., 1983; Jha and Srinivasan, 1999; Srinivasan and Jha, 2001; Dorosh, 2001). The idea that trade can stabilize consumption has long been recognized in the literature. Timmer (2008) argued for a move away from national food security stocks towards food security via trade and production based on comparative advantage.

In general, global food production is more stable than the regional or national production, and thus free trade should be able to achieve greater stability in prices and consumption. In the words of Gilbert (2011), "If supply (harvest) shocks are largely uncorrelated across countries, governments can import when they need to do so without, on average paying high prices". The caveat introduced by Gilbert acknowledges that the contribution of trade would depend on the correlation of production shocks across countries.

The recommendation that trade (along with targeted safety nets) ought to be a principal component of food security policy is part of the policy paradigm advocated by economists (Gouel, 2013). In practice, many countries have rejected the paradigm. Studies have found the transmission of world price shocks to domestic prices to be generally limited (Baquedano and Liefert, 2014; Ceballos et al., 2017; Dawe et al., 2015;

De Janvry and Sadoulet, 2010; Gilbert, 2011; Minot, 2011; Mundlak and Larson, 1992; Robles et al., 2010).

A possible explanation is suggested by a parallel literature, according to which, countries use trade policies to insulate their domestic markets from price volatility in the global market. During price spikes, countries attempt to maximize their share of the global market. Exporting countries restrict exports while importing countries drop tariffs. The opposite happens when there are surpluses. When all countries attempt to insulate their domestic markets simultaneously, these render global food markets extremely thin and can magnify volatility in global food prices (Abbott, 2011; Martin and Anderson, 2011; Giordani et al., 2016; Gilbert and Morgan, 2010; Mitra and Josling, 2009; Headey, 2011; Slayton, 2009). A typical instance that has been cited widely is the behavior of rice markets during 2007/08. It is believed that government actions of panic buying (by importers) and export prohibitions (by exporters) contributed to the price spikes (Dawe and Slayton, 2011; Timmer, 2008; Wright, 2011). The unreliability in world food markets, when needed most, would lead to serious doubts on their efficiency in providing insurance against adverse production shocks.

Although the literature assigns risk sharing to be the primary contribution of international trade to food security, this has not been tested or quantified in the literature. This is the point of departure for this paper. The paper explicitly formulates the risk sharing hypothesis and takes it to data examining the contribution of trade and storage. While the literature documents low price transmission and market insulating behavior, Figure 2 shows that countries do achieve some consumption smoothing relative to the variability in their production. How much of it is because of trade? Or is it because of storage? These are the questions that can be asked within a risk sharing framework.

It should also be noted that relative to the literature, this paper shifts the focus from prices to quantities [1]. The explicit formulation of a risk sharing hypothesis directs attention to how staple food consumption reacts to country specific and aggregate production shocks. Since it is consumption that is the direct determinant of welfare, these questions permit a direct link between production shocks and welfare.

The canonical model of risk sharing predicts that when it is optimal, consumption of the economic unit (individual, household or country) varies only with the economic outcome of the aggregate of the economic units (village, district, the world) and is uncorrelated with the economic outcome of the economic unit (Townsend, 1987). Even though such a prediction is the outcome of a complete markets model without transactions costs or information failures, real world institutions including transfers between households or between governments, may approximate formal insurance markets (Townsend, 1994). A large literature has tested this prediction using household data and using country level data seeking to know how the data deviates from the complete markets benchmark.

This paper is most closely related to the literature on international consumption risk sharing that has sought to examine whether national aggregate consumption is fully insured against national risks. Most papers find that consumption risk sharing even within the developed countries falls well short of the optimal benchmark (Canova

[1] Jha et al. (2016) is an exception. That paper also looks at consumption variability and how that is affected by domestic and foreign production shocks. However, the paper's estimation and results do not occur within a well-defined risk sharing framework.

and Ravn, 1996; Crucini, 1999; Lewis, 1996).

This literature has been extended in several ways. Kose et al. (2009) apply the risk sharing framework to a large group of developed and developing countries to contrast risk sharing across these groups and to examine the effects of financial globalization. Other studies have examined intra-national risk sharing (between states or provinces) or national risk sharing within monetary unions (Asdrubali et al., 1996; Asdrubali and Kim, 2008; Crucini and Hess, 2000; Sørensen and Yosha, 1998).

This paper extends the risk sharing framework to food staple markets. Unlike the literature which considers risk sharing in a composite commodity (e.g., GDP or household consumption), the staples here can be aggregated in physical units whether for consumption or for production shocks. While that is the advantage of considering individual commodities, the empirical challenge is to address the non-separability in preferences across commodities that naturally arise when endowments are multi-good. In addition, these preferences may vary across countries. These complications may lead to unobserved heterogeneity in the impact of both aggregate and idiosyncratic shocks. Besides addressing these challenges, the paper also investigates how heterogeneity in risk sharing relates to observable characteristics such as country per capita income.

3 Theoretical Framework

The theoretical structure in this section closely follows the setup in Cochrane (1991) and Mace (1991) with the only difference being that rather than assuming one aggregate consumption good, as is standard in the literature, we solve for a case where the consumer chooses over multiple commodities. We assume that there is a representative consumer in each country with preferences defined over J commodities. Without loss of generality, these J commodities can either be different goods or different varieties of a single good, some of them can be food commodities and the rest non food commodities. Uncertainty is introduced as finite states of the world denoted by s^t in each time period t. The representative consumer's utility function is non-separable in the J goods.

$$U_i = u_i(x_{i1s^t}, ..., x_{iJs^t}) \tag{1}$$

where, x_{ijs^t} is an individual i's consumption of good j in state s at time period t. We assume that $u_i(.)$ is strictly increasing, concave and twice differentiable function. The functional form of the utility is allowed to vary across consumers hence the curvature of the function and risk aversion can be heterogeneous across consumers. Each consumer i is endowed with w_{ijs^t} units of the j goods in state s of time period t, where each state occurs with a probability π_s^t and $\sum_{s^t} \pi_{s^t} = 1$. Following the literature, we consider the optimal risk sharing problem as social planner maximizing weighted sum of expected utilities of individuals subject to the aggregate resource constraints.

The expected lifetime utility function of agent i is expressed as

$$E(U)_i^{lifetime} = \sum_{t=1}^{\infty} \rho_i^t \sum_{s^t} \pi_{s^t}[u_i(x_{i1s^t}, ..., x_{iJs^t})] \tag{2}$$

where $\rho_i \in (0,1)$ is the discount factor for agent i. Ex-ante efficiency requires that the allocation of resources across states is efficient such that no state-contingent exchange can improve both agents' expected utilities. The ex-ante efficient risk sharing allocation is the solution of the following program.

$$Max \sum_{i=1}^{N} \omega_i E(U)_i^{lifetime} \tag{3}$$

where, ω_i is the weight of consumer i in the planner's problem with $0 < \omega_i < 1$ and $\sum_{i=1}^{N} \omega_i = 1$. Subject to the following aggregate resource constraints.

$$\sum_{i=1}^{N} x_{ijs^t} = \sum_{i=1}^{N} w_{ijs^t} = X_{js^t} \tag{4}$$

for all J commodities and for all states of the world s^t. Note that the analysis would remain unchanged if we extend the structure to include production of commodities. The planner can solve the production problem first by allocating aggregates across states and time periods and then determine the optimal consumption allocation, taking the produced aggregates as endowments (Cochrane, 1991). The first order conditions of the social planner's problem, with respect to jth commodity is

$$\rho_i^t \omega_i \frac{\partial u_i(x_{i1s^t}, ..., x_{iJs^t})}{\partial x_{ijs^t}} = \mu_{js^t} \tag{5}$$

where μ_{js^t} is the Lagrangian multiplier of the aggregate resource constraint of the food commodity $j \in J$ divided by the probability of state s^t. For each individual

i, there will J such first order conditions. To derive the comparative statics we total differentiate 5.

$$\rho_i^t \omega_i \left[\frac{\partial^2 u_i(x_{i1s^t}, ..., x_{iJs^t})}{\partial x_{ijs^t} \partial x_{i1s^t}} dx_{i1s^t} + ... + \frac{\partial^2 u_i(x_{i1s^t}, ..., x_{iJs^t})}{\partial x_{ijs^t} \partial x_{iJs^t}} dx_{iJs^t} \right] = d\mu_{js^t} \tag{6}$$

To remove the $\rho_i^t \omega_i$ from 6 we divide it by 5 and write it as

$$\frac{u_{i,j1}}{u_{i,j}} dx_{i1s^t} + ... + \frac{u_{i,jJ}}{u_{i,j}} dx_{iJs^t} = \frac{d\mu_{js^t}}{\mu_{js^t}} \tag{7}$$

where $u_{i,jj'} = \frac{\partial^2 u_i(x_{i1s^t},...,x_{iJs^t})}{\partial x_{ijs^t} \partial x_{ijs^t}}$ and $u_{i,j} = \frac{\partial u_i(x_{i1s^t},...,x_{iJs^t})}{\partial x_{ijs^t}}$. For an individual i, we will have J such system of equations which can be written in matrix form as

$$AX = \Pi \tag{8}$$

where A is a $J \times J$ matrix with each element of the form $u_{i,jj'}$, X is a $J \times 1$ vector of differentials with respect to each good J (each element is of the form dx_{ijs^t}) and Π is the $J \times 1$ vector of relative change in the Lagrangian multiplier with respect to each good J. Solving 8 using Cramer's rule we get

$$X = A^{-1}\Pi \tag{9}$$

$$dx_{ijs^t} = \sum_{j' \in J} \beta_{i,jj'} \frac{d\mu_{j's^t}}{\mu_{j's^t}} \tag{10}$$

where $\beta_{i,jj'}$ are the elements of the matrix A^{-1} and are composed of the direct and cross partial derivatives of the utility function. Two points are worth noting from 10. One, the change in the optimal allocation of a good j is associated with only the relative change in the Lagrangian multipliers of aggregate resource constraints and is independent of the individual consumer's endowment of j. Two, the effect of change in aggregate resources on optimal allocation will be heterogeneous across consumers as the parameter $\beta_{i,jj'}$ will vary across individuals. This heterogeneous effect of aggregate resources arises because we allow the functional form of utility to vary across consumers. What is important to note here is 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. This is the main implication of assuming a non separable utility function. To contrast this with the case of separable utility we consider an example of a two good separable utility function.

$$U_i = u_i(x_{it}) + v_i(y_{it}) \tag{11}$$

Assume that $u_i(x_{it}) = -x_{it}^{-a_i}$ and $u_i(y_{it}) = -y_{it}^{-b_i}$, where $a_i, b_i > 0$ and the subscript s^t for state is replaced with t for time, then the necessary condition for optimal risk allocation can be expressed as [2]

$$ln\left(\frac{x_{it}}{x_{it-1}}\right) = \alpha_i^x + \left(\frac{\frac{1}{(a_i+1)}}{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{(a_i+1)}}\right)\frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{x_{it}}{x_{it-1}}\right) \tag{12}$$

$$ln\left(\frac{y_{it}}{y_{it-1}}\right) = \alpha_i^y + \left(\frac{\frac{1}{(b_i+1)}}{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{(b_i+1)}}\right)\frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{y_{it}}{y_{it-1}}\right) \tag{13}$$

Notice that now each of the first order conditions is independent of the aggregate resource constraint of the other commodity. Therefore, the optimal allocations of, say, food staple x can be analyzed independently of the optimal allocations of food staple y. This implication that individual consumption does not depend on individual endowments but only on aggregate endowment forms the basis of the commonly used tests of risk sharing.

4 Data, Descriptive Statistics and Correlations

To test the risk sharing hypothesis we primarily rely on the Food and Agriculture Organization's (FAO) 'Food Balance Sheets' dataset (FAOSTAT, 2014). The food balance sheets provide country level time series (1961-2013) of production, domestic supply, consumption, stocks and trade of major agricultural commodities. This enables us to construct large unbalanced panels. Our analysis focuses on three important staple food commodities, viz., wheat, rice and maize. The FAO dataset differentiates between food consumption and domestic supply. They are calculated as

[2] For detailed derivation of these first order conditions refer to appendix A.

$$\text{Domestic supply} = \text{Production} + \text{Imports} - \text{Exports} + \text{Stock variation}$$

$$\text{Food consumption} = \text{Domestic supply} - \text{Seed} - \text{Feed} - \text{Industrial use} - \text{Other uses} - \text{Waste}$$

We consider food consumption as our dependent variable in the tests of risk sharing. The aggregates of consumption and production are converted into their per capita equivalents using the population figures from the World Bank's World Development Indicators (WDI) database. Further the data are log transformed and then first differenced to get year-on-year growth rates.

Table 1 presents the standard deviation in consumption and production magnitudes. Global production is least variable for rice and most variable for maize. The last column of table 1 that shows average world trade of the three commodities (wheat, rice and maize) as proportion of the world production gives us the extent to which this potential of trade is actually utilized. In terms of total trade volume, wheat has been the most traded commodity with about 19% of the production being traded, followed by maize (12%) and rice (4%). This suggests that consumption risk sharing would also be greatest for wheat markets.

Figure 4 plots the trends in trade of rice, wheat and maize as proportion of their respective outputs. Volume of rice trade was almost stagnant until the 1990s but started showing significant rising trend afterwards. The reason for this rising export-output ratio was the export liberalization in India in 1993 and the rise of Vietnam as a major rice exporter (Jha et al., 2016). There is much variation in the volume of trade in the case of wheat but there is no visible trend. Maize trade increased in 1970s and peaked in 1980 after which it has shown a declining trend.

4.1 Correlations

As a step towards testing the predictions of efficient risk sharing hypothesis, first we examine the correlation of growth in domestic consumption with the growth in domestic production and with the growth in world consumption each of rice, wheat and maize. Figure 5 summarizes these correlations. The solid lines show the trend in median decadal moving average correlations of domestic and world consumption growth and the dashed lines show the trend in correlations of domestic consumption with domestic production. The estimated correlation coefficients between domestic consumption and world consumption are well below unity while domestic consumption is found to be highly correlated with domestic production for the entire period. This indicates a low degree of consumption smoothing across countries. Further, there is no clear trend in correlations of domestic consumption with world consumption but the correlation of domestic consumption with domestic production for all the commodities declines overtime, suggesting an improvement in the degree of consumption smoothing. The gap between the two lines is particularly large for rice and maize suggesting these markets perform worse in terms of risk sharing.

Further we estimate these correlations by income levels of the countries. Following the World Bank classification, we consider the four groups of low income, lower middle income, upper middle income and high income countries. For the sake of brevity, Figure 6 displays these results only for low income and high income countries. There is considerable heterogeneity, between markets and between the high and low income countries, in the estimated correlations. For all the commodities, the correlation between domestic consumption and domestic production (dashed line) is higher for low income countries compared to the high income countries. For maize, the difference is stark between low and high income countries indicating that low-income countries are unable to insure domestic consumption against domestic production shocks.

5 Tests of Risk Sharing

5.1 Benchmark Specification

Based on the theoretical framework, tests of risk sharing regress growth rate of per capita country consumption on an aggregate shock and growth of per capita country production. The basic regression specification is as below

$$c_{it} = \alpha_i + \mu_t + \gamma y_{it} + \epsilon_{it} \tag{14}$$

where c and y denote the growth rates of per capita consumption and production respectively for country i at time t, α_i is a dummy variable for country i and μ_t is a time dummy that measures aggregate shock. Under full risk sharing, after controlling for aggregate shocks, consumption should be independent of idiosyncratic shocks, thus the optimal risk sharing hypothesis is $\gamma = 0$.

Rejection of the hypothesis implies that agents are not able to fully insure themselves from idiosyncratic supply shocks, hence consumption will be correlated with production. In that case $(1 - \gamma)$ can be interpreted as a measure of the degree of insurance or risk sharing achieved (Asdrubali et al., 1996; Crucini, 1999; Crucini and Hess, 2000). Several studies (Asdrubali et al., 1996; Lewis, 1996; Sørensen and Yosha, 1998; Sørensen et al., 2007; Kose et al., 2009) have conducted test of risk sharing based on a version of the specification in equation (14). The idea is that time dummies will remove the common component in both the consumption and production growth and therefore γ can be interpreted as the effect of idiosyncratic production growth on idiosyncratic consumption growth. Thus, a two way fixed effects specification provides a simple way to control for unobserved heterogeneity at country level and common time effects for all countries.

Non-stationarity of the variables in equation (14) may lead to spurious estimates of slope coefficient. To test for stationarity in the time series of these variables, we conduct panel unit root tests, and the results are reported in appendix B (table B1). It can be seen that while the variables are non-stationary in levels, the null of unit roots are rejected for log first differences. In all the regressions reported in this paper, variables are transformed to log first differences. We also test for serial correlation and heteroscedasticity in the errors of our basic fixed effects specification (equation 14). The F statistic for test of serial correlation is statistically significant at 1% level for rice market indicating the presence of serial correlation. The χ^2 statistic for heteroscedasticity is significant at 1% level for all three commodities indicating the presence of heteroscedasticity (appendix B table B2). To take care of these we estimate country-clustered standard errors.

The first column of Table 2 is a regression of the consumption growth rate on growth rate of domestic output (y_{it}) without the controls of country and time dummies for each of the three food staples. The second column adds the country dummies while the third column (the preferred specification) includes time dummies as well. The 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. Conceptually, the time dummy provides greater control for aggregate shocks. As noted earlier, if the utility function is not additively separable across the commodities, the aggregate shock is a vector of shocks to aggregate consumption of all the commodities in the utility function. The time dummy provides a control without requiring the researcher to take a view on the structure of the utility function.

The estimates of γ (the coefficient of y_{it}) are significantly different from zero for rice, wheat and maize, and therefore, the optimal risk sharing hypothesis is rejected. These results reinforce our earlier observation that commodity markets seem unable to completely insulate domestic consumption from idiosyncratic production shocks. The regression results reinforce our observation that none of the commodity markets are able to achieve full insulation from idiosyncratic supply shocks. Comparing the degree of risk sharing across food markets (Table 2), we find that wheat market performs the best, providing 97% insurance against domestic production shocks. This is followed by maize (88%) and rice (81%) markets.

5.2 Adding Controls and Trends

We test the robustness of our results in table 2 from additional controls such as shocks to per capita gross domestic product at constants prices (GDP), fluctuations in the national GDP deflator, fluctuations in the nominal exchange rate and an indicator variable for when the country joined World Trade Organization (WTO). These results are presented in specifications 1 to 5 in table 3. The control variables are statistically insignificant and do not influence the magnitude of the coefficient on production shocks (y_{it}). We also test for time trends by interacting y_{it} by linear time trend in equation (14). The coefficient on the interaction term (specification 6, table 3) is statistically significant and negative for rice indicating that risk sharing in rice market has improved overtime.

In addition to the above robustness exercise, we perform three additional robustness tests in the appendix C. In C.1 we check for the robustness of our results using an alternative dataset from the 'Production, Supply and Distribution' database of the United States Department of Agriculture's Foreign Agriculture Service (FAS) (USDA, 2014) database. The γ coefficients continue to be highly significant. They are also larger for each of the commodities. Compared to the FAO data, risk sharing is lower in the USDA data. In C.2, we test the 'strict exogeneity' assumption inherent in a fixed effects model, that there is no correlation between production shock in country i in year t and the lag and lead error terms within a country. The efficient risk-sharing hypothesis continues to be rejected. Compared to the benchmark specification, the magnitude of risk sharing is higher. Finally, in C.3 we address the concern that measurement errors in consumption and production may bias the estimates of risk sharing. The problem of measurement errors in complicated by the fact that consumption in our data is derived as a residual as production that is netted out of net trade and storage therefore it is natural to assume that consumption errors would nest in it the errors in income, trade, storage. We first derive the bias in the estimated coefficient and show that under the nested measurement error structure the direction of bias is indeterminate. We address the bias by implementing the Lewbel (2012) instrumental variable estimator and find these estimates comparable to the estimates from our benchmark specification.

5.3 Heterogeneity in the Slope Coefficient

Equation (14) assumes that coefficients of the individual production shock and that of the aggregate production shock are the same across the cross- sectional units. Although risk sharing tests typically model the slope parameter, i.e., the coefficient of the country production shock as homogeneous, the theoretical framework that gives rise to equation (14) imposes no such restriction. Suppose, in fact, the slope parameter is heterogeneous (the next section extends the model to heterogeneity in the aggregate shock as well). A more general version of equation (14) is

$$c_{it} = \alpha_i + \mu_t + \gamma_i y_{it} + \epsilon_{it} \tag{15}$$

where $\gamma_i = \gamma + \eta_{it}$ such that η_{it} is a mean zero random variable. Substituting for γ_i, we get

$$c_{it} = \alpha_i + \mu_t + \gamma y_{it} + (\eta_{it} y_{it} + \epsilon_{it}) \tag{16}$$

A fixed effects estimation of (16) is inconsistent whenever the deviation η_{it} is correlated with the sample variance of y_{it} (Wooldridge, 2003). A consistent estimator is the mean group estimator (Pesaran and Smith, 1995). It is obtained by estimating (15) for each country. The average of the estimated slope coefficients in the individual country regressions is the estimate of the average effect, γ. The first row of Table 4 displays the mean group estimates of γ for the three food staple markets. Notice that allowing for heterogeneity leads to a decrease in the magnitude of the estimates for wheat and maize, therefore, improves the risk sharing performance of these markets.

5.4 Heterogeneity in the Slope Coefficient and Aggregate Shocks

If time effects, which capture aggregate shocks, are heterogeneous across countries then the two-way specification in (14) could lead to biased estimates of the degree of risk sharing. Divergent preferences is an immediate cause of heterogeneity. For instance, as consumption patterns differ across countries, a global supply shock in rice matters more to some countries than others.

The gravity model of trade that relates bilateral trade flows to distance could be another reason for heterogeneity in the incidence of aggregate shocks. Countries distant from major producers are less affected by aggregate shocks than those that are geographically closer. For these reasons, consider the heterogeneous coefficients version on equation (14) as

$$c_{it} = \alpha_i + \gamma_i y_{it} + \lambda_i \mu_t + \epsilon_{it} \tag{17}$$

where μ_t, the aggregate shock is the unobserved common factor with heterogeneous effects. Because a country is the cross-sectional unit in our panel, a model with country-time fixed effects is not estimable. We use Pesaran (2006) common correlated effects framework to model the unobserved heterogeneity in aggregate shocks. Averaging (17) across the cross-section units, we get

$$\frac{1}{N}\sum_{i=1}^{N} c_{it}^{j} = \frac{1}{N}\sum_{i=1}^{N}\alpha_i + \frac{1}{N}\sum_{i=1}^{N}\gamma_i y_{it} + \frac{1}{N}\mu_t\sum_{i=1}^{N}\lambda_i + \frac{1}{N}\sum_{i=1}^{N}\epsilon_{it} \tag{18}$$

The γ_i's follow a random coefficient model. Let $\gamma_i = \gamma + v_{it}$ where v_{it} is a mean zero random variable that is distributed independently of y_{it}. Then the above equation becomes

$$\bar{c}_t = \bar{\alpha} + \gamma\bar{y}_t + \mu_t\bar{\lambda} + \bar{\epsilon}_t + \frac{1}{N}\sum_{i=1}^{N} y_{it}v_{it} \tag{19}$$

where the variables headed by a bar are the cross-sectional averages. For large N, the averages converge to the population magnitudes. In particular, the last two terms vanish. Hence the aggregate shock μ_t can be consistently estimated by a linear combination of the country fixed effect and the cross-sectional averages of country consumption and output. Pesaran uses this insight to show that the slope coefficients γ_i can be consistently estimated by a regression of the form for each of the countries

$$c_{it} = \alpha_i + \gamma_i y_{it} + \delta_i\bar{c}_t + \zeta_i\bar{y}_t + \epsilon_{it} \tag{20}$$

Pesaran shows that the average of the estimates of γ_i is a consistent estimator of γ and is called the common correlated effect mean group estimator (CCEMG). It is easy to see that slope homogeneity is a special case and the consistency results apply here as well. The CCEMG estimates are displayed in Table 4. In terms of magnitude, these are comparable to the mean group estimates. Pareto optimal risk sharing is rejected in all the three food staples. The extent of risk sharing is much greater in wheat markets compared to rice or maize.

5.5 Clustered Aggregate Shocks

A possible explanation for the failure of full risk sharing could be that the world is divided into trading blocs and alliances. As a result, the relevant risk sharing group (and therefore, the relevant aggregate shock) is not the entire world but the group to which the country belongs. If the group membership is well known, then a version of (14) with fixed effects for the group would be the appropriate estimation strategy. But while one may guess and construct such group membership, errors in classification would undermine confidence in the estimates. Bonhomme and Manresa (2015) provide an approach to allow for 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 adhoc assignment of units to groups, the group-specific time patterns and individual group membership are left unrestricted, and are estimated from the data. In this framework, equation (14) becomes

$$c_{it} = \alpha_i + \mu_{g_i t} + \gamma y_{it} + \epsilon_{it} \tag{21}$$

where $\mu_{g_i t}$ is a time fixed effect specific to countries belonging to group i. For given values of the parameters, minimizing a least squares sum of residuals over all possible groupings of the countries leads to a group assignment that is a function of the given parameters. The group fixed 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 (cross-sectional units) and large T (time units). The number of groups is fixed beforehand and chosen by the researcher.

We vary the number of groups from 2 to 7. Figure 7 shows the GFE estimates to be robust across these specifications. The last row of Table 4 reports the GFE estimates when we assume the number of groups to be five. As can be seen, the estimates are close to the estimates from the benchmark specification. Allowing for clustered aggregate shocks does not change the narrative of incomplete risk sharing and how it varies across food staples.

6 Heterogeneity in Risk Sharing by Income

The previous section found that the average extent of risk sharing is robust to unobserved heterogeneity in the parameters of equation (14). An observed source of heterogeneity could be country income. The heterogeneity in correlation trends across country-groups based on their income levels (Figure 6) suggests that the degree of risk sharing is heterogeneous across countries and that it varies over time. To evaluate the relationship between the degree of risk sharing and the income level we allow γ to vary across income groups of countries (INC_g) with country-group specific linear time trend. Mathematically, this can be expressed as:

$$\gamma = \delta_1 + \sum_{g=2}^{4} \delta_g INC_g + \theta_1 t + \sum_{g=2}^{4} \theta_g t \times INC_g \tag{22}$$

where INC_g is dummy variable for each income group g, and t is the linear time trend. The results are presented in Table 5. The degree of risk sharing is the lowest (γ highest) for low income countries (base category) and increases with income. For example, rice consumption in low income countries is insured only against 52% of the shocks to production whereas high income countries domestic consumption is insured to the extent of 93% of the shocks to production (Table 5 column 1). A similar situation is observed in the case of wheat and maize. The difference in the degree of risk sharing between low income and the high income countries for both rice and wheat is statistically significant.

The difference in the extent of risk sharing can also be seen graphically in Figure 8 which displays the marginal impacts of the idiosyncratic production shock on consumption growth rates for the different country groups. These marginal impacts are evaluated at 1987 - the mid-point of the period 1961 to 2013. The other notable result from Table 5 is that γ_i declines and risk sharing improves over time for low income countries with respect rice and wheat but not for maize.

7 Contribution of Trade and Storage

In principle, international trade in the staple foods could achieve the risk sharing ideal (Gouel, 2016). However, because of trade impediments, either because of tariffs or other trade policies or because of trade costs, economies may not be completely open. In this case, inter-year storage could also contribute to risk sharing (Gouel, 2013). In this section, we adapt the framework of Asdrubali et al. (1996) to quantify the contribution of trade and stocks to risk sharing. Consider the following identity,

$$Y_{it} = \frac{Y_{it}}{Y_{it}^{NX}} \times \frac{Y_{it}^{NX}}{S_{it}} \times \frac{S_{it}}{C_{it}} \times C_{it} \tag{23}$$

where Y_{it}, S_{it} and C_{it} are the per capita production, per capita domestic supply and per capita consumption in country i at time period t respectively. Y_{it}^{NX} is defined as the production left after net exports. Then the domestic supply will be equal to the sum of production left after trade and change in stocks. Not all food grain left after trade and change in stocks is used for human consumption. As described in the data section the food balance sheets data reports food grain used as seed, animal feed, for industrial purposes, other uses and wasted. Removing this component from the domestic supply gives us the consumption aggregate. The variance in per capita production can be decomposed as [3].

$$Var(y_{it}) = Cov(y_{it}, y_{it} - y_{it}^{NX}) + Cov(y_{it}, y_{it}^{NX} - s_{it}) + Cov(y_{it}, s_{it} - c_{it}) + Cov(y_{it}, c_{it}) \tag{24}$$

where $y_{it} = \Delta lnY_{it}$, $y_{it}^{NX} = \Delta lnY_{it}^{NX}$, $s_{it} = \Delta lnS_{it}$ and $c_{it} = \Delta lnC_{it}$. Dividing by the variance of y_{it} we get

$$1 = \frac{Cov(y_{it}, y_{it} - y_{it}^{NX})}{Var(y_{it})} + \frac{Cov(y_{it}, y_{it}^{NX} - s_{it})}{Var(y_{it})} + \frac{Cov(y_{it}, s_{it} - c_{it})}{Var(y_{it})} + \frac{Cov(y_{it}, c_{it})}{Var(y_{it})} \tag{25}$$

$$1 = \gamma^T + \gamma^S + \gamma^{SFIOW} + \gamma \tag{26}$$

$$1 - \gamma = \gamma^T + \gamma^S + \gamma^{SFIOW} \tag{27}$$

Under full risk sharing, after controlling for aggregate shocks, consumption should be independent of idiosyncratic production shocks, i.e., $\gamma = 0$. It can be seen from the above that $(1 - \gamma)$ is the proportion of consumption variability that is insured. Hence $(1-\gamma)$ can be interpreted as a measure of the degree of insurance or risk sharing. The above identity decomposes the degree of risk sharing $(1 - \gamma)$ into risk sharing due

[3] Detailed derivation is presented in appendix D.

to trade γ^T, change in stocks γ^S and due to the seed, feed, industrial and other use and waste component γ^{SFIOW}. Clearly γ^T, γ^S and γ^{SFIOW} can be computed as slope coefficients of an appropriate regressions.

To quantify the contributions of trade, changes in stocks and the residual, we estimate the following regressions.

$$y_{it} - y_{it}^{NX} = \alpha_i^T + \mu_t^T + \gamma^T y_{it} + \epsilon_{it}^T \tag{28}$$

$$y_{it}^{NX} - s_{it} = \alpha_i^S + \mu_t^S + \gamma^S y_{it} + \epsilon_{it}^S \tag{29}$$

$$s_{it} - c_{it} = \alpha_i^{SFIOW} + \mu_t^{SFIOW} + \gamma^{SFIOW} y_{it} + \epsilon_{it}^{SFIOW} \tag{30}$$

$$c_{it} = \alpha_i + \mu_t + \gamma y_{it} + \epsilon_{it} \tag{31}$$

The results are displayed in Table 6. Column 4 of Table 6 is the same as column 3 of Table 2 because equation (31) is the benchmark specification that was already reported in Table 2. From columns (1), it is clear that trade is the principal contributor to risk sharing for all of the three commodities. Of the risk sharing that is achieved (i.e., $(1-\gamma)$), trade is responsible for 55% of it in the case of rice, 64% in wheat and 60% in the case of maize.

The absolute contribution of trade to smoothing domestic production shocks is higher in the case of wheat (62%) than maize (52%) and rice (44%). This is expected, as wheat is one of the most traded food commodities in the global food market. Also distortions in global food market are lower for wheat than for rice.

In the case of maize, trade could insure domestic consumption against 52% of the fluctuation in its domestic production, an estimate closer to that for rice. This is contrary to our expectation as the total volume of maize exports far exceeds that for rice. A possible explanation for this could be the difference in types/varieties of maize being traded in the international market. Dawe et al. (2015) while studying price behavior of staple food commodities in low- and middle-income countries find that domestic maize prices are more volatile than the prices of rice and wheat because of the thin global market for white maize which is primarily used for human consumption more so in sub Saharan Africa. Maize is a staple food crop in sub Saharan Africa and accounts for $30-50\%$ of the total household consumption expenditure.

8 Conclusions

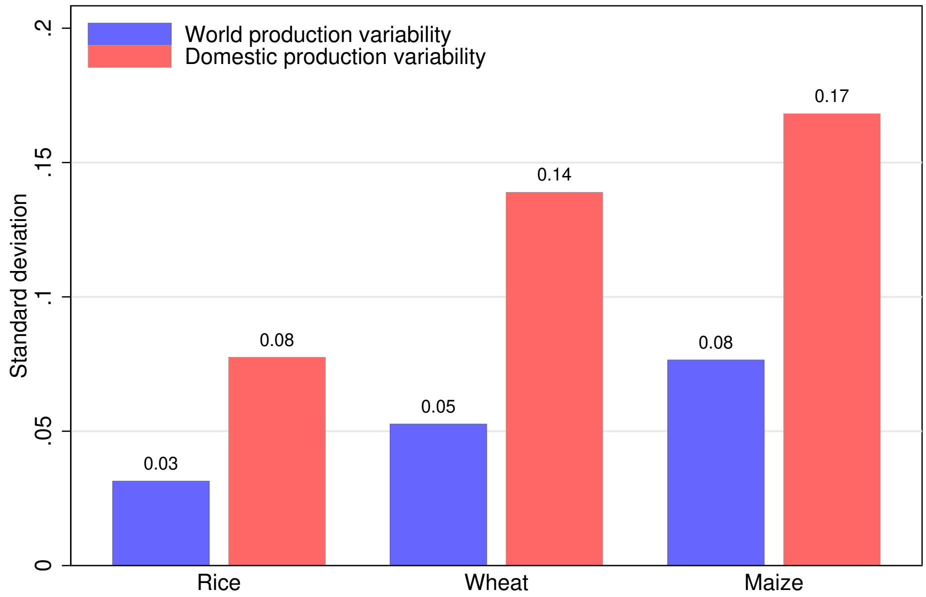
Greater stability in the growth of global food production as compared to that in the national or regional production theoretically implies tremendous potential for trade to share risk across countries. However, this idea of risk sharing has not been formally tested in the world food markets. In this paper, we try to fill this gap in literature using efficient risk sharing hypothesis as a benchmark to look at the potential of trade in insulating domestic consumption against domestic production shocks, and its importance in relation to domestic food stocks.

For observers of world food markets, the rejection of the efficient risk sharing hypothesis is probably not surprising. Similarly, the superior performance of the wheat market in providing insurance is also possibly an expected finding. However, the finding that the maize market performs just as poorly as the rice market is unexpected. Both these markets are characterized by horizontal and vertical differentiation of varieties (which in turn, is a reflection of imperfect substitutability) and that possibly limits the ability of the market to provide insurance. Another noteworthy finding is the dominant role of trade in providing insurance for all of the markets. Countries have been following the prescription of economists that trade is, in most cases, a cheaper way of stabilizing consumption than storage.

While global governance would have to be concerned by the limited risk sharing achieved by maize and rice markets, there is also an additional concern that such risk sharing is even lower for poorer countries. In the case of rice, for example, low-income countries are able to achieve only 52% of full insurance relative to 93% attained by high-income countries. A similar situation is observed in the case of wheat. Improving the insurance for poor countries would be vital to achieve food security. This paper provides the grounds for such a discussion.

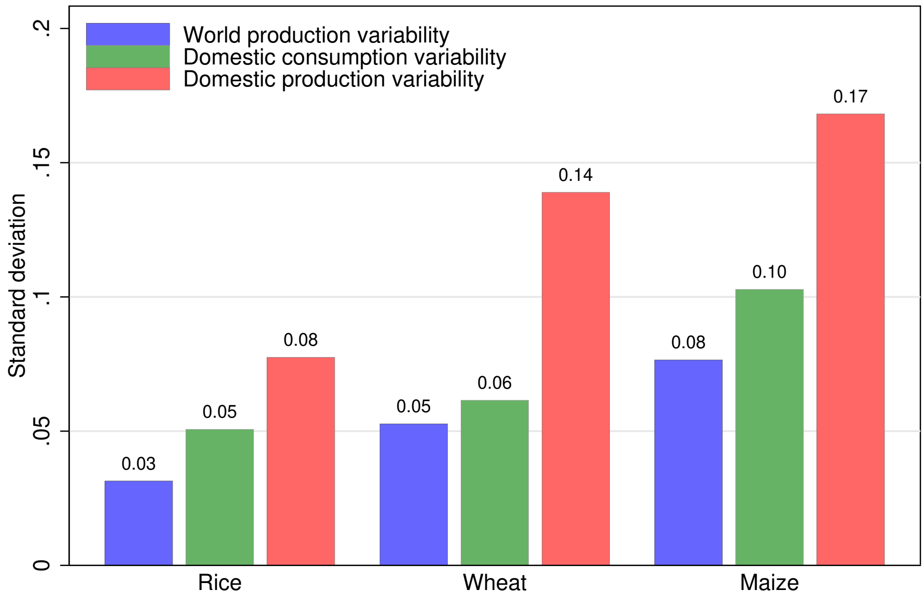
Figures

Figure 1: Production Variability of Rice, Wheat and Maize: 1961-2013



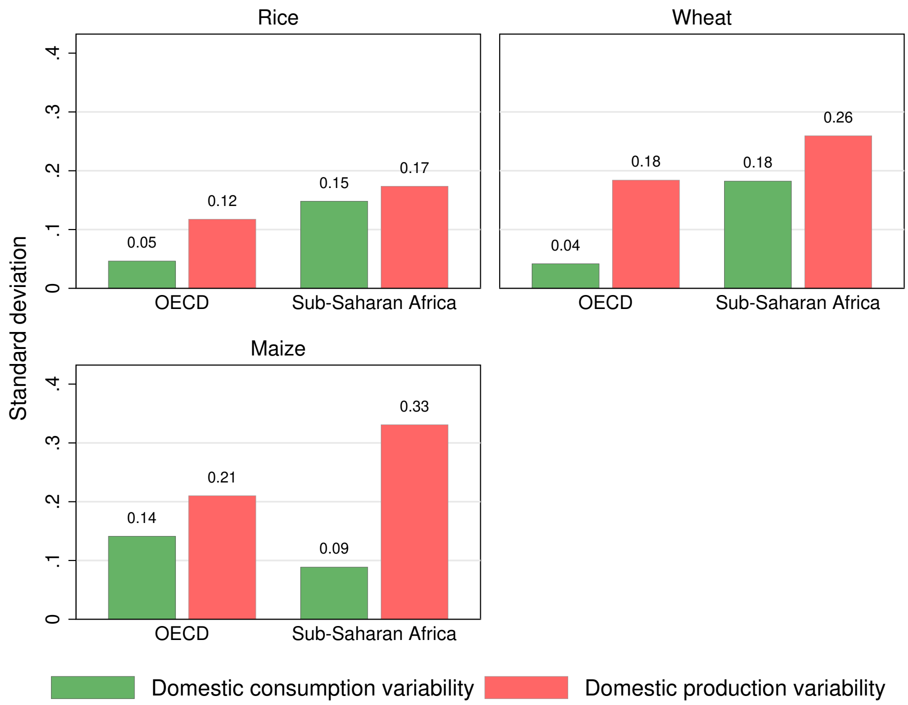
Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database. The world production variability is estimated as the standard deviation of the growth rates of world production per capita. The domestic production variability is estimated as the world production share weighted average of the standard deviation of country specific per capita production growth rates. Averaged over 109, 115 and 141 countries for rice, wheat and maize respectively.

Figure 2: Production and Consumption Variability of Rice, Wheat and Maize: 1961-2013



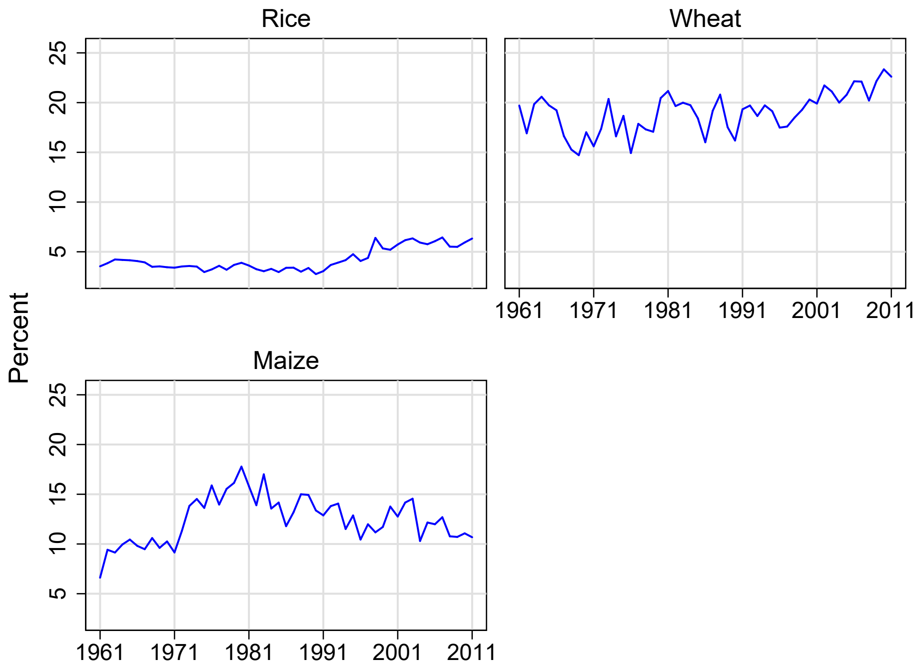
Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database. The world production variability is estimated as the standard deviation of the growth rates of world production per capita. The domestic consumption variability is estimated as the world consumption share weighted average of the standard deviation of country specific per capita consumption growth rates. The domestic production variability is estimated as the world production share weighted average of the standard deviation of country specific per capita production growth rates. Averaged over 109, 115 and 141 countries for rice, wheat and maize respectively.

Figure 3: Production and Consumption Variability between OECD and Sub-Saharan Africa: 1961-2013



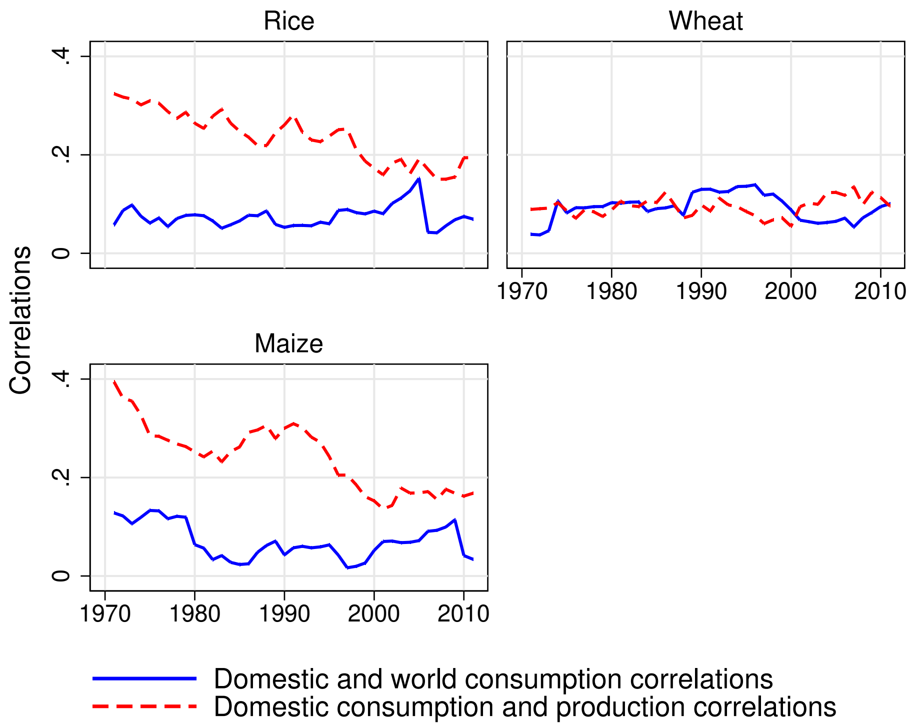
Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database. The domestic consumption variability is estimated as the consumption share weighted average of the standard deviation of country specific per capita consumption growth rates. The domestic production variability is estimated as the production share weighted average of the standard deviation of country specific per capita production growth rates. The number of countries for rice, wheat and maize is 10, 30, 22 for OECD and 34, 22 and 38 for Sub-Saharan Africa respectively.

Figure 4: Trends in World Exports as a Share of World Production (%): 1961-2013.



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

Figure 5: Median 10 Year Rolling Correlations: 1961-2013

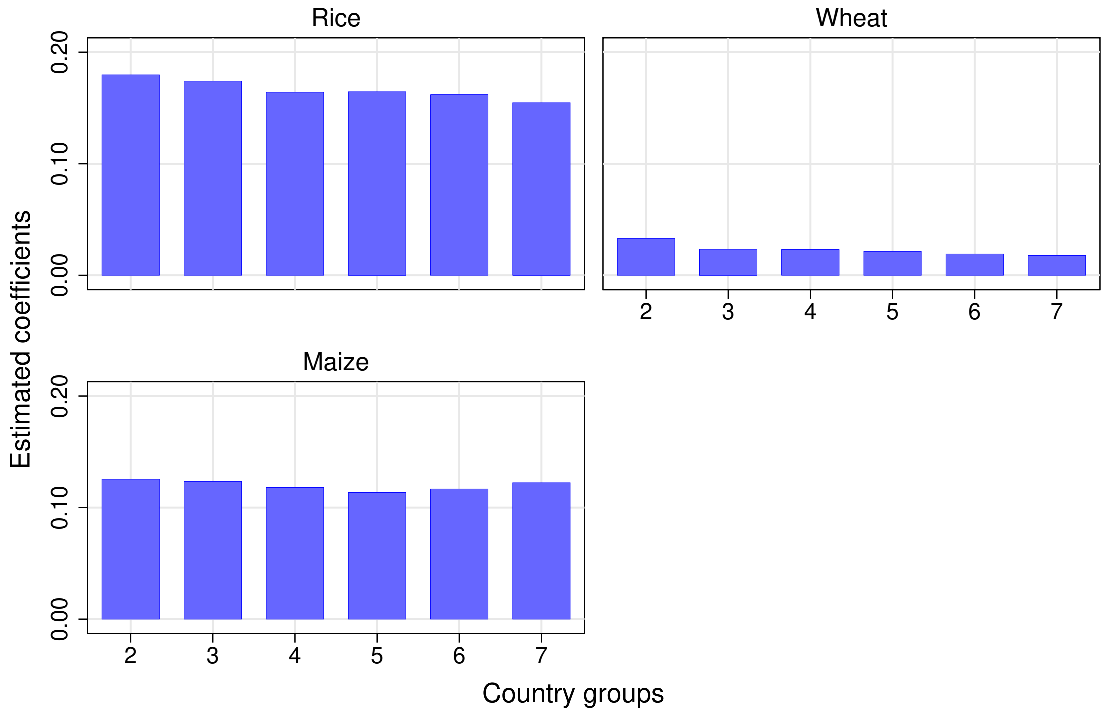


Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database.

Figure 6: Median 10 Year Rolling Correlations by Income: 1961-2013

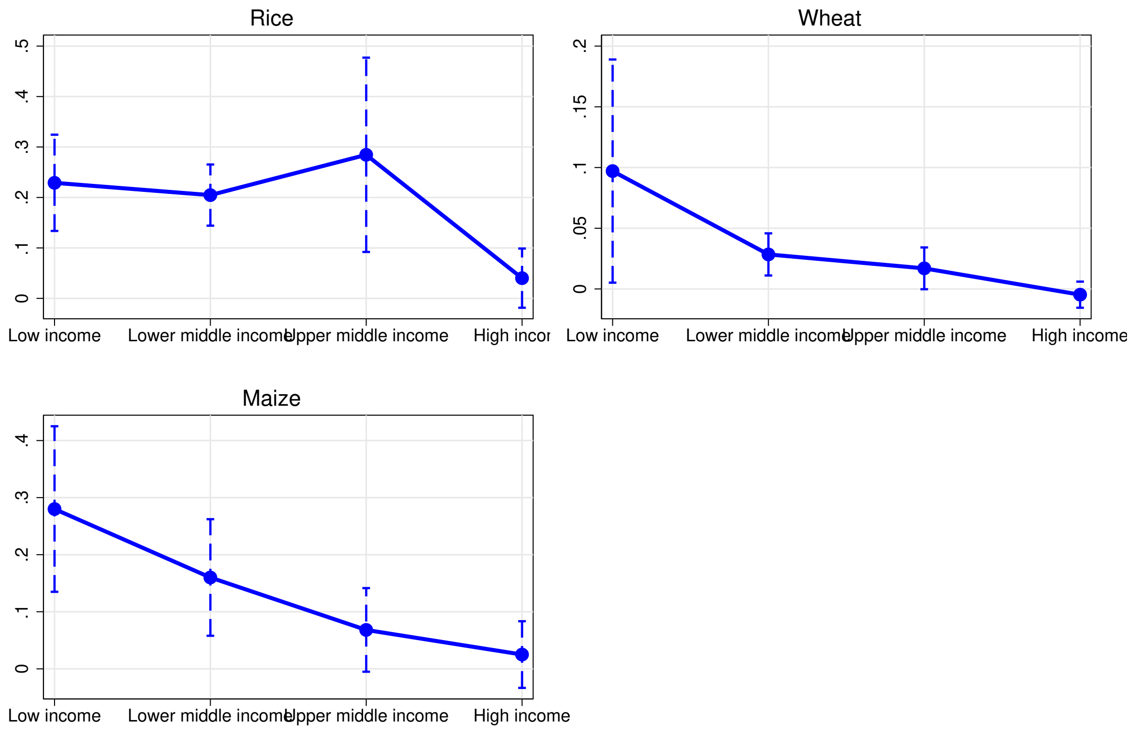
Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database.

Figure 7: Risk Sharing and Endogenous Group Membership: Estimates of γ from Group Fixed Effects Estimator



The figure displays the estimated coefficient γ (correlation between domestic consumption growth and production growth) from the group fixed effects estimator. Each bar represents the estimate of γ from a separate regression where the number on the horizontal axis is the number of country groups specific time fixed effects that were included in the regression.

Figure 8: Risk Sharing Improves with Income



The figure displays the estimated coefficient γ (correlation between domestic consumption growth and production growth) for low income, lower middle income, upper middle income and high income countries.

Tables

Table 1: Volatility in Production and Consumption: Domestic and World Aggregates

	Domestic variability		World variability		Average share of exports
	c	y	c	y	in world production
Rice	0.05	0.08	0.02	0.03	4.27
Wheat	0.06	0.14	0.02	0.05	18.46
Maize	0.10	0.17	0.02	0.08	12.20
Overall	0.07	0.14	0.02	0.05	11.64

Authors' estimates based on the food balance sheet data from the Food and Agriculture Organization's (FAO) database. c and y denote per capita consumption and production growth. Time period is 1961-2013. The world consumption and production variability is estimated as the standard deviation of the growth rates of world production and consumption per capita. The domestic consumption variability is estimated as the world consumption share weighted average of the standard deviation of country specific per capita consumption growth rates. The domestic production variability is estimated as the world production share weighted average of the standard deviation of country specific per capita production growth rates. Averaged over 109, 115 and 141 countries for rice, wheat and maize respectively.

Table 2: Test of Risk Sharing: Benchmark Specification

	(1)	(2)	(3)	(4)
Dependent variable:	per capita consumption growth			
(a) Rice				
y_{it}	0.194***	0.193***	0.193***	0.190***
	(0.028)	(0.029)	(0.029)	(0.029)
$\bar{c}_t$				0.613***
				(0.174)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	5070	5070	5070	5070
(b) Wheat				
y_{it}	0.032***	0.032***	0.034***	0.034***
	(0.012)	(0.012)	(0.011)	(0.012)
$\bar{c}_t$				0.543***
				(0.119)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	4805	4805	4805	4805
(c) Maize				
y_{it}	0.126***	0.125***	0.125***	0.125***
	(0.027)	(0.028)	(0.028)	(0.028)
$\bar{c}_t$				0.996***
				(0.211)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	5940	5940	5940	5940

The table presents the estimates of γ as defined in equation (14). Bar over variables denote cross sectional averages. Figures in parenthesis 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: 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}	0.190***	0.189***	0.189***	0.189***	0.190***	0.296***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.056)
GDP shocks		0.026	0.013	0.012	0.013	
		(0.064)	(0.066)	(0.069)	(0.069)	
Inflation shocks			-0.016	-0.014	-0.015	
			(0.010)	(0.015)	(0.016)	
Exchange rate shocks				-0.002	-0.002	
				(0.013)	(0.013)	
WTO					-0.007*	
					(0.003)	
$y_{it} \times T$						-0.004*
						(0.002)
N	4000	4000	4000	4000	4000	5070
(b) Wheat						
y_{it}	0.020**	0.019**	0.019**	0.019**	0.019**	0.048*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.025)
GDP shocks		0.081	0.083	0.083	0.083	
		(0.059)	(0.059)	(0.063)	(0.063)	
Inflation shocks			0.002	0.002	0.001	
			(0.007)	(0.010)	(0.010)	
Exchange rate shocks				0.000	0.000	
				(0.008)	(0.008)	
WTO					-0.002	
					(0.003)	
$y_{it} \times T$						-0.001
						(0.001)
N	3599	3599	3599	3599	3599	4805
(c) Maize						
y_{it}	0.119***	0.119***	0.119***	0.119***	0.119***	0.182***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.060)
GDP shocks		-0.030	-0.019	-0.029	-0.029	
		(0.098)	(0.102)	(0.099)	(0.099)	
Inflation shocks			0.013	0.023	0.022	
			(0.014)	(0.017)	(0.017)	
Exchange rate shocks				-0.011	-0.010	
				(0.009)	(0.009)	
WTO					-0.007	
					(0.006)	
$y_{it} \times T$						-0.002
						(0.001)
N	4609	4609	4609	4609	4609	5940

The table presents the estimates of γ from specifications with additional control variables. T denotes linear time trend. All specifications include country fixed effects and year dummies. Figures in parenthesis 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: Some Additional Models: Heterogeneity in Slope Coefficient and Aggregate Shocks

	(1)	(2)	(3)
Dependent variable: per capita consumption growth rate	Rice	Wheat	Maize
Mean group (MG) estimator	0.195***	0.015**	0.102***
	(0.024)	(0.006)	(0.018)
Common correlated effects mean group (CCEMG) estimator	0.197***	0.019***	0.122***
	(0.025)	(0.007)	(0.019)
Group fixed effects (GFE) estimator	0.164***	0.021***	0.114***
	(0.024)	(0.007)	(0.027)

The table presents the estimates of γ from estimators which are robust to heterogeneity in idiosyncratic and aggregate shocks. 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 5: Heterogeneity in Risk Sharing by Income

	(1)	(2)	(3)
	Rice	Wheat	Maize
Dependent variable: per capita consumption growth rate			
y_{it}	0.478***	0.207**	0.398**
	(0.124)	(0.083)	(0.159)
$y_{it}\times$ Lower middle income	-0.246	-0.159*	-0.104
	(0.150)	(0.088)	(0.198)
$y_{it}\times$ Upper middle income	-0.238	-0.177*	-0.383**
	(0.170)	(0.090)	(0.170)
$y_{it}\times$ High income	-0.406***	-0.220**	-0.183
	(0.135)	(0.087)	(0.183)
$y_{it} \times T$	-0.009***	-0.004**	-0.004
	(0.003)	(0.002)	(0.004)
$y_{it} \times T\times$ Lower middle income	0.008*	0.004**	-0.0004
	(0.004)	(0.002)	(0.005)
$y_{it} \times T\times$ Upper middle income	0.011*	0.004**	0.006
	(0.006)	(0.002)	(0.004)
$y_{it} \times T\times$ High income	0.008**	0.004***	-0.002
	(0.003)	(0.002)	(0.005)
N	4868	4546	5662

The table presents results form a specification where we allow γ to vary across country groups and have a linear time trend. Base category is low income countries. T denotes 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. All specifications include country fixed effects and year dummies. Figures in parenthesis are standard errors robust to heteroscedasticity and within-country serial correlation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Estimates of Contribution of Trade and Storage in Risk Sharing

	(1)	(2)	(3)	(4)
	Trade component	Storage component	SFIOW component	Residual
Rice	0.443***	0.344***	0.0222***	0.190***
	(0.061)	(0.049)	(0.005)	(0.028)
Wheat	0.618***	0.310***	0.038***	0.034***
	(0.051)	(0.046)	(0.007)	(0.012)
Maize	0.523***	0.273***	0.075***	0.129***
	(0.057)	(0.036)	(0.019)	(0.028)

The table presents the estimates of trade component (γ^T), storage (γ^S) and SFIOW (γ^{SFIOW}) in risk sharing in (1), (2) and (3). Column (4) presents the estimates of γ as residual. SFIOW denotes the Seed, feed, industrial use, other uses and waste component. All specifications include country fixed effects and year dummies. Figures in parenthesis are standard errors robust to heteroscedasticity and within-country serial correlation. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Appendix

A Separable Utility and the Test of Risk Sharing

Consider the two good separable utility function

$$U_i = u_i(x_{it}) + v_i(y_{it}) \tag{A1}$$

where, $u_i(.)$ and $v_i(.)$ are strictly increasing, concave and twice differentiable functions. Each consumer i is endowed with $w^x_{is^t}$ and $w^y_{is^t}$ units of the two goods in state s^t of time period t, where each state occurs with a probability π_{s^t} and $\sum_{s^t} \pi_{s^t} = 1$. Following the literature, we consider the optimal risk sharing problem as social planner maximizing weighted sum of expected utilities of individuals subject to the aggregate resource constraints.

The expected lifetime utility function of agent i is expressed as

$$E(U)_i^{lifetime} = \sum_{t=1}^{\infty} \rho_i^t \sum_{s^t} \pi_{s^t}[u_i(x_{is^t}) + v_i(y_{is^t})] \tag{A2}$$

where $\rho_i \in (0, 1)$ is the discount factor for agent i. Ex-ante efficiency requies that the allocation of resources across states is efficient such that no state-contingent exchange can improve both agents' expected utilities. The ex-ante efficient risk sharing allocation is the solution of the following program.

$$Max \sum_{i=1}^{N} \omega_i E(U)_i^{lifetime} \tag{A3}$$

where, ω_i is the weight of consumer i in the planner's problem with $0 < \omega_i < 1$ and $\sum_{i=1}^{N} \omega_i = 1$, subject to aggregate resource constraints.

$$\sum_{i=1}^{N} x_{is^t} = \sum_{i=1}^{N} w_{is^t}^{x} = X_{s^t}, \forall s^t \tag{A4}$$

$$\sum_{i=1}^{N} y_{is^t} = \sum_{i=1}^{N} w_{is^t}^{y} = Y_{s^t}, \forall s^t \tag{A5}$$

The resultant Lagrangian is

$$\mathcal{L} = \sum_{i=1}^{N} \omega_i \sum_{t=1}^{\infty} \rho_i^t \sum_{s^t} \pi_{s^t} [u_i(x_{is^t}) + v_i(y_{is^t})] + \lambda_{s^t}^{x} (X_{s^t} - \sum_{i=1}^{N} x_{is^t}) + \lambda_{s^t}^{y} (Y_{s^t} - \sum_{i=1}^{N} y_{is^t}) \tag{A6}$$

where $\lambda_{s^t}^{x}$ and $\lambda_{s^t}^{y}$ denote the Lagrange multiplier associated with the resource constraints for good x and y in state s^t respectively, then the first order conditions of the social planner's problem, with respect to the two commodities are

$$\rho_i^t \omega_i u_i^{'}(x_{is^t}) = \mu_{s^t}^{x} \tag{A7}$$

$$\rho_i^t \omega_i u_i^{'}(y_{is^t}) = \mu_{s^t}^y \tag{A8}$$

where $\mu_{s^t}^j$ is the Lagrangian multiplier of the aggregate resource constraint of the food commodity $j (j = x, y)$ divided by the probability of state s^t. Notice that each of the first order conditions is independent of the aggregate resource constraint of the other commodity. Therefore, the optimal allocations of, say, food staple x can be analyzed independently of the optimal allocations of food staple y.

The above first order conditions imply that the (discounted) product of the weight, ω_i, and marginal utility of individual i with respect to a food staple j is independent of the individual consumer's endowment of j. An individual's optimal allocation for consumption of commodity j depends only on the aggregate endowment of that commodity. Whenever two states of nature s and s' have the same level of aggregate resources, then for each agent i, consumption in state s must be the same as in state s'. For example, if $u_i(x_{it}) = -x_{it}^{-a_i}$ and $u_i(y_{it}) = -y_{it}^{-b_i}$, where $a_i, b_i > 0$ and the subscript s^t for state is replaced with t for time, then the necessary condition for optimal risk allocation for x can be expressed as

$$-\rho_i^t \omega_i a_i x_{it}^{-(a_i+1)} = \mu_t^x \tag{A9}$$

The one period lag of A9 is

$$-\rho_i^{(t-1)} \omega_i a_i x_{it-1}^{-(a_i+1)} = \mu_{t-1}^x \tag{A10}$$

Dividing A9 by A10 we get

$$\rho_i \left(\frac{x_{it}}{x_{it-1}} \right)^{-(a_i+1)} = \frac{\mu_t^x}{\mu_{t-1}^x} \tag{A11}$$

We want to solve for $\frac{\mu_t^x}{\mu_{t-1}^x}$. Taking log on both sides we get

$$ln\rho_i - (a_i+1) ln \left(\frac{x_{it}}{x_{it-1}} \right) = ln \left(\frac{\mu_t^x}{\mu_{t-1}^x} \right) \tag{A12}$$

Or,

$$ln \left(\frac{x_{it}}{x_{it-1}} \right) = \frac{1}{(a_i+1)} ln\rho_i - \frac{1}{(a_i+1)} ln \left(\frac{\mu_t^x}{\mu_{t-1}^x} \right) \tag{A13}$$

Taking averages

$$\frac{1}{N} \sum_N ln \left(\frac{x_{it}}{x_{it-1}} \right) = \frac{1}{N} \sum_N \frac{1}{(a_i+1)} ln\rho_i - \frac{1}{N} \sum_N \frac{1}{(a_i+1)} \left(\frac{\mu_t^x}{\mu_{t-1}^x} \right) \tag{A14}$$

and solving for $ln\left(\frac{\mu_t^x}{\mu_{t-1}^x}\right)$ we get the following expression.

$$ln \left(\frac{\mu_t^x}{\mu_{t-1}^x} \right) = -\frac{1}{\frac{1}{N}\sum_N \frac{1}{(a_i+1)}} \frac{1}{N} \sum_N ln \left(\frac{x_{it}}{x_{it-1}} \right) + \frac{1}{\frac{1}{N}\sum_N \frac{1}{(a_i+1)}} \frac{1}{N} \sum_N \frac{1}{(a_i+1)} ln\rho_i \tag{A15}$$

Substituting the expression for $ln\left(\frac{\mu_t^x}{\mu_{t-1}^x}\right)$ in A15 back in A13 the first order condition can be written as

$$ln\left(\frac{x_{it}}{x_{it-1}}\right) = \alpha_i^x + \left(\frac{\frac{1}{(a_i+1)}}{\frac{1}{N}\sum_N \frac{1}{(a_i+1)}}\right)\frac{1}{N}\sum_N ln\left(\frac{x_{it}}{x_{it-1}}\right) \tag{A16}$$

Similarly, the first order condition for y is

$$ln\left(\frac{y_{it}}{y_{it-1}}\right) = \alpha_i^y + \left(\frac{\frac{1}{(b_i+1)}}{\frac{1}{N}\sum_N \frac{1}{(b_i+1)}}\right)\frac{1}{N}\sum_N ln\left(\frac{y_{it}}{y_{it-1}}\right) \tag{A17}$$

where $\alpha_i^x = \frac{1}{(a_i+1)}ln\rho_i - \left(\frac{\frac{1}{(a_i+1)}}{\frac{1}{N}\sum_N \frac{1}{(a_i+1)}}\right)\frac{1}{N}\sum_N \frac{1}{(a_i+1)}ln\rho_i$ and $\alpha_i^y = \frac{1}{(b_i+1)}ln\rho_i - \left(\frac{\frac{1}{(b_i+1)}}{\frac{1}{N}\sum_N \frac{1}{(b_i+1)}}\right)\frac{1}{N}\sum_N \frac{1}{(b_i+1)}ln\rho_i$.

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	277.87	-0.40	0.69	2.23	673.44	-15.87	-14.66	20.68
	(0.02)	(0.34)	(0.76)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita supply	233.46	1.52	1.58	0.16	733.97	-17.92	-16.62	23.50
	(0.42)	(0.94)	(0.94)	(0.44)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita production	222.86	0.74	0.69	-0.33	815.66	-19.94	-17.93	27.31
	(0.62)	(0.77)	(0.76)	(0.63)	(0.00)	(0.00)	(0.00)	(0.00)
				Wheat				
Log per capita consumption	277.87	-0.40	0.69	2.23	673.44	-15.87	-14.66	20.68
	(0.02)	(0.34)	(0.76)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita supply	233.46	1.52	1.58	0.16	733.97	-17.92	-16.62	23.50
	(0.42)	(0.94)	(0.94)	(0.44)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita production	222.86	0.74	0.69	-0.33	815.66	-19.94	-17.93	27.31
	(0.62)	(0.77)	(0.76)	(0.63)	(0.00)	(0.00)	(0.00)	(0.00)
				Maize				
Log per capita consumption	277.87	-0.40	0.69	2.23	673.44	-15.87	-14.66	20.68
	(0.02)	(0.34)	(0.76)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita supply	233.46	1.52	1.58	0.16	733.97	-17.92	-16.62	23.50
	(0.42)	(0.94)	(0.94)	(0.44)	(0.00)	(0.00)	(0.00)	(0.00)
Log per capita production	222.86	0.74	0.69	-0.33	815.66	-19.94	-17.93	27.31
	(0.62)	(0.77)	(0.76)	(0.63)	(0.00)	(0.00)	(0.00)	(0.00)

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

Table B2: Tests of Serial Correlation and Heteroscedasticity

Tests	Statistic	Probability
Rice		
Wooldridge test for null of no serial correlation in panel-data	$F(1,113) = 17.63$	$Prob. > F = 0.0001$
Modified Wald test for group-wise heteroscedasticity	$\chi^2(114) = 1.8e+05$	$Prob > \chi^2 = 0.0000$
Wheat		
Wooldridge test for null of no serial correlation in panel-data	$F(1,121) = 3.630$	$Prob. > F = 0.0591$
Modified Wald test for group-wise heteroscedasticity	$\chi^2(122) = 1.7e+05$	$Prob. > \chi^2 = 0.0000$
Maize		
Wooldridge test for null of no serial correlation in panel-data	$F(1,143) = 2.853$	$Prob. > F = 0.0934$
Modified Wald test for group-wise heteroscedasticity	$\chi^2(150) = 7.0e+06$	$Prob. > \chi^2 = 0.0000$

Note: All tests conducted on the benchmark specification in equation 14.

C Robustness Checks

C.1 Estimates from Alternative Data Source

As a robustness check we estimate our benchmark specification 14 using the data from the 'Production, Supply and Distribution' database of the United States Department of Agriculture's Foreign Agriculture Service (FAS) (USDA, 2014) database. Like the main dataset (FAO Food Balance Sheets) used in the paper, the FAS also collects data on country level consumption, production, trade and storage aggregates for agricultural commodities. The FAS database does not have an equivalent food consumption aggregate as reported in the FAO dataset and reports domestic supply as consumption. Therefore, the robustness tests are conducted on domestic supply, i.e., production left after net exports and change in stocks. For comparison, we also report the results from our main dataset (FAO) with domestic supply as the dependent variable. The results of the sensitivity analysis are reported in table C1. Although the complete risk sharing hypothesis is rejected with the USDA data, the estimated γ's (coefficient of y_{it}) are larger in magnitude.

C.2 Lagged and Lead Production Shocks and Lagged Dependence

In this section we test the robustness of risk sharing coefficient to lagged and lead production and lagged consumption shocks. Specification (1) to (4) of table C2 presents the results from regressions with lagged and lead production shocks as additional regressors. In specification (5) we present results with lagged consumption shock as an additional regressor. Since with lagged dependent variable, fixed effects estimator is

Table C1: Robustness Check Using USDA Data

	(1)	(2)
	FAO	USDA
Dependent variable: per capita supply growth		
(a) Rice		
y_{it}	0.213***	0.335***
	(0.027)	(0.036)
N	5070	4382
(b) Wheat		
y_{it}	0.072***	0.123***
	(0.014)	(0.022)
N	4805	3475
(c) Maize		
y_{it}	0.227***	0.430***
	(0.037)	(0.048)
N	6394	5002

Notes: All specifications include country fixed effects and year dummies. Figures in parenthesis are standard errors robust to heteroscedasticity and within-country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

biased; we use the Arellano and Bond (1991) estimator and treat both lagged consumption and production shocks as endogenous.

C.3 Measurement Errors in Production and Consumption Aggregates

In this section we address the issue that measurement errors in both consumption and production aggregates may influence the estimates of risk sharing. We are interested in estimating the following model.

$$c_i = \alpha + \gamma y_i + \epsilon_i \tag{C1}$$

Where y_i and c_i are the per capita consumption and production growth of country i. For simplicity, we suppress the time subscript and assume that the country and time fixed effects are netted out from c_i and y_i. The measures of consumption and

Table C2: Robustness of estimates to lagged and lead production growth and lagged dependence

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	Arellano-Bond
Dependent variable: per capita consumption growth rate					
(a) Rice					
y_{it}	0.186***	0.176***	0.195***	0.197***	0.172***
	(0.027)	(0.026)	(0.029)	(0.029)	(0.027)
y_{it-1}	-0.008	-0.010			
	(0.025)	(0.027)			
y_{it-2}		-0.001			
		(0.012)			
y_{it+1}			0.004	0.003	
			(0.013)	(0.013)	
y_{it+2}				-0.007	
				(0.012)	
c_{it-1}					-0.250***
					(0.023)
N	4944	4821	4943	4819	4835
(b) Wheat					
y_{it}	0.032***	0.028**	0.036***	0.038***	0.027**
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)
y_{it-1}	-0.005	-0.006			
	(0.008)	(0.009)			
y_{it-2}		-0.000			
		(0.007)			
y_{it+1}			0.010	0.012	
			(0.007)	(0.008)	
y_{it+2}				0.006	
				(0.007)	
c_{it-1}					-0.231***
					(0.051)
N	4666	4529	4666	4529	4553
(c) Maize					
y_{it}	0.131***	0.133***	0.131***	0.134***	0.111***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.026)
y_{it-1}	0.033**	0.039**			
	(0.014)	(0.015)			
y_{it-2}		0.019			
		(0.013)			
y_{it+1}			0.013	0.021*	
			(0.012)	(0.012)	
y_{it+2}				0.021	
				(0.018)	
c_{it-1}					-0.192***
					(0.031)
N	5792	5653	5783	5632	5593

Notes: Specifications 1 to 4 include country fixed effects and year dummies. Specification 4 has lagged dependent variable and is consistently estimated using Arellano and Bond (1991) GMM estimator. Figures in parenthesis are standard errors robust to heteroscedasticity and within-country serial correlation. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

production in our dataset are measured with an error. Then we define the observed consumption and production aggregates as

$$\bar{y}_i = y_i + u_i \tag{C2}$$

$$\bar{c}_i = c_i + u_i + v_i \tag{C3}$$

where y and c are the true production and consumption and u and v are the measurement errors. We assume that the errors in variables are classical, i.e., the measurement errors are uncorrelated with the true values and uncorrelated with each other. The only exception is that measured consumption nests the measurement error in production. Consumption is derived as a residual from production that is netted out of net trade and storage therefore we assume that consumption errors would nest in it the errors in income, trade, storage. Since the relation between consumption and income is essentially additive, it is natural to think of the consumption error term as where the measurement error in consumption is because of measurement error in income and (independent) measurement error in other components. The equation C1 in terms of the measured c and y can be written as.

$$\bar{c}_i = \alpha + \gamma \bar{y}_i + (1 - \gamma)u_i + v_i + \epsilon_i \tag{C4}$$

Consider the least squares estimate of γ for the observed c and y.

$$\hat{\gamma} = \frac{Cov(\bar{c}_i, \bar{y}_i)}{Var(\bar{y}_i)} \tag{C5}$$

Which can be written as

$$\hat{\gamma} = \frac{Cov(\alpha + \gamma\bar{y}_i + (1-\gamma)u_i + v_i + \epsilon_i, \bar{y}_i)}{Var(\bar{y}_i)} \tag{C6}$$

Simplifying further it can be shown that

$$plim\hat{\gamma} = \gamma - \gamma\frac{Var(u_i)}{Var(\bar{y}_i)} + \frac{Var(u_i)}{Var(\bar{y}_i)} \tag{C7}$$

The second term in equation C7 is due to measurement error in production shocks and leads to a downward bias in γ. However, as the third term, which is due to the nested production measurement error in the consumption, introduces an upward bias to the estimates. If this is strong, then this could be why measured risk sharing is low (when it might actually not be the case). This implies that the estimated γ may either be an under or an over estimate of the true γ.

$$\gamma = \frac{plim\hat{\gamma} - \dfrac{Var(u_i)}{Var(\bar{y}_i)}}{1 - \dfrac{Var(u_i)}{Var(\bar{y}_i)}} \tag{C8}$$

Let a denote the relative noise in the production series, i.e., $a = \frac{Var(u_i)}{Var(\bar{y}_i)}$ then $\gamma = \frac{plim\hat{\gamma}-a}{1-a}$. It is easy to see that at $a = 0, \gamma = \hat{\gamma}$ and at $a = \gamma, \hat{\gamma} = 0$. Also $\frac{d\gamma}{da} = \frac{(\hat{\gamma}-1)}{(1-a)^2} < 0$.

Hence the true covariation between c and y is equal to measured when relative noise is zero. When relative noise rises, the true covariation will fall (and it will be lower than measured covariation) until it will be zero when relative noise is equal to $\hat{\gamma}$.

To deal with the bias in $\hat{\gamma}$ due to measurement errors we use the Lewbel (2012) instrumental variable strategy. Lewbel (2012) shows that in the absence of an instrumental variable correlated with the mismeasured regressor, γ can be identified in this model 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 about the Lewbel estimator, we refer the reader to Lewbel (2012). Several other studies, for example Emran and Shilpi (2012), Lin et al. (2017), Mishra and Smyth (2015) and Emran and Hou (2013) have relied on this strategy for identification. Lewbel's approch 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. For identification, the Lewbel's two-step estimator relies on two conditions: (1) The set of control variables should be uncorrelated with product of errors in the main specification and the first stage regression, and (2) the set of control variables should be correlated with squared residuals of the first stage regression. Lewbel shows that for this condition to be satisfied, there must be heteroscedasticity in error terms in 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 regression for rice, wheat and maize to be heteroscedastic.

Table C3 presents the results from the Lewbel estimator. The estimated co-

Table C3: Instrumental Variable Estimates

	(1) Rice	(2) Wheat	(3) Maize
Dependent variable: per capita consumption growth rate			
y_{it}	0.200***	0.026*	0.094**
	(0.037)	(0.016)	(0.041)
N	4726	4405	5535
Breusch-Pagan test $\chi^2(1)$	39.67	25.02	6.43
p-value	0.00	0.00	0.01

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

efficients are comparable in magnitude to the estimates reported in table 2. More importantly, our finding that the wheat market is closest to efficient risk sharing and the rice market worst, is robust to measurement errors in consumption and production aggregates.

D Decomposition of Cross Sectional Production Variance

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

$$Y_{it}^{NX} = Y_{it} - NX_{it} \tag{D1}$$

where

$$NX_{it} = Exports_{it} - Imports_{it} \tag{D2}$$

is net exports. Define domestic supply as

$$S_{it} = Y_{it}^{NX} + \Delta B_{it} \tag{D3}$$

where ΔB_{it} is the change in stocks. Domestic consumption is defined as

$$C_{it} = S_{it} - SFIOW_{it} \tag{D4}$$

where $SFIOW_{it}$ denotes food grain either used as seed, feed, industrial processing, other uses or wasted. Production for country i at time period t can then be expressed as

$$Y_{it} = \frac{Y_{it}}{Y_{it}^{NX}} \times \frac{Y_{it}^{NX}}{S_{it}} \times \frac{S_{it}}{C_{it}} \times C_{it} \tag{D5}$$

Taking logs on both sides

$$lnY_{it} = (lnY_{it} - lnY_{it}^{NX}) + (lnY_{it}^{NX} - lnS_{it}) + (lnS_{it} - lnC_{it}) + lnC_{it} \tag{D6}$$

First differencing

$$\Delta lnY_{it} = (\Delta lnY_{it} - \Delta lnY_{it}^{NX}) + (\Delta lnY_{it}^{NX} - \Delta lnS_{it}) + (\Delta lnS_{it} - \Delta lnC_{it}) + \Delta lnC_{it} \quad \text{(D7)}$$

Multiplying by ΔlnY_{it} on both sides and taking expectations, we get the following decomposition of cross-sectional variance of production:

$$\begin{aligned} Var(\Delta lnY_{it}) &= Cov(\Delta lnY_{it}, \Delta lnY_{it} - \Delta lnY_{it}^{NX}) \\ &+ Cov(\Delta lnY_{it}, \Delta lnY_{it}^{NX} - \Delta lnS_{it}) \\ &+ Cov(\Delta lnY_{it}, \Delta lnS_{it} - \Delta lnC_{it}) \\ &+ Cov(\Delta lnY_{it}, \Delta lnC_{it}) \end{aligned} \quad \text{(D8)}$$