Essays on Risk, Insurance and Welfare

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Thesis submitted to the Indian Statistical Institute in partial fulfillment of the requirements for the degree of Doctor of Philosophy

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To my family and friends

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Chapter 1

Introduction and Main Results

1.1 Background

Economic agents are exposed to a variety of risks. These risks can generally be categorized into either idiosyncratic individual specific risks or aggregate risks faced jointly by a group of individuals co-inhabiting in villages, communities or countries. Since exposure to both kinds of risks can be welfare reducing, economists for a long time have been interested in studying the role of various formal and informal risk pooling mechanisms in mitigating agents' exposure to these shocks. The possibility of risk pooling within communities or countries arises from the idea that idiosyncratic risks across individuals, communities or countries are unlikely to be perfectly correlated. Hence, trade across agents can facilitate risk sharing. This holds true in a theoretical model of risk averse agents with stochastic endowments, where the first best allocation amounts to individual consumption being perfectly correlated with aggregate shocks and entirely independent of their own endowments. This is the main prediction of the risk sharing hypothesis. Chapter 2 of this dissertation uses this risk sharing hypothesis, popular in development economics and international macroeconomics literature to evaluate the allocative efficiency of global food markets.

Risk sharing mechanisms fail if shocks are experienced across agents or communities. Such shocks are correlated and survive pooling and aggregation. It is well known that exposure to correlated shocks under credit constraints can translate into poverty traps. This understanding has led to the emergence of formal insurance markets and insurance products specifically designed to insure farmers in developing countries from most common form of aggregate shocks i.e., rainfall shocks. Chapter 3 of this dissertation therefore looks at the design risk in rainfall based index insurance contracts in India and studies its implications for optimal demand for rainfall insurance.

Although exposure to shocks is welfare reducing, the welfare impacts of a correlated shock may not be homogeneous. A good example of common shocks having heterogeneous welfare impacts across population groups is the food price shocks experienced recently in 2007 and then again in 2011. This idea of price changes having heterogeneous impacts across individuals was explored empirically in Deaton (1989) who proposed that a net food consumer household will experience welfare losses from high food prices but a net food producer will gain. The final chapter of this dissertation uses this insight from Deaton's net benefit approach to econometrically identify the income and consumption effects of food price shocks on the dietary diversity of households in India.

Another dimension shared between chapters 2 and 3 of this dissertation is related to the nature of aggregate and idiosyncratic shocks. Conceptually, idiosyncratic shocks will cancel out with aggregation when these are linearly additive. In such a scenario, there is a possibility of insurance through arbitrage. The second chapter, therefore, evaluates the contributions of this arbitrage in risk sharing within the global food markets. This chapter considers consumption variability as the dependent variable and hence directs attention to the variable that matters in economic models. But what if the idiosyncratic shocks are multiplicative rather than additive and are spatially correlated? Such shocks will survive aggregation with the consequence that these will be experienced widely. This will manifest into 'tail dependence' in the joint distribution of risks. Under tail dependence, extreme shocks show greater association than moderate shocks. The third chapter of this dissertation builds on this idea and tests for tail dependence in joint distribution of rainfall and yields in India. The chapter uses state of the art techniques to estimate copulas of these joint distributions which are then embedded into simulations of a conceptual model of a farmer's demand for insurance. The final chapter directs attention toward the welfare effects of aggregate shocks. More specifically, it directs attention toward heterogeneity in welfare effects of food price shocks. In this chapter we use a unique identification strategy that exploits the natural suitability endowments of a region to separate the income effect and consumption effect of food price shocks on household welfare.

The next three sections provide an overview of the three essays in this dissertation. The following chapters describe in detail the motivation, methodology and main findings.

1.2 International Risk Sharing for Food Staples

The sharp surge in global food prices in the years 2006-08 has led to concerns about the functioning of global food markets. Rising food prices and high volatility, as witnessed in 2008, pose a threat to food security of the poor especially in developing countries as they spend a significant part of their income on food (Ivanic and Martin, 2008; Ivanic et al., 2012; Ivanic and Martin, 2014).

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.

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. The primary objective of this chapter is to examine the performance of world markets for grains (maize, rice and wheat) in a risk sharing framework. The chapter is related to the optimal risk-sharing hypotheses that have been formulated and tested in finance, macro-economics and in development economics. In this literature, the risk sharing hypothesis has been formulated in the context of one composite good (for instance, household income or country GDP). We extend it to the case where endowments are multi-good (specifically, food and non-food) and are stochastic.

This chapter adopts the predictions of efficient risk sharing hypothesis as a benchmark. A necessary condition for efficient risk sharing is that consumption growth rates should be perfectly correlated with aggregate shocks and independent of domestic production growth rates. We find that the efficient risk sharing hypothesis is rejected for the global food markets. However, the global wheat market is closest to the efficient risk sharing allocation. On average, trade and stocks jointly provide insurance against production shocks to the extent of 87% in case of wheat, followed by rice (66%) and maize (57%). However, the contribution of trade here is dominant. Of the insurance that is achieved, trade is responsible for more than 80% of it, in each of the three markets. Further, by allowing the degree of risk sharing to vary by low income, lower middle income, upper middle income and high income country groups we find that the degree of risk sharing is positively associated with income levels of countries.

1.3 Basis Risk in Index Insurance: Lower Tail Dependence and the Demand for Weather Insurance

Agriculture and agriculture-based livelihoods in developing countries are highly prone to weather shocks. There is substantial evidence that rural households in high risk environment stick to low return subsistence agriculture and cope with a correlated shock by liquidating productive assets to maintain consumption thus remain trapped in poverty (Rosenzweig and Binswanger, 1993; Carter and Barrett, 2006; Dercon and Christiaensen, 2011).

Even though farmers in developing countries are typically poor and even though they bear the burden of volatile income streams, formal insurance products have had limited success (Mobarak and Rosenzweig, 2013). The difficulties of administering first best insurance programs tailored to production histories of individual farmers have led to index insurance products where payouts are triggered by an index such as rainfall, temperature or local average yields. Premium setting is relatively easier because past data on indices of weather and average yield are more readily available than on individual production histories. As individual farmers have little or no influence on payouts, index-based insurance products are also less likely to fail due to asymmetry in information between the insurer and the insured. Despite the promise of index insurance, the record is mixed. In particular, the uptake of index insurance is poor, especially when it is not subsidized (Binswanger-Mkhize, 2012; Jensen and Barrett, 2017; Jensen et al., 2016).

This chapter examines how rainfall insurance contracts in India can be designed to reduce basis risk. Our approach exploits the idea that the joint distribution of rainfall and output might be characterized by tail dependence. This means that the associations between yield losses and index losses are stronger for large deviations than for small deviations. The major implication is that the value (to farmers) of index-based insurance relative to actuarial cost is highest for insurance against extreme or catastrophic losses (of the index) than for insurance against all losses. In simpler words, basis risk is least for large deviations of the index. The goal of this chapter is to test this hypothesis. The chapter estimates tail dependence in the joint distribution of weather (i.e., rainfall) and yields using a district level data set for all India for 9 major crops. Using maximum likelihood methods, we estimate a number of copulas from the parametric families of elliptical copulas and the Archimedean copulas. The best-fit copulas are joined to a conceptual model of an insurance purchaser. The simulation of the copulas allows us to estimate the optimal insurance cover for a variety of insurance contracts that vary according to the index threshold value that triggers payout. These results are compared to those obtained from a copula without tail dependence (the Gaussian copula).

We find that station level rainfall in India do exhibit tail-dependence and the joint distribution of district level crop yields for nine major crops and rainfall index also exhibit tail-dependence. This implies that the associations between yield losses and index losses are stronger for large deviations than for small deviations. Alternatively, the basis risk is least for large deviations of the index. This is also confirmed by simulations that show that value to a risk averse farmer of index-based insurance relative to actuarial cost is highest for insurance against extreme or catastrophic losses (of the index) than for insurance against all losses. Because of tail-dependence, the demand for commercially priced rainfall insurance is more likely to be positive when coverage is restricted to extreme losses.

1.4 The Welfare Impacts of High Food Prices: Resource Endowments and Spill-Over Effects

Several studies, using Deaton's (1989) net benefit approach, have predicted that rising food prices would lead to worsening of poverty in the developing world (Ivanic and Martin, 2008; De Hoyos and Medvedev, 2011; Ivanic et al., 2012). But these predictions of rising food prices increasing global poverty have not fully realized. It is argued that the net benefit approach provides good approximations of welfare losses when price changes are marginal but may lead to misleading conclusions when food price changes are large and sustained, as has been observed during the global food price crisis.

A few studies have used reduced form regressions of household welfare on food prices to directly estimate such impacts. However, these studies have ignored the heterogeneity in welfare impacts of high food prices and also lack a formal identification strategy that accounts for unobservables that simultaneously influence household welfare and food price changes.

An exception is the study by Tandon (2015) that identifies welfare impacts of food prices in India based on a difference-in-difference strategy. Tandon's identification strategy relies on one of the main insights from net benefit approach that households' exposure to food price shocks is proportional to its budget share. But exposure to food price changes also depend on their production structure.

This chapter empirically examines the impact of high food prices on household welfare in India. Our main contribution is to econometrically incorporate both kinds of exposure, consumption and production, and to disentangle the consumption and income effect of food price changes on household welfare. We construct a district level panel of dietary diversity, defined as the share of calories from rice and wheat in total calories, and staple food price index constructed as a weighted average of state specific rice and wheat retail prices. Our identification strategy exploits the exogenous cross sectional variation in the natural suitability for food cultivation, based on crop suitability indices from the Food and Agricultural Organization (FAO)'s Global Agro-Ecological Zones (GAEZ) database, to separate rural households into net food consumers and producers thereby separating the total effect into consumption and income effects. Finally, to identify how households engaged in different sectors of the local economy within food producing regions are affected by change in food prices, these consumption and income effects are estimated for subsamples of households based on their primary occupation.

We find a robust negative consumption effect of high food prices on households' welfare and dietary diversity. But this effect is found to be smaller for rural households residing in districts suitable for food cultivation. Therefore, the welfare effects of high food prices vary spatially with the natural suitability of food cultivation with regions highly suitable for food cultivation experiencing lower welfare losses from high food prices. The welfare enhancing income effects are strongest for the laborer and cultivator households and almost completely offset their negative consumption effects. Interestingly, the income effects are also present for households not directly engaged in cultivation and agricultural activities within the food suitable rural regions. This provides for a direct evidence of the spill-over effects and induced general equilibrium responses of high food prices on the local economy.

Chapter 2

International Risk Sharing for Food Staples

2.1 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, 0.06 for wheat and 0.10 for maize. On the other hand, production at a country level is highly variable. Figure 2.1 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.

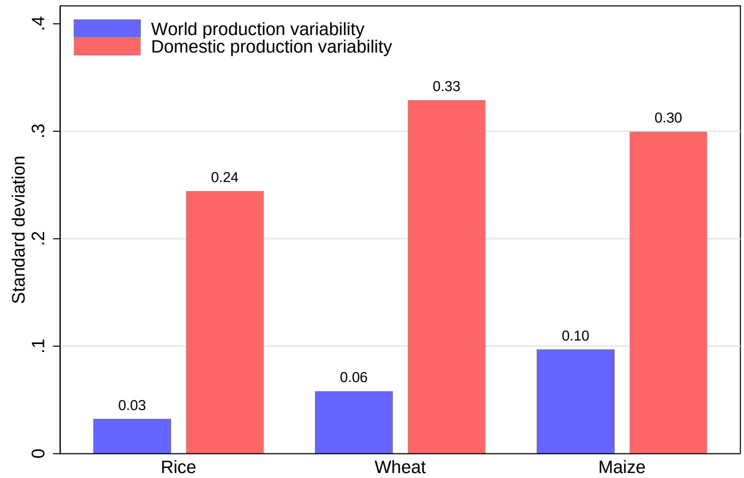


Figure 2.1: Production Variability of Rice, Wheat and Maize: 1961-2013

Notes: Authors' estimates based on United States Department of Agriculture's (USDA) database. Country specific standard deviation is calculated for countries with at least 20 years of data on production and consumption hence we are left with 91, 78 and 109 countries for rice, wheat and maize respectively.

Figure 2.2 adds the variability of individual country consumption to the global and individual country production variability plotted in Figure 2.1. It can be seen that while, on average, individual country staple food consumption variability is lower than production variability, it is, however, many magnitudes higher than the global variability in food production. Figure 2.2 suggests, that while there is some consumption smoothing, global food markets fall well short of the risk sharing ideal.

Figure 2.2 also points to heterogeneity across commodities. Despite, higher production variability, wheat markets seem to achieve greater risk sharing than the other staples. Figure 2.3 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 wheat that the African countries display substantial consumption smoothing.

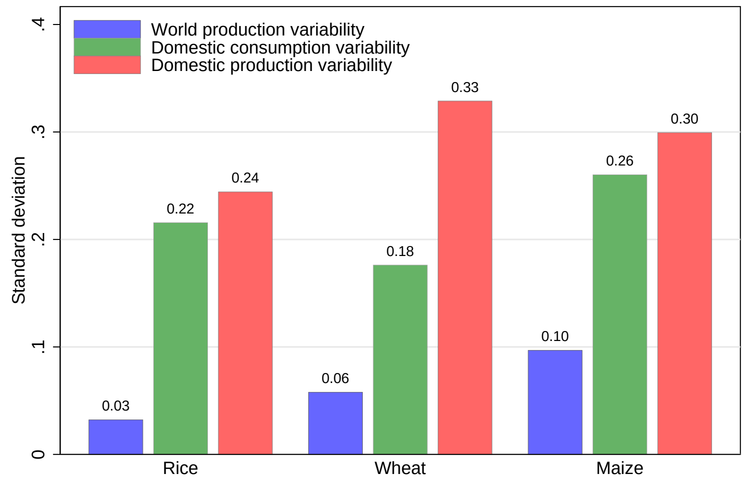


Figure 2.2: Production and Consumption Variability of Rice, Wheat and Maize: 1961-2013

Notes: Authors' estimates based on United States Department of Agriculture's (USDA) database. Country specific standard deviation is calculated for countries with at least 20 years of data on production and consumption hence we are left with 91, 78 and 109 countries for rice, wheat and maize respectively.

Figures 2.2 and 2.3 are the motivation for this chapter. First, it formally tests for risk sharing in the markets for maize, rice and wheat. Second, the chapter 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 chapter 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.

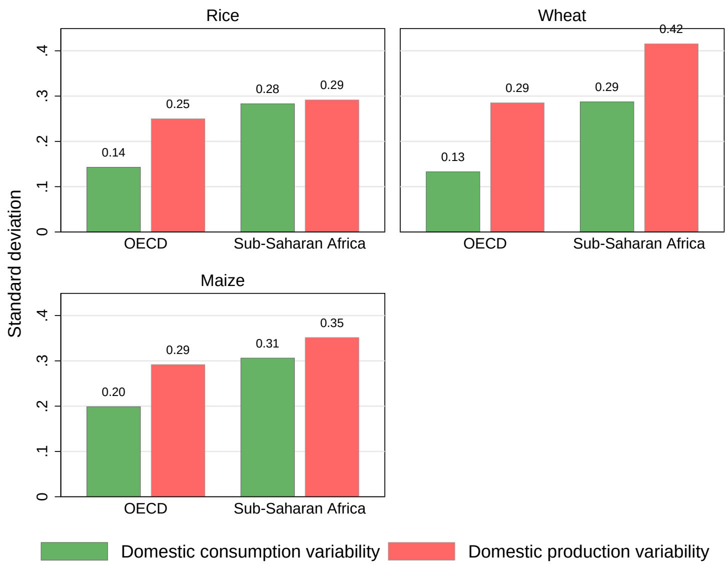


Figure 2.3: Production and Consumption Variability between OECD and Sub-Saharan Africa: 1961-2013

Notes: Authors' estimates based on United States Department of Agriculture's (USDA) database. Country specific standard deviation is calculated for countries with at least 20 years of data on production and consumption. The sample of countries for calculating consumption and production variability in rice, wheat and maize are 5, 11, 10 for OECD and 28, 14 and 36 for Sub-Saharan Africa respectively.

There is a large literature on the functioning of world markets for the basic staples. Two components of literature are particularly relevant to this chapter. 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 chapter 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 chapter 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 chapter is tethered more closely to the theory of risk sharing than the macro literature. As the preliminary evidence (for instance, Figure 2.3) 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.

2.2 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 chapter. The chapter 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 2.2 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 chapter shifts the focus from prices to quantities. [1] The explicit formulation of a risk

[1] Jha et al. (2016) is an exception. That paper also looks at consumption variability and how

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 chapter 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 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

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.

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 chapter 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 chapter also investigates how heterogeneity in risk sharing relates to observable characteristics such as country per capita income.

2.3 Theoretical Framework

We assume that there is a representative consumer in each country with preferences defined over the two staple food commodities, x and y and a non-food commodity z. [2] The representative consumer's utility function is additively separable between the food commodities and the non-food commodities and is given as below.

$$U_i = u_i(x_i, y_i) + v_i(z_i) \tag{2.1}$$

[2]The extension to three food staples is trivial and is avoided here to simplify exposition.

where, $u_i(.)$ and $v_i(.)$ are strictly increasing, concave and twice differentiable functions. Each consumer i is endowed with $w^x_{is^t}$, $w^y_{is^t}$ and $w^z_{is^t}$ units of the three goods in state s^t of time period t, where each state occurs with a probability π^t_s 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

$$E(U)_i^{lifetime} = \sum_{t=1}^{\infty} \rho_i^t \sum_{s^t} \pi_{s^t}[u_i(x_{is^t}, y_{is^t}) + v_i(z_{is^t})] \tag{2.2}$$

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.

$$Max \sum_{i=1}^{N} \omega_i E(U)_i^{lifetime} \tag{2.3}$$

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 aggregate resource constraints.

$$\sum_{i=1}^{N} x_{is^t} = \sum_{i=1}^{N} w^x_{is^t} = X_{s^t}, \forall s^t \tag{2.4}$$

$$\sum_{i=1}^{N} y_{is^t} = \sum_{i=1}^{N} w^y_{is^t} = Y_{s^t}, \forall s^t \tag{2.5}$$

$$\sum_{i=1}^{N} z_{is^t} = \sum_{i=1}^{N} w^z_{is^t} = Z_{s^t}, \forall s^t \tag{2.6}$$

Consider first the case where the food sub-utility function $u_i(x_i, y_i)$ is additively separable in its arguments. The first order conditions of the social planner's problem, with respect to the food commodities are

$$\rho_i^t \omega_i u_i^{'}(x_{is^t}) = \mu_{s^t}^x \tag{2.7}$$

$$\rho_i^t \omega_i u_i^{'}(y_{is^t}) = \mu_{s^t}^y \tag{2.8}$$

where $\mu_{s^t}^j$ is the Lagrange 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 can be expressed as

$$ln\left(\frac{x_{it}}{x_{it-1}}\right) = \left(\frac{\frac{1}{(a_i+1)}}{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{(a_i+1)}}\right)\frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{x_{it}}{x_{it-1}}\right) \tag{2.9}$$

$$ln\left(\frac{y_{it}}{y_{it-1}}\right) = \left(\frac{\frac{1}{(b_i+1)}}{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{(b_i+1)}}\right)\frac{1}{N}\sum_{i=1}^{N} ln\left(\frac{y_{it}}{y_{it-1}}\right) \tag{2.10}$$

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.

But what if the food sub-utility function is non-separable across the two food staples? Then it is easy to see that consumption allocations of x and y would not be independent of each other. It turns out that allocation of a good depends not only on aggregate endowments of the same good but also of the other good. However, it continues to be true that allocations do not depend on individual endowments of either good. These results are derived and presented in the appendix to this chapter (A).

2.4 Data, Descriptive Statistics and Correlations

To test the risk sharing hypothesis we primarily rely on the 'Production, Supply and Distribution' database of the United States Department of Agriculture's Foreign Agriculture Service (FAS). The data-set provides country level time series (1961-2013) of production, consumption, stocks and trade of major agricultural commodities (https://apps.fas.usda.gov/psdonline). This enables us to construct large unbalanced panels. The FAS database reports data for agricultural marketing years. We convert marketing years into calender years based on the starting date of the marketing year. Our analysis focuses on three important staple food commodities, viz., wheat, rice and maize. The consumption aggregate that we use in our analysis is reported as domestic consumption in the FAS database and is equivalent to domestic supply, i.e., production left after net exports and change in stocks.

As a robustness check, this chapter also uses a second data set on country level production and consumption that comes from the Food and Agriculture Organization (FAO) of the United Nations (http://www.fao.org/faostat).

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 2.1: Volatility in Production and Consumption: Domestic and World Aggregates

	Average country standard deviation		World standard deviation		Average share of exports exports in
	c	y	c	y	world production
Rice	0.22	0.24	0.02	0.03	4.93
Wheat	0.18	0.33	0.02	0.06	20.09
Maize	0.26	0.30	0.03	0.10	13.47
Overall	0.22	0.29	0.03	0.06	12.83

Notes: Authors' estimates based on United States Department of Agriculture's (USDA) database. c and y denote per capita consumption and production growth. Time period is 1961-2013. Country specific standard deviation is calculated for countries with at least 20 years of data on production and consumption. Number of countries used are 91, 78 and 109 for rice, wheat and maize respectively.

Table 2.1 presents the standard deviation in consumption and production magnitudes. Global production is least variable for rice and most variable for wheat. The last column of table 2.1 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 20% of the production being traded, followed by corn

(14%) and rice (5%). This suggests that consumption risk sharing would also be greatest for wheat markets.

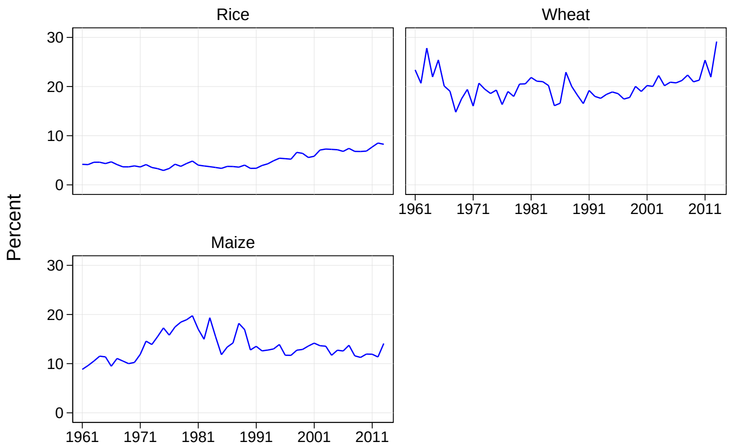


Figure 2.4: Trends in World Exports as a Share of World Production (%): 1961-2013.

Figure 2.4 plots the trends in trade of rice, wheat and corn 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.

2.4.1 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 2.5 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.

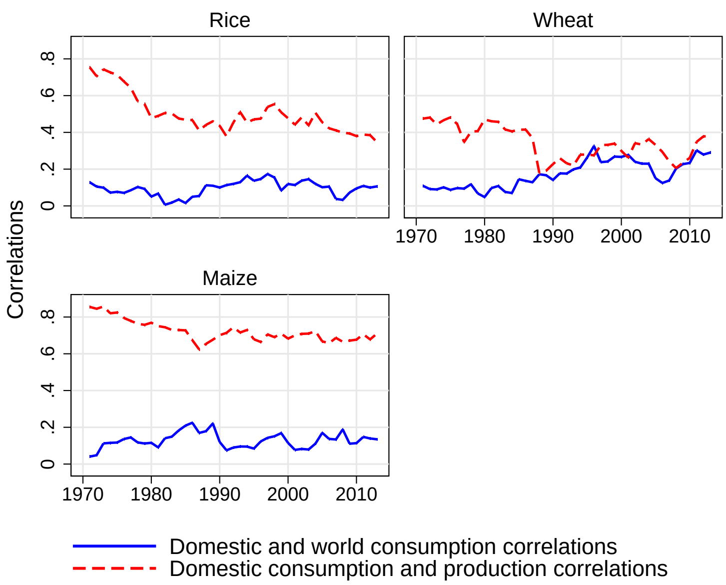


Figure 2.5: Median 10 Year Rolling Correlations: 1961-2013

Further we estimate these correlations by income levels of the countries. Following the World Bank classification, we consider the four groups

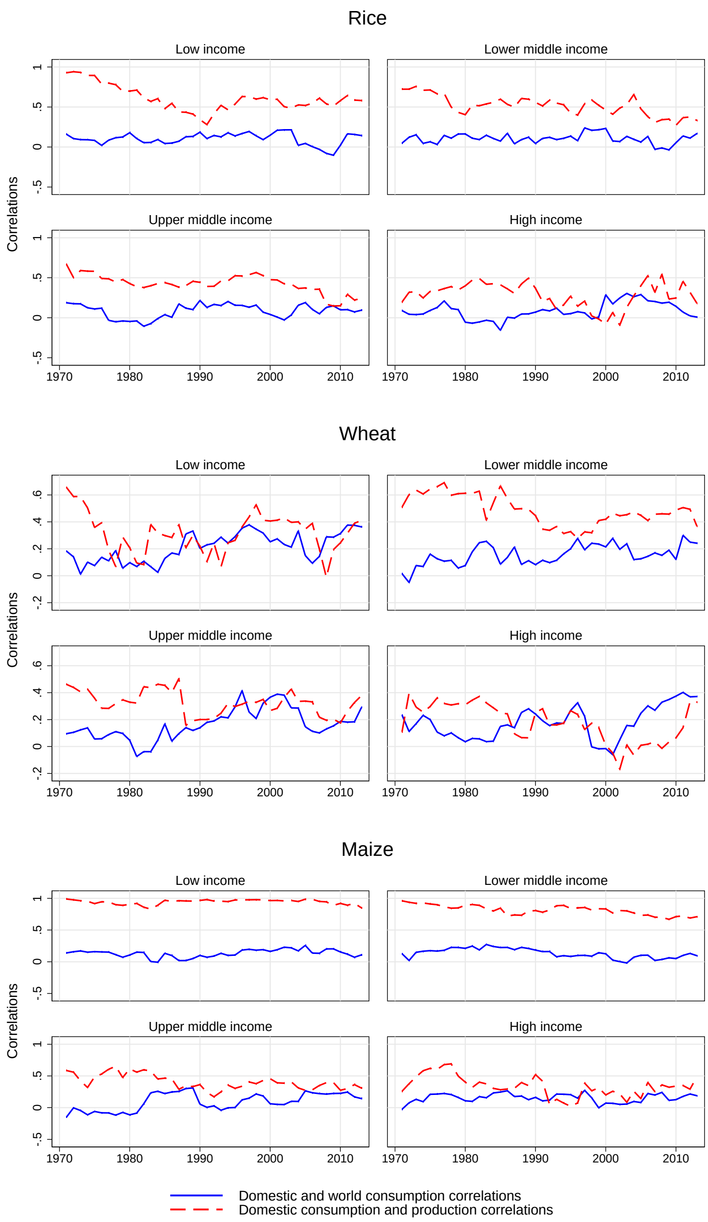


Figure 2.6: Median 10 Year Rolling Correlations by Income: 1961-2013

of low income, lower middle income, upper middle income and high income countries. Figure 2.6 displays these results for low income, lower middle income, upper middle 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.

2.5 Tests of Risk Sharing

2.5.1 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

$$c_{it} = \alpha_i + \mu_t + \gamma y_{it} + \epsilon_{it} \tag{2.11}$$

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 (2.11). 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 (2.11) 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 A (table A.1). 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 chapter, 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 2.11). The F statistic for test of serial correlation and the χ^2 statistic for heteroscedasticity are significant at 1% level indicating the presence of both serial correlation and heteroscedasticity (appendix A table A.2). To take care of these we estimate country-clustered standard errors.

Table 2.2: Test of Risk Sharing: Benchmark Specification

	(1)	(2)	(3)	(4)
Dependent variable:	per capita consumption growth			
(a) Rice				
y_{it}	0.335***	0.335***	0.335***	0.331***
	(0.036)	(0.036)	(0.036)	(0.036)
$\bar{c}_t$				0.747***
				(0.129)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	4382	4382	4382	4382
R^2	0.155	0.16	0.174	0.169
(b) Wheat				
y_{it}	0.126***	0.127***	0.123***	0.124***
	(0.021)	(0.021)	(0.022)	(0.021)
$\bar{c}_t$				0.738***
				(0.136)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	3475	3475	3475	3475
R^2	0.05	0.057	0.091	0.08
(c) Maize				
y_{it}	0.432***	0.431***	0.430***	0.426***
	(0.047)	(0.048)	(0.048)	(0.048)
$\bar{c}_t$				0.520***
				(0.114)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	5002	5002	5002	5002
R^2	0.26	0.268	0.279	0.276

Notes: 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.

The first column of Table 2.2 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 market is able to achieve full insulation from idiosyncratic supply shocks. Comparing the degree of risk sharing across food markets (Table 2.2), we find that wheat market performs the best, providing 87% insurance against domestic production shocks. This is followed by rice (66%) and maize (57%) markets.

2.5.2 Adding Controls and Trends

We test the robustness of our results in table 2.2 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 2.3. The additional control variables are statistically insignificant and don't influence the coefficient of per capita production growth (y_{it}). We also test for linear trends in the slope coefficient by interacting y_{it} by a linear trend in equation 2.11. The coefficient on the interaction term (specification 6, table 2.3) is statistically significant and negative for rice and wheat indicating that risk sharing in rice and wheat markets has improved overtime.

2.5.3 Heterogeneity in the Slope Coefficients

Equation (2.11) 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 (2.11) imposes no such restriction. Suppose, in fact, the slope parameter is heterogeneous. A more general version of equation (2.11) is

$$c_{it} = \alpha_i + \mu_t + \gamma_i y_{it} + \epsilon_{it} \tag{2.12}$$

where $\gamma_i = \gamma + \eta_{it}$ such that η_{it} is a mean zero random variable.

Table 2.3: 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}	0.312***	0.312***	0.312***	0.312***	0.311***	0.484***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.063)
GDP shocks		0.085	0.086	0.085	0.079	
		(0.075)	(0.075)	(0.074)	(0.070)	
Inflation shocks			0.000	0.001	-0.002	
			(0.008)	(0.013)	(0.012)	
Exchange rate shocks				-0.001	0.001	
				(0.012)	(0.011)	
WTO					0.007	
					(0.004)	
$y_{it} \times T$						-0.005**
						(0.002)
N	3644	3644	3644	3644	3644	4382
R^2	0.157	0.157	0.157	0.157	0.141	0.182
(b) Wheat						
y_{it}	0.091***	0.091***	0.092***	0.091***	0.093***	0.216***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)	(0.043)
GDP shocks		-0.014	-0.008	-0.010	-0.017	
		(0.170)	(0.177)	(0.178)	(0.164)	
Inflation shocks			0.006	0.009	0.002	
			(0.011)	(0.013)	(0.013)	
Exchange rate shocks				-0.003	-0.002	
				(0.007)	(0.008)	
WTO					0.003	
					(0.005)	
$y_{it} \times T$						-0.003***
						(0.001)
N	2735	2735	2735	2735	2735	3475
R^2	0.083	0.083	0.083	0.083	0.041	0.097
(c) Maize						
y_{it}	0.409***	0.407***	0.407***	0.407***	0.407***	0.437***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.080)
GDP shocks		0.167	0.162	0.158	0.168	
		(0.125)	(0.130)	(0.129)	(0.125)	
Inflation shocks			-0.006	-0.001	-0.001	
			(0.013)	(0.020)	(0.022)	
Exchange rate shocks				-0.005	-0.007	
				(0.010)	(0.011)	
WTO					0.001	
					(0.006)	
$y_{it} \times T$						-0.0002
						(0.002)
N	4145	4145	4145	4145	4145	5002
R^2	0.274	0.275	0.275	0.275	0.263	0.279

Notes: All specifications include country fixed effects and time dummies. T denoted linear time trend. 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.

Substituting for γ_i, we get

$$c_{it} = \alpha_i + \mu_t + \gamma y_{it} + (\eta_{it} y_{it} + \epsilon_{it}) \tag{2.13}$$

A fixed effects estimation of (2.13) 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 (2.12) 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 2.4 displays the mean group estimates of γ for the three food staple markets. Notice that allowing for heterogeneity increases the magnitude of the estimates and, therefore, lowers the risk sharing performance of these markets.

2.5.4 Heterogeneity in Aggregate Shocks

If time effects, which capture aggregate shocks, are heterogeneous across countries then the two-way specification in (2.11) could lead to biased estimates of the degree of risk sharing. Heterogeneity can arise for a number of reasons. For instance, as consumption patterns differ across countries, a global supply shock in rice matters more to some countries than others. Heterogeneity could also arise if countries differ in the extent to which the food staples are substitutes to one another.

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. In such a framework, we would rewrite equation (2.11) as

$$c_{it} = \alpha_i + \gamma_i y_{it} + \lambda_i \mu_t + \epsilon_{it} \tag{2.14}$$

where μ_t, the aggregate shock is the unobserved common factor with heterogeneous effects. Averaging across the cross-section units, we get

$$\frac{1}{N}\sum_{i=1}^{N} c_{it}^{j} = \frac{1}{N}\sum_{i=1}^{N}\alpha_i + \frac{1}{N}\sum_{i=1}^{N}\gamma_i y_{it} + \frac{1}{N}\mu_t\sum_{i=1}^{N}\lambda_i + \frac{1}{N}\sum_{i=1}^{N}\epsilon_{it} \tag{2.15}$$

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

$$\bar{c}_t = \bar{\alpha} + \gamma\bar{y}_t + \mu_t\bar{\lambda} + \bar{\epsilon}_t + \frac{1}{N}\sum_{i=1}^{N} y_{it}v_{it} \tag{2.16}$$

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

$$c_{it} = \alpha_i + \gamma_i y_{it} + \delta_i\bar{c}_t + \zeta_i\bar{y}_t + \epsilon_{it} \tag{2.17}$$

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 2.4. 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.

2.5.5 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 (2.11) 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 (2.11) becomes

$$c_{it} = \alpha_i + \mu_{g_i t} + \gamma y_{it} + \epsilon_{it} \tag{2.18}$$

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.

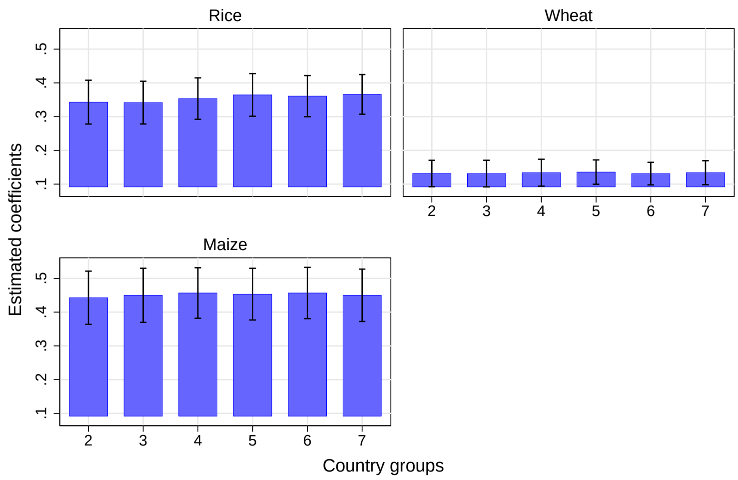


Figure 2.7: Risk Sharing and Endogenous Group Membership: Estimates of γ from Group Fixed Effects Estimator

We vary the number of groups from 2 to 7. Figure 2.7 shows the GFE estimates to be robust across these specifications. The last row of Table 2.4 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.

Table 2.4: 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	0.426***	0.144***	0.555***
	(0.032)	(0.018)	(0.035)
Common correlated effects mean group (CCEMG) estimator	0.429***	0.145***	0.553***
	(0.032)	(0.017)	(0.035)
Group fixed effects (GFE) estimator	0.364***	0.136***	0.453***
	(0.039)	(0.036)	(0.042)

Notes: Table shows the estimates of coefficient on per capita production growth rate. Figures in parenthesis are standard errors robust to heteroscedasticity and within-country serial correlation. Number of 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.

2.6 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 (2.11). An observed source of heterogeneity could be country income. The heterogeneity in correlation trends across country-groups based on their income levels (Figure 2.6) 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:

$$\gamma = \delta_1 + \sum_{g=2}^{4} \delta_g INC_g + \theta_1 t + \sum_{g=2}^{4} \theta_g t \times INC_g \tag{2.19}$$

where INC_g is dummy variable for each income group g, and t is the linear time trend. The results are presented in Table 2.5. 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 25% of the shocks to production whereas high income countries domestic consumption is insured to the extent of 75% of the shocks to production (Table 2.5 column 1). A similar situation is observed in the case of maize. The difference in the degree of risk sharing between low income and the high income countries for both rice and maize is statistically significant.

Table 2.5: Heterogeneity in Risk Sharing by Income

	(1)	(2)	(3)
	Rice	Wheat	Maize
Dependent variable: per capita consumption growth rate			
y_{it}	0.742***	0.312***	0.795***
	(0.0800)	(0.116)	(0.125)
$y_{it}\times$ Lower middle income	-0.300**	0.0189	0.0778
	(0.135)	(0.153)	(0.158)
$y_{it}\times$ Upper middle income	-0.406***	-0.169	-0.528***
	(0.126)	(0.121)	(0.150)
$y_{it}\times$ High income	-0.480***	-0.142	-0.555***
	(0.160)	(0.146)	(0.162)
$y_{it} \times T$	-0.00928***	-0.00580**	-0.000696
	(0.00302)	(0.00253)	(0.00275)
$y_{it} \times T\times$ Lower middle income	0.00322	0.000802	-0.0104***
	(0.00469)	(0.00349)	(0.00394)
$y_{it} \times T\times$ Upper middle income	0.00893*	0.00493*	-0.000115
	(0.00468)	(0.00277)	(0.00341)
$y_{it} \times T\times$ High income	0.00559	0.00117	-0.00419
	(0.00450)	(0.00336)	(0.00520)
N	4382	3475	5002
R^2	0.169	0.0673	0.337

Notes: 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.

The difference in the extent of risk sharing can also be seen graphically in Figure 2.8 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 2.5 is that γ_i declines and risk sharing improves for low income countries with respect to wheat and rice but not for maize.

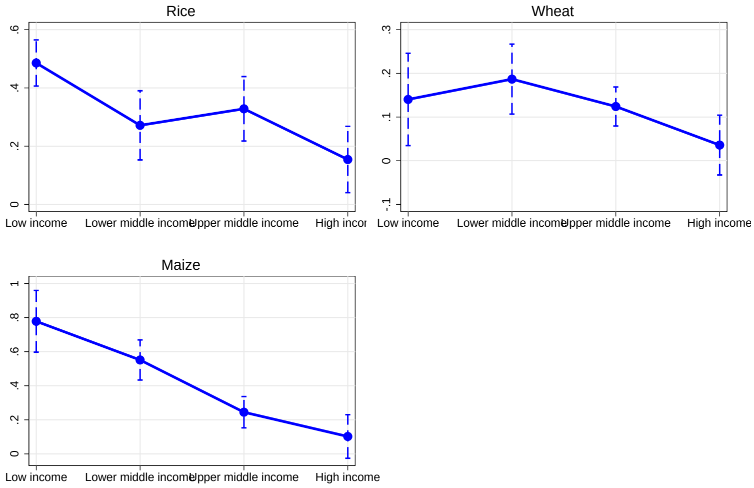


Figure 2.8: Risk Sharing Improves with Income

2.7 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,

$$Y_{it} = \frac{Y_{it}}{Y_{it}^{NX}} \times \frac{Y_{it}^{NX}}{S_{it}} \times S_{it} \tag{2.20}$$

where Y_{it} and S_{it} are the per capita production and supply 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. If we assume that domestic supply (S)

equals consumption (C) then the variance in per capita production can be decomposed as. [3]

$$Var(y_{it}) = Cov(y_{it}, y_{it} - y_{it}^{NX}) + Cov(y_{it}, y_{it}^{NX} - c_{it}) + Cov(y_{it}, c_{it}) \tag{2.21}$$

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

$$1 = \frac{Cov(y_{it}, y_{it} - y_{it}^{NX})}{Var(y_{it})} + \frac{Cov(y_{it}, y_{it}^{NX} - c_{it})}{Var(y_{it})} + \frac{Cov(y_{it}, c_{it})}{Var(y_{it})} \tag{2.22}$$

$$1 = \gamma^{T} + \gamma^{S} + \gamma \tag{2.23}$$

$$1 - \gamma = \gamma^{T} + \gamma^{S} \tag{2.24}$$

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 to trade γ^{T} and change in stocks γ^{S}. Clearly γ^{T} and γ^{S} can be computed as slope

[3] Detailed derivation is presented in appendix A section A.3.

coefficients of an appropriate regressions.

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

$$y_{it} - y_{it}^{NX} = \alpha_i^T + \mu_t + \gamma^T y_{it} + \epsilon_{it}^T \tag{2.25}$$

$$y_{it}^{NX} - c_{it} = \alpha_i^S + \mu_t + \gamma^S y_{it} + \epsilon_{it}^S \tag{2.26}$$

$$c_{it} = \alpha_i + \mu_t + \gamma y_{it} + \epsilon_{it} \tag{2.27}$$

The results are displayed in Table 2.6. Column 3 of Table 2.6 is the same as column 3 of Table 2.2 because equation (2.27) is the benchmark specification that was already reported in Table 2.2. From columns (1) and (2), 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 82% of it in the case of rice and wheat and 86% in the case of maize.

Table 2.6: Estimates of Contribution of Trade and Storage in Risk Sharing

	(1)	(2)	(3)
	Contribution of trade	Contribution of storage	Residual
Dependent variable: per capita consumption growth rate			
Rice	0.542***	0.124***	0.335***
	(0.046)	(0.031)	(0.036)
Wheat	0.714***	0.163***	0.123***
	(0.044)	(0.038)	(0.022)
Maize	0.493***	0.077***	0.430***
	(0.053)	(0.018)	(0.048)

Notes: Table shows the estimates of coefficient on per capita production growth rate. 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.

The absolute contribution of trade to smoothing domestic production shocks is higher in the case of wheat (71%) than rice (54%) and maize (49%). 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 49% 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.

2.8 Robustness Check

As a robustness check we reproduce table 2.2 using the consumption and production data from FAO. The results of the sensitivity analysis are reported in table 2.7. Although the complete risk sharing hypothesis is rejected with the FAO data, the estimated γ (coefficient of y_{it}) is smaller in magnitude.

2.9 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 chapter, we try to

Table 2.7: Robustness Check Using FAO Data

	(1)	(2)	(3)	(4)
Dependent variable:	per capita consumption growth			
(a) Rice				
y_{it}	0.215***	0.214***	0.213***	0.211***
	(0.027)	(0.028)	(0.027)	(0.027)
$\bar{c}_{it}$				0.583***
				(0.159)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	5070	5070	5070	5070
R^2	0.099	0.107	0.117	0.112
(b) Wheat				
y_{it}	0.073***	0.073***	0.072***	0.073***
	(0.014)	(0.014)	(0.014)	(0.014)
$\bar{c}_{it}$				0.637***
				(0.122)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	4805	4805	4805	4805
R^2	0.023	0.037	0.053	0.045
(c) Maize				
y_{it}	0.225***	0.225***	0.227***	0.224***
	(0.036)	(0.036)	(0.037)	(0.036)
$\bar{c}_{it}$				0.675***
				(0.120)
Country dummies	No	Yes	Yes	Yes
Time dummies	No	No	Yes	No
N	6394	6394	6394	6394
R^2	0.101	0.114	0.125	0.122

Notes: 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.

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 25% of full insurance relative to 75% attained by high-income countries. A similar situation is observed in the case of maize. Improving the insurance for poor countries would be vital to achieve food security. This chapter provides the grounds for such a discussion.

Chapter 3

Basis Risk in Index Insurance: Lower Tail Dependence and the Demand for Weather Insurance

3.1 Introduction

Agriculture and agriculture-based livelihoods in developing countries are highly prone to weather shocks. Although there exist various informal mechanisms in rural communities that allow farmers to pool their idiosyncratic risks, such insurance is often partial and, moreover, provide limited insurance to individual households when risks are correlated and widespread. [1] Extreme climate events such as droughts, floods and heat waves which affect farming communities in a region simultaneously are instances of correlated and widespread risks. There is substantial evidence that rural households in high

[1] The literature on risk sharing in communities is large. Overviews include Bardhan and Udry (1999), Fafchamps (2003), Morduch (1999, 2005), Townsend (1994).

risk environment stick to low return subsistence agriculture and cope with a correlated shock by liquidating productive assets to maintain consumption thus remain trapped in poverty (Rosenzweig and Binswanger, 1993; Carter and Barrett, 2006; Dercon and Christiaensen, 2011).

Even though farmers in developing countries are typically poor and even though they bear the burden of volatile income streams, formal insurance products have had limited success (Mobarak and Rosenzweig, 2013). The difficulties of administering first best insurance programs tailored to production histories of individual farmers have led to index insurance products where payouts are triggered by an index such as rainfall, temperature or local average yields. Premium setting is relatively easier because past data on indices of weather and average yield are more readily available than on individual production histories. As individual farmers have little or no influence on payouts, index-based insurance products are also less likely to fail due to asymmetry in information between the insurer and the insured. Despite the promise of index insurance, the record is mixed. In particular, the uptake of index insurance is poor, especially when it is not subsidized (Binswanger-Mkhize, 2012; Jensen and Barrett, 2017; Jensen et al., 2016).

The literature has highlighted many reasons for the low uptake. These include the unfamiliarity among farmers with formal insurance, the lack of trust in the insurance provider and the difficulties of communication resulting in poor understanding of the insurance product. Poor farmers also face liquidity constraints and insurance demand is highly sensitive to price (Cole et al., 2013, 2014; Giné et al., 2008).

However, even if the above factors were absent, research has highlighted the fundamental constraint of basis risk which occurs because of imperfect correlation between the index and farmer losses. If the association is weak, then index insurance might not be reliable (Morsink et al., 2016; Elabed et al., 2013). Research has shown, both theoretically and empirically, that basis risk reduces the demand for insurance (Clarke, 2016; Elabed and Carter, 2015; Giné et al., 2008; Hill et al., 2016). The importance of acknowledging basis risk is stressed in a recent study that states "Discerning the magnitude and distribution of basis risk should be of utmost importance for organizations promoting index insurance products, lest they inadvertently peddle lottery tickets under an insurance label" (Jensen et al., 2016).

Index insurance products are, at best, designed to offer protection against aggregate or covariate risks (Miranda, 1991; Ramaswami and Roe, 2004; Carter et al., 2014). The lack of a perfect association between the index and losses at the farmer level can, therefore, arise either because the index is not accurate or the idiosyncratic losses are substantial. While previous work has established the sensitivity of insurance demand and farmer welfare to basis risk, there has not been much work on contract design that reduces basis risk. Chantarat et al. (2013) described an index based livestock insurance where the contract was based on a regression of historic mortality rates on an index of vegetative cover and therefore, was designed to minimize basis risk. In a similar vein, this chapter examines how rainfall insurance contracts in India can be designed to reduce basis risk. However, we do not use regression-based methods because a least squares fit is based on the idea of linear correlation. Our approach exploits the idea that the joint distribution of rainfall and output might be characterized by tail dependence. This means that the associations between yield losses and index losses are stronger for large deviations than for small deviations. The major implication is that the value (to farmers) of index-based insurance relative to actuarial cost is highest for insurance against extreme or catastrophic losses (of the index) than for insurance against all losses. Or in simpler words, basis risk is least for large deviations of the index. The goal of this chapter is to test this hypothesis.

The contribution of this chapter is two-fold. First, it adds to the slender work on how contracts can be designed to lower basis risk. Second, it uses general measures of association (rather than the linear concept of correlation) to characterize the dependence between the index and crop losses. Previous work has recognized that lower tail dependence characterizes the joint distribution of spatial yields (Du et al., 2017; Goodwin, 2014; Goodwin and Hungerford, 2015) and also the joint distribution of spatial rainfall (Aghakouchak et al., 2010). The chapter argues that these two facts imply that the joint distribution of rainfall and yields will also exhibit lower tail dependence. Testing this hypothesis and examining its implications for the design of insurance is the contribution of this chapter.

The chapter estimates the tail dependence in the joint distribution of weather (i.e., rainfall) and yields using a district level data set for all India for 9 major crops. Using maximum likelihood methods, the chapter estimates a number of copulas from the parametric families of elliptical copulas and the Archimedean copulas. The best-fit copulas are joined to a conceptual model of an insurance purchaser. The simulation of the copulas allows us to estimate the optimal insurance cover for a variety of insurance contracts that vary according to the index threshold value that triggers payout. These results are compared to those obtained from a copula without tail dependence (the Gaussian copula).

A preview of the findings is as follows. We find that station level rainfall in India do exhibit tail dependence and the joint distribution of district level crop yields for nine major crops and rainfall index also exhibit tail dependence. This implies that the associations between yield losses and index losses are stronger for large deviations than for small deviations. Or that the basis risk is least for large deviations of the index. This is also confirmed by simulations that show that value to a risk averse farmer of index-based insurance relative to actuarial cost is highest for insurance against extreme or catastrophic losses (of the index) than for insurance against all losses. Because of tail dependence, the demand for commercially priced rainfall insurance is more likely to be positive when coverage is restricted to extreme losses.

3.2 Relation to Literature

There is no universally accepted definition of basis risk. However, it is commonly understood to arise from the imperfect association between farm level losses and the index that triggers insurance payments. As a result, losses that are actually incurred may not always be compensated by insurance. A particularly stark case is when the farmer suffers a loss but receives no payout. Clarke (2016) refers to the probability of such an event as basis risk. Higher is this probability, greater is the basis risk. In these states of high marginal utility, not only does the farmer *not* receive indemnities but actually suffers cash outflow to pay premiums. For this reason, a risk averse farmer would not want to buy 'too much' of insurance. Higher basis risk reduces the demand for insurance.

A simple model is useful to clarify basis risk and to understand the contribution of this chapter. An index insurance is offered to farmers in a region R (village, cooperative, or other units of aggregation). Consider the following model of yield risk. [2]

$$y_{ir} = \mu_{iR}\eta_{iR} \tag{3.1}$$

where μ_{iR} is the expected yield of producer i in region R and η_{iR} is a unit mean random variable capturing the risks of farming. η_{iR} is a product of two independent unit mean shocks - an aggregate or covariate shock θ_R that affects all farmers in the region and an idiosyncratic shock e_{iR} that affects only producer i and is given by

$$\eta_{iR} = e_{iR}\theta_R \tag{3.2}$$

Assuming each producer's share of land in the region is w_{iR}, the area yield for the region R is

$$y = \theta_R \sum_{(i \in R)} w_{iR}\mu_{iR}e_{iR} \tag{3.3}$$

Let $\mu_R = \sum_i w_{iR}\mu_{iR}$ denote the expected area yield. Then the area yield can be approximated as [3]

$$y = \theta_R\mu_R \tag{3.4}$$

Therefore, in this model, the aggregate shock θ_R is completely cap-

[2]The model is drawn from Ramaswami and Roe (2004).

[3]$\sum_{(i \in R)} w_{iR}\mu_{iR}e_{iR} = \sum_{(i \in R)} w_{iR}(\mu_{iR} - \mu_R)(e_{iR} - \bar{e}) + \mu_R\bar{e}_R$ where $\bar{e}_R = \sum_i w_{iR}e_{iR}$. The first term is approximately zero (independence of idiosyncratic shocks from expected yield) and in the second term the average idiosyncratic shock is approximately equal to its mean, i.e., 1.

tured by area yield. Finally, insurance payouts z to every insured farmer in the region R is a function of the value of an index x_R. While the exact function is unimportant here, a typical insurance contract is of the form

$$z_R = max\{\alpha(x_m - x_R), 0\} \tag{3.5}$$

where x_m and α are positive parameters of the contract. x_m is a deductible. If x_m is high, the insurance covers small and large losses. If it is low, the insurance provides only catastrophic cover.

With reference to this model, basis risk can be quantified in various ways. A simple approach is to examine the correlation between farm yield y_{iR} and insurance payments z_R or the index x_R. As this assumes, basis risk is constant for all values for the index, this chapter will consider general dependence structures that incorporate non-linear association. In particular, it may be important to consider the association between yield and the index when the index losses are large. Morsink et al. (2016) propose two measures of the reliability of index insurance. The first metric is the probability of not receiving an insurance payout in the event of a catastrophic loss. The second measure is the ratio of expected payout to premium in the event of a catastrophic loss. This chapter considers a further nuance: what is the basis risk (or the reliability of index insurance) for different values of the deductible? In particular, is the basis risk appreciably lower for a low x_m?

The literature has distinguished between two sources of basis risk (Jensen et al., 2016; Morsink et al., 2016). First, if the index is poorly chosen, then aggregate shocks might not be sufficiently sensitive to the index. This has been called insured peril basis risk (Morsink et al., 2016) or design risk

(Jensen et al., 2016). In the model described above, area yield is a sufficient statistic for the aggregate shock. However, computation of area yield involves crop cutting experiments or other means of assessing average yield. The greater administrative costs might lead insurance companies to choose an easily measurable weather parameter such as rainfall to approximate the aggregate shock. The problem is that average yield may depend on rainfall as well as other factors such as hailstorms, or pests that affect the entire region. We can write

$$y_R = f(I_R, \nu_R) \tag{3.6}$$

where I_R is an index of rainfall and ν_R stands in for all other factors that affect average yield. The absence of a perfect association between rainfall and average yield constitutes the design risk in this model.

Clarke et al. (2012) analyze this source of basis risk in 270 weather insurance contracts in a state of India. They estimate that there is a one-in-three chance of not receiving insurance payout in the event of a total production loss (of area average yield). In a follow-up analysis, Clarke (2016) argued that, if the contracts were priced commercially (i.e., unsubsidized), the basis risk in them was so great as to reduce optimal demand to zero.

The model described above assumed that all producers in the region R face the same aggregate shock. However, even within a small region, rainfall may not occur uniformly. On the other hand, the index of rainfall is computed from one point in the region. Another source of design risk is, therefore, the imperfect association between rainfall at the farm location and rainfall at the weather station. Previous research has measured such design risk by the distance from the farm to the weather station (that measures the index). This has been shown to reduce insurance demand (Mobarak and Rosenzweig, 2013; Hill et al., 2016).

Even if the index accurately captures aggregate shocks, a second source of basis risk comes from the fact that the aggregate shock is only one component of loss. In particular, individual specific shocks not captured by the index could also lead to a weak association between the losses in the index and individual farm output losses. Such basis risk has been called production smoothing basis risk (Morsink et al., 2016). Ramaswami and Roe (2004) showed that if individual and aggregate shocks interact multiplicatively (as in above model), then even if index insurance insures aggregate shocks perfectly (i.e., no design risk), the presence of uninsured individual specific risks could reduce the demand for index insurance. [4] Empirically, Jensen et al. (2016), using a unique household level panel, analyze the different sources of basis risk for an index based livestock contract offered in Northern Kenya. They find that the livestock contract did reduce household exposure to aggregate risk, principally, droughts. On average, risk exposure to covariate shocks dropped by about 63%. The failure to reach 100% reflects the design errors in the contract. While the contract was not designed to reduce idiosyncratic risk, such risks were large. Even at the smallest levels of aggregation, idiosyncratic risk accounted for about two-thirds of all risk. Reducing design risk by choosing a better index cannot help in dealing with idiosyncratic risk. The policy imperative would be to keep the aggregation (i.e, region R) as small as possible to minimize idiosyncratic risk.

[4]This is true for all risk averse individuals with convex marginal utility. If individual and aggregate shocks interact additively as in Miranda (1991), then idiosyncratic shocks have no consequence for insurance decision although they do matter to utility (Ramaswami and Roe, 2004).

The fact that index insurance can at best deal with aggregate risk suggests that traditional mechanisms of informal insurance would continue to be important in dealing with idiosyncratic risk. If informal networks provide substantial insurance, it would ameliorate the basis risk in index insurance because of idiosyncratic risk and therefore increase the uptake of index insurance. This hypothesis was tested and confirmed by Mobarak and Rosenzweig (2012) and Dercon et al. (2014).

This chapter is about reducing the design error component of basis risk in rainfall insurance contracts. By considering general dependence structures, the chapter opens the door to the possibility that basis risk might vary according to the magnitude of the loss in the index. This possibility is empirically explored by estimating copulas of the distribution of rainfall and yields. While the analysis covers 9 crops across 311 districts from 1966 to 2011, it is limited by the aggregation at the district level. For this reason, the chapter cannot throw light on the basis risk due to uninsured idiosyncratic risk.[5] What the research does is to examine the basis risk that arises by using a weather index (rainfall) to measure aggregate or covariate risk. Related papers that share this objective include Clarke (2016), Clarke et al. (2012) and Morsink et al. (2016).

While this literature provides methods to characterize basis risk, this chapter advances the research by a formal examination of tail dependence and its implications for redesigning contracts to reduce basis risk. A small literature has begun to explore copula based characterizations of joint distributions to explore the spatial correlations of yield and the implications of pricing premiums (Du et al., 2017; Goodwin, 2014; Goodwin and Hungerford, 2015).

[5]This is a limitation shared with much of the literature (e.g., Clarke, 2016) because of the absence of farm level panel data.

The chapter extends the application of these methods to a characterization of basis risk in rainfall insurance contracts.

3.3 Background Evidence: Tail Dependence in Rainfall

In the model described in the last section, area average yield was the correct index for local aggregate shocks. More generally, we can let

$$y_{iR} = \mu_{iR}\eta_{iR} \tag{3.7}$$

where the composite risk is some unspecified function of idiosyncratic and aggregate shock. In other words,

$$\eta_{iR} = g(e_{iR}, \theta_R) \tag{3.8}$$

The average yield is

$$y = \sum_{(i \in R)} w_{iR}\mu_{iR}\eta_{iR} \tag{3.9}$$

Once again denoting the expected area yield $\mu_R \equiv \sum_i w_{iR}\mu_{iR}$, we can decompose the right hand side of above as

$$\sum_{(i \in R)} w_{iR}\mu_{iR}\eta_{iR} = \sum_{(i \in R)} w_{iR}(\mu_{iR} - \mu_R)(\eta_{iR} - \bar{\eta}_R) + \mu_R\bar{\eta}_R \tag{3.10}$$

where $\bar{\eta}_R = \sum_i w_{iR}\eta_{iR}$. If the yield risks are independent of mean yield, the first term is approximately zero. Hence we can approximate area average yield as

$$y = \mu_R \sum_{(i \in R)} w_{iR} g(e_{iR}, \theta_R) \tag{3.11}$$

In this more general model, it is no longer sufficient to represent aggregate shocks by average yield. It also depends on the entire distribution of idiosyncratic shocks.

In either model, in so far as rainfall is only one component of aggregate shocks, a rainfall insurance contract would suffer from design basis risk. Ideally, this should be investigated by examining the association between area average yields and the rainfall index that is computed from a weather station within the region. Because of data considerations, we estimate the tail dependence and the copulas of joint distributions of area average yields and area average rainfall.[6] However, this is not a major limitation because tail dependence in the joint distribution of these averages implies tail dependence in the joint distribution of area average yield and a rainfall index.

The reason is as follows. From other parts of the world, it has been found that rainfalls within a region are not only strongly correlated but, in

[6] Clark's (2016) computations of basis risk in weather insurance products from a state in India is also based on associations of area average yield and area average rainfall.

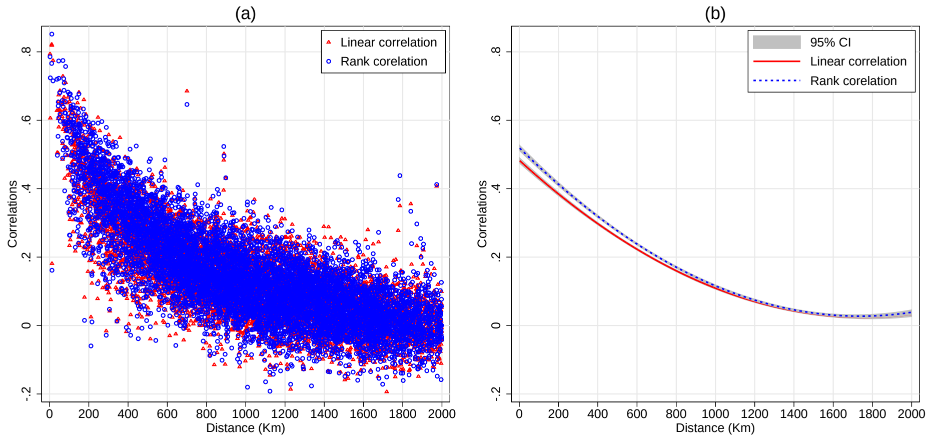
fact, are characterized by tail dependence (e.g., Aghakouchak et al., 2010). Thus, an association of large deviations of area average yield with large deviations of area average rainfall automatically translates to an association of large deviations of area average yield with large deviations of a rainfall index derived from a location within that area.

To confirm the key fact of tail dependence in the distribution of rainfall in India, we use rainfall data from 137 weather stations of the Indian Meteorological Department. The complete data series is available from 1966 to 2007. Rainfall is highly seasonal, and bulk of it is received during June to October. To make rainfall series comparable across stations and months, we standardize rainfall by months.

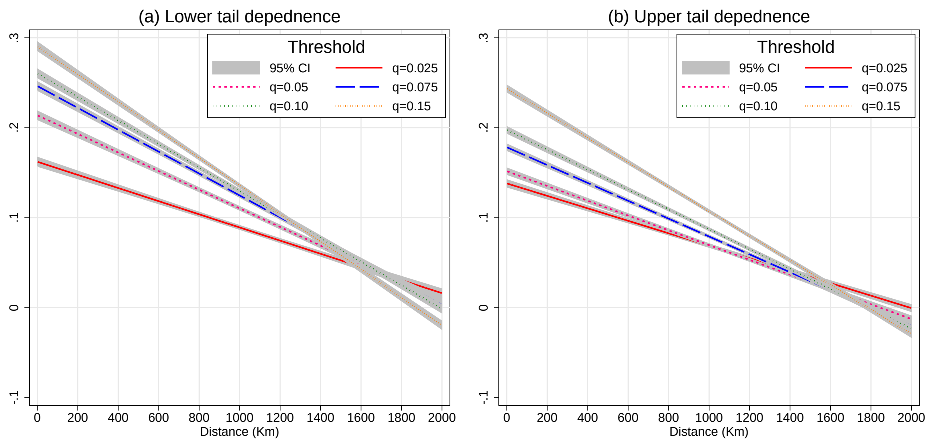
Figure 3.1a shows scatter plot of pair wise linear and rank correlations between all the possible combinations of rainfall stations as a function of the distance between them. The right panel of the figure shows the best fit curve to the rainfall station pair correlations. These clearly show that the joint association between rainfalls at two stations is inversely related to the distance between them. Interestingly the curve for rank correlation is above the curve for linear correlation when two stations are close to each other. But, the difference between the two narrows down as the distance between the stations increases. This is an indication of tail dependence in rainfall as rank correlation is better suited at capturing nonlinear relationships between the variables.[7]

Correlation is a global measure of association whereas we are interested in the association between random variables when they are at their extremes. To study the behavior of joint distribution of rainfalls at extremes

[7]Goodwin (2001) reports a similar finding for spatial correlations between yields.



(a) Correlation and Distance



(b) Nonparametric Tail Dependence and Distance

Figure 3.1: Dependence in Pairwise Station Rainfalls

we create a dataset of all possible combinations of rainfall station pairs. Using this, for each station pair, we generate a new dataset of lower and upper tail dependence coefficients.[8]

We use a nonparametric estimator of tail dependence (Frahm et al., 2005; Patton, 2013). The estimator is given as:

$$\hat{\lambda}^U = 2 - \frac{log(1 - 2(1-q) + T^{-1}\sum_{t=1}^{T} 1\{G(Y) \leq 1-q, F(X) \leq 1-q\})}{log(1-q)}, q \approx 0 \tag{3.12}$$

$$\hat{\lambda}^U = 2 - \frac{log(T^{-1}\sum_{t=1}^{T} 1\{G(Y) \leq 1-q, F(X) \leq 1-q\})}{log(1-q)}, q \approx 0 \tag{3.13}$$

The tail dependence statistic looks at a specific portion of tail in the joint distribution. Therefore, a threshold q needs to be specified for estimation. This choice of q involves trade off in terms of bias in the estimate and its

[8]Tail dependence coefficients quantify the degree of dependence in the lower left quadrant or upper right quadrant of a bivariate distribution. Let X and Y be the continuous random variables with distribution functions F and G, respectively. Then, the lower tail dependence coefficient, λ^L, is the probability that one variable takes an extremely low value, given that the other variable also takes an extremely low value. Similarly, the upper tail dependence coefficient, λ^U, is the probability that one variable takes an extremely high value, given that the other variable also takes an extremely high value. Mathematically, these can be expressed as:

$$\lambda^L = \lim_{q \longrightarrow 0} P(G(Y) \leq q \mid F(X) \leq q)$$

$$\lambda^U = \lim_{q \longrightarrow 1} P(G(Y) > q \mid F(X) > q)$$

where both $\lambda^L, \lambda^U \in (0, 1]$. For a set of random variables to be tail-dependent the limits of the conditional probabilities in above equations should be non-zero. Tail dependence coefficients are better measures than linear correlation as they provide more detailed information on the joint dependence structure of random variables (Patton, 2013). Since a bivariate normal distribution does not exhibit tail dependence, the presence of tail dependence in data goes against the assumption of joint normality.

variance. For small (large) values of q the variance is large (small) and the bias is small (large). Note that the smaller the value of threshold q the more extreme deviations the tail dependence statistic will capture.

Figure 3.1b shows the best fitted curves for the lower and upper tail dependence statistic for pair-wise rainfalls as a function of the distance between the stations. The tail dependence declines with distance, but the rate of decline is slower for lower values of q. We model this behavior econometrically in the following way.

$$\lambda_{ij} = \beta_1 Ln(Distance)_{ij} + \beta_2 q + \beta_3 Ln(Distance)_{ij} \times q + \alpha_i + \tau_j + \varepsilon_{ij} \quad (3.14)$$

where λ_{ij} the estimated tail dependence coefficient between rainfalls measured at two stations i and j, $Ln(Distance)_{ij}$ is the distance in kilometers between the two stations and q is the threshold chosen for the tail dependence statistic. The interaction coefficient captures the interplay between distance and extreme events. Table 3.1 shows the estimated coefficients from the regressions. The coefficient of the interaction term is negative and statistically significant. Since lower values of q correspond to more extreme deviations in rainfall the analysis reveals that extreme deviations in rainfall are more widespread as compared to moderate deviations. Hence, extreme rainfall shocks will survive spatial aggregation in comparison to moderate shocks. If yield across farms are dependent on local rainfall, then it will also inherit the tail dependence property. The implication of this finding is that an extreme rainfall anomaly will lead to spatially correlated crop losses.

As a robustness check, we also test for tail dependence between

Table 3.1: Extreme Events, Tail Dependence and Distance

	(a) Weather station data		(b) Gridded data	
	Upper $\hat{\lambda}^L$	Lower $\hat{\lambda}^U$	Upper $\hat{\lambda}^L$	Lower $\hat{\lambda}^U$
$\log(Distance)$	-0.06***	-0.06***	-0.10***	-0.09***
	(0.004)	(0.003)	(0.003)	(0.002)
q	2.49***	2.32***	3.96***	3.89***
	(0.240)	(0.205)	(0.094)	(0.062)
$\log(Distance) \times q$	-0.31***	-0.29***	-0.50***	-0.49***
	(0.035)	(0.030)	(0.013)	(0.008)
Constant	0.53***	0.50***	0.81***	0.65***
	(0.027)	(0.021)	(0.023)	(0.016)
Observations	55896	55896	381276	381276
Adjusted R^2	0.48	0.47	0.67	0.68

Notes: The dependent variable are the estimated nonparametric tail dependence coefficients. The tail dependence statistic varies between 0 and 1. The regressions include station (grid point) fixed effects. Figure in parenthesis are standard errors clustered at rainfall station level. Panel (a) shows results from the data on actual rainfalls measured at 137 weather stations spread all over India. Panel (b) shows results from the Indian meteorology department's high resolution gridded rainfall data based on rainfall records from 6995 rain gauge stations in India. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

the station-level rainfall by fitting different copula models on station-pairs with distance less than or equal 2000 kilometers. The appendix B.1 provides details of how bivariate distributions are modeled by a copula. The chapter considers the commonly used parametric families of elliptical copulas and the Archimedean copulas. Their statistical properties are also summarized in the appendix B.1. The copula is estimated by standard methods. Marginal distributions are estimated non-parametrically and substituted in the copula. The dependence parameters are estimated in the second step. These details are also provided in the appendix B.1.

The Students t copula is the best fit for almost half of the station-pairs, followed by Plackett and rotated Clayton copula (table 3.2a). The Students t copula exhibits both upper and lower tail dependence. This indicates that rainfall in general exhibits a stronger association in case of both extremely low and extremely high deviations from the normal. The mean values of the tail dependence coefficients based on the copula parameter for all the station-pairs

Table 3.2: Dependence in Pairwise Station Rainfalls

(a) Copula Fitted to Pairwise Rainfalls

Copula model	Station pairs	Percent
Gaussian	354	4.43
Clayton	437	5.46
Rotated Clayton	950	11.88
Plackett	1204	15.05
Frank	318	3.98
Gumbel	188	2.35
Rotated Gumbel	698	8.73
Student's t	3849	48.12
Total	7998	100

(b) Estimated Tail Dependence based on Fitted Copula and Distance

		Distance between pair of stations in kilometers					
	Copula	2-479	498-776	777-1033	1033-1287	1287-1572	1573-1999
Lower	Rotated Clayton	0.183	0.019	0.01	0.009	0.006	0.003
		(0.236)	(0.039)	(0.02)	(0.025)	(0.019)	(0.013)
	Rotated Gumbel	0.284	0.209	0.163	0.146	0.133	0.129
		(0.09)	(0.06)	(0.043)	(0.032)	(0.02)	(0.019)
	Student's t	0.573	0.523	0.503	0.493	0.49	0.482
		(0.051)	(0.034)	(0.031)	(0.026)	(0.026)	(0.024)
	Total	0.353	0.336	0.292	0.237	0.194	0.172
		(0.274)	(0.238)	(0.238)	(0.236)	(0.231)	(0.226)
Upper	Rotated Clayton	0.126	0.064	0.026	0.017	0.006	0.003
		(0.094)	(0.058)	(0.04)	(0.031)	(0.014)	(0.008)
	Rotated Gumbel	0.294	0.185	0.149	0.149	0.133	0.122
		(0.091)	(0.054)	(0.032)	(0.037)	(0.014)	-
	Student's t	0.573	0.523	0.503	0.493	0.49	0.482
		(0.051)	(0.034)	(0.031)	(0.026)	(0.026)	(0.024)
	Total	0.348	0.324	0.28	0.228	0.185	0.165
		(0.276)	(0.247)	(0.247)	(0.241)	(0.235)	(0.229)

Note: Standard deviation in parenthesis.

are presented in table 3.2b and show a declining strength of association when the distance between two stations increases. This is similar to the pattern observed in the non-parametric tail dependence coefficients.

3.4 The Joint Distribution of Average Area Yields and Average Area Rainfall

We now turn to the association between average area yield and average area rainfall. District yields are collected from the district database of the International Crops Research Institute for the Semi-Arid Tropics ICRISAT (http://vdsa.icrisat.ac.in/vdsa-database.htm) that is compiled from various official sources. To maintain consistency and comparability of time series across districts, data of the bifurcated districts is returned to the parent district based on the district boundaries in 1966.

The database covers 15 major crops across 311 districts in 19 states from the year 1966-67 to 2011-12. India receives 85% of its annual rainfall during the monsoon months of June to September. A rainfall insurance contract is meaningful therefore for crops grown during this period. These are called the *kharif* season crops (June to October). In the data set, these crops are Maize, Cotton, Sorghum, Finger millet, Pigeon pea, Soybean, Pearl millet, Groundnut and Rice. [9] Crop yields typically exhibit significant upward trends overtime due to technological changes. Yield deviations are estimated by fitting a linear trend to log yields of each crop of each district.

The high resolution gridded rainfall data from the Indian Meteorolog-

[9]Maize and groundnut are cultivated around the year.

ical Department is used to construct total *kharif* season rainfall as cumulative rainfall for the months from June to October. The cumulative seasonal rainfall is transformed to standardized deviations from their long term normals.

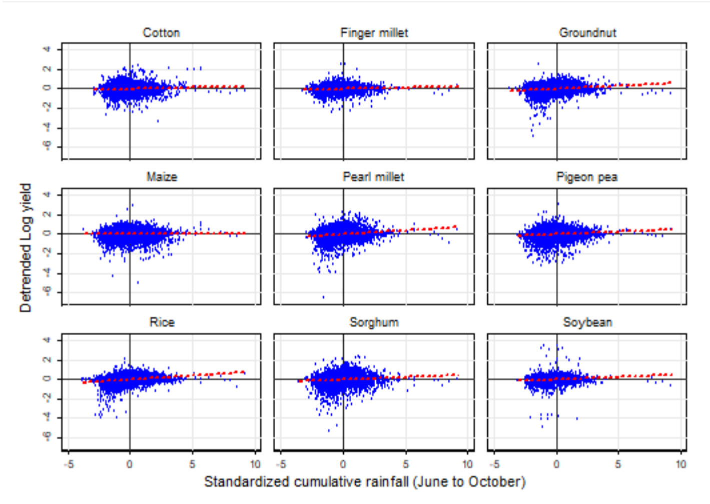
Table 3.3 presents coefficients of linear and rank correlation between yield and rainfall deviations. As expected, both measures show a statistically significant positive association between yield and rainfall deviations, despite some difference in their magnitude. Figure 3.2 shows the scatter plot of rainfall and yield deviations. Figure 3.2a shows scatter plots of yield and rainfall deviations along with the linear fit.

Table 3.3: Linear and Rank Correlation between Yield and Rainfall Deviations

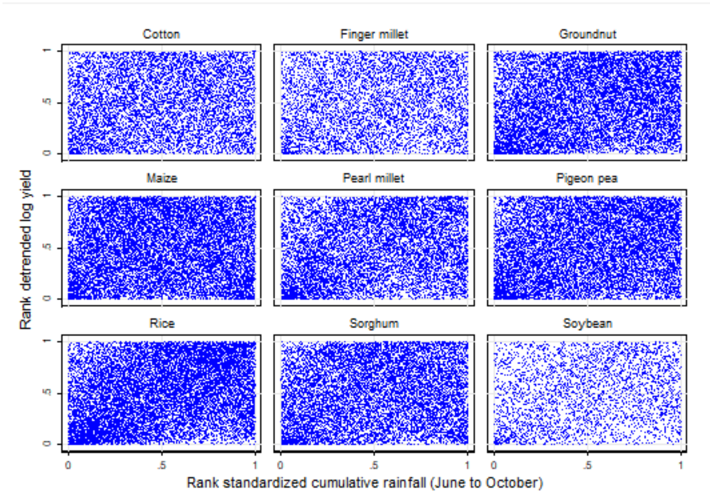
	(1)	(2)
Crops	Linear correlation	Rank correlation
Maize	0.023	0.004
	(0.009)	(0.01)
Cotton	0.072	0.073
	(0.012)	(0.015)
Sorghum	0.104	0.109
	(0.01)	(0.01)
Finger millet	0.107	0.086
	(0.014)	(0.015)
Pigeonpea	0.145	0.131
	(0.009)	(0.009)
Soybean	0.169	0.122
	(0.018)	(0.017)
Pearl millet	0.183	0.183
	(0.011)	(0.011)
Groundnut	0.177	0.180
	(0.01)	(0.01)
Rice	0.277	0.267
	(0.008)	(0.009)

Note: Bootstrapped (200 replications) standard errors in parenthesis.

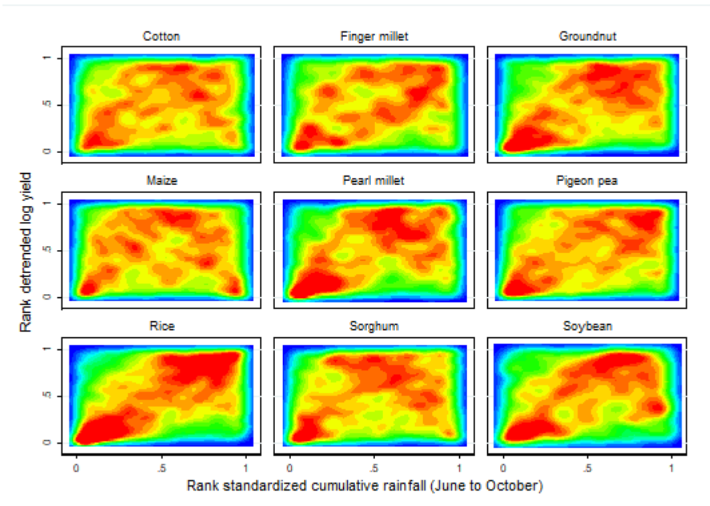
A crude test for the presence of tail dependence in a pair of variables is to examine the scatterplot of these variables (after transforming to uniform scores based on the empirical distribution) for clustering at the extremes (Joe, 2014). For different values of q we can also compute conditional quantile dependence probabilities for the lower (p^L) and higher (p^U) extremes of the



(a) Scatter Plot of Yield and Rainfall Deviations



(b) Scatter Plot of Ranks of Yield and Rainfall Deviations



(c) Kernel Density Plots of Ranks of Yield and Rainfall Deviations

Figure 3.2: Joint Distribution of Yield and Rainfall Deviations

transformed variables as:

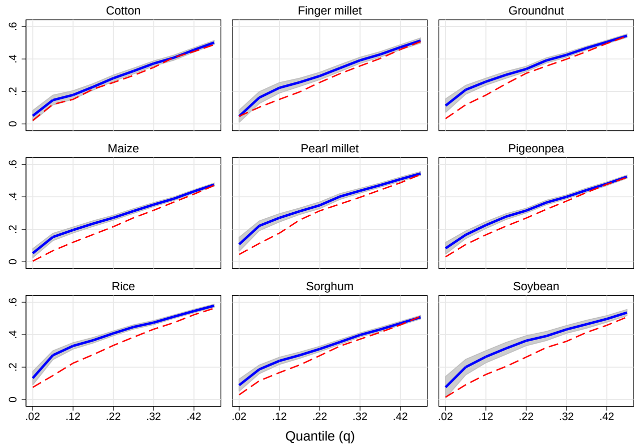
$$p^L = \frac{1}{Tq} \sum_{(t=1)}^{n} 1\{U_{Yt} \leq q \mid U_{Xt} \leq q\} \tag{3.15}$$

$$p^U = \frac{1}{T(1-q)} \sum_{(t=1)}^{n} 1\{U_{Yt} \leq q \mid U_{Xt} \leq q\} \tag{3.16}$$

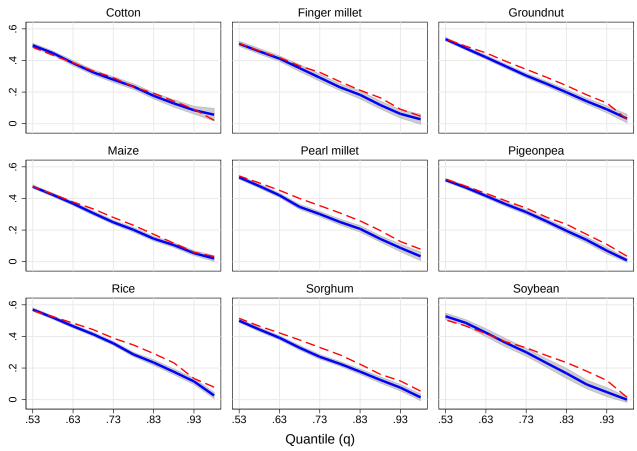
Where U_{Yt} and U_{Xt} are the scores of Y and X based on their empirical distribution.

In figures 3.2b and 3.2c we present the scatter and bivariate kernel density plots of the rank-based empirical marginal distribution of yield and rainfall deviation. We observe clustering of rank scores (for yield and rainfall deviations) in the lower-left corner of scatter plots for many of the crops. Such a clustering corresponds to extreme shortfalls in yield and rainfall, and implies greater probability of simultaneous occurrence of these events.

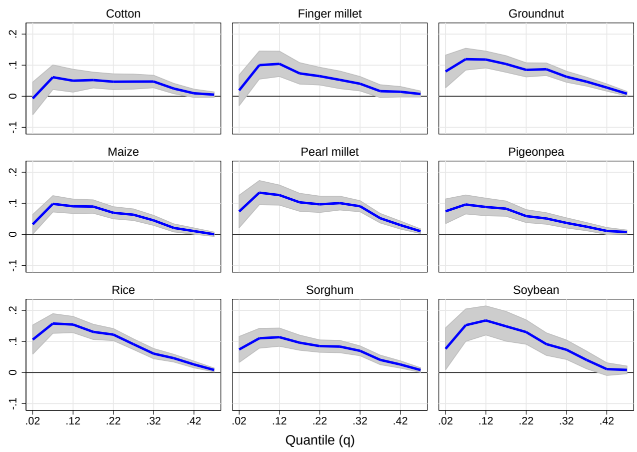
The scatter plots of rank-based empirical distributions indicates that association between yield and rainfall index may not be linear. Therefore, we test for the presence of tail dependence in their joint distribution using the conditional quantile dependence probabilities. Figure 3.3 shows estimated lower tail (panel 3.3a) and upper tail (panel 3.3b) quantile dependence plots; and the difference between the two (panel 3.3c). For comparison we also present the quantile dependence from the moments matched bivariate normal distribution as dashed line in this figure. For all crops the quantile dependence probability at the lower tail of the joint distribution is greater than the same exhibited by normal distribution. This again is evidence of lower tail dependence in crop yield and rainfall deviations. The quantile dependence



(a) Lower Tail



(b) Upper Tail



(c) Difference in Upper and Lower Tail Dependence

Figure 3.3: Tail Dependence at Different Quantiles

plots for the upper tail don't show any evidence of tail dependence in the joint distribution of yield and rainfall distribution. We also find strong evidence that the joint distribution of crop yield and rainfall deviations exhibit asymmetric tail dependence. The difference between the upper and lower quantile dependence is statistically significant and is greater at lower quantiles (figure 3.3c). These results clearly reveal that the bivariate normal distribution is unsuitable to model the joint distribution of yields and rainfalls.

Table 3.4: Log Likelihood from Different Copula Models

Crops	Gaussian	Clayton	Rotated Clayton	Plackett	Frank	Gumbel	Rotated Gumbel	Student's t
Cotton	20.4	33.7	8.3	18.8	18.4	-12.7	16.0	24.3
Finger millet	27.9	51.5	3.2	31.8	31.1	-9.8	43.3	29.9
Groundnut	183.8	254.9	56.6	175.3	171.8	92.0	235.2	196.9
Maize	3.5	31.4	-0.01	3.6	3.5	-138.5	-31.6	11.9
Pearl millet	165.8	224.7	52.7	154.9	152.0	81.2	214.7	173.6
Pigeon pea	124.8	172.6	29.1	123.9	122.9	39.8	151.9	125.8
Rice	548.3	680.9	204.2	544.4	533.5	334.4	665.8	567.6
Sorghum	68.4	125.9	10.8	56.8	55.7	-8.8	104.0	76.9
Soybean	43.6	68.4	7.5	48.5	48.1	14.0	63.2	45.8

Note: Log likelihood values estimated from copula models.

We use copula functions to capture the asymmetric dependence between yield and rainfall deviations by fitting copulas to rank-based empirical marginal distributions of yield and rainfall deviations.[10] Based on the log likelihood values, the Clayton copula is the best model to describe the dependence between yield and rainfall deviations (Table 3.4). This is not surprising as Clayton copula exhibits only lower tail dependence and no upper tail dependence. The worst performing copula models are one with zero lower tail dependence and allow only upper tail dependence like Gumbel and rotated Clayton. Table 3.5 presents the parameters of the Clayton copula with bootstrapped standard errors and lower tail dependence based on the fitted copula parameter.

[10] As mentioned earlier, the procedure used to estimate bivariate copulas is explained in Appendix B.1.

Table 3.5: Clayton Copula Model Parameter Estimates

Crops	Parameter Estimates	Standard errors	Tail dependence
Cotton	0.107	0.014	0.0015
Finger millet	0.158	0.018	0.0125
Groundnut	0.260	0.013	0.0695
Maize	0.074	0.011	0.0001
Pearl millet	0.271	0.015	0.0776
Pigeon pea	0.201	0.012	0.0319
Rice	0.415	0.014	0.1878
Sorghum	0.176	0.012	0.0195
Soybean	0.246	0.025	0.0597

The estimated copula density for different crops is presented in Figure 3.4. As expected, all crops show significantly higher density at the lower tail. This further confirms that the association between yield and rainfall deviations is stronger at the lower tail. This means when rainfall is abnormally low, yield losses are widespread. Therefore, the basis risk is low for extreme shortfall in rainfall.

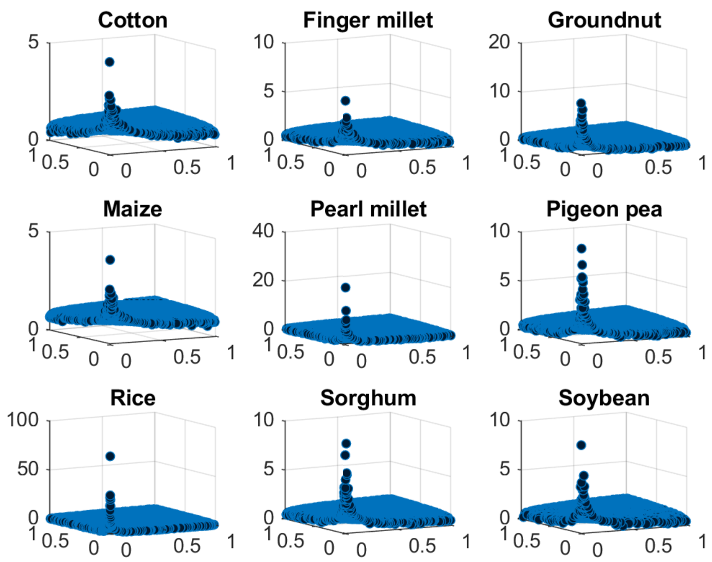


Figure 3.4: Estimated Copula Density by Crops

As a robustness check, we fit all the selected eight copula models to each district that has at least 40 data observations. Based on the log likelihood values and the AIC criterion, we choose the one that best describes the dependence. Table 3.6 summarizes the results. For example, in the case of rice Clayton copula gives best fit for 40 percent of the 274 rice growing districts. Student's t copula is the next best. Across all crops about 70% of the cases are accounted by either the Clayton copula or the Student's t copula. These findings clearly indicate nonlinearity in association between weather and yield risk and have implications for the demand for insurance and thus, its design.

Table 3.6: Percent Districts with Best Fit Copula

Crops	Gaussian	Clayton	Rotated Clayton	Plackett	Frank	Gumbel	Rotated Gumbel	Student's t	Total
Cotton	12	37	10	7	7	3	2	44	122
	(9.84)	(30.33)	(8.2)	(5.74)	(5.74)	(2.46)	(1.64)	(36.07)	(100)
Finger millet	2	28	5	3	5	0	4	24	71
	(2.82)	(39.44)	(7.04)	(4.23)	(7.04)	(0)	(5.63)	(33.8)	(100)
Groundnut	9	77	8	15	8	3	11	57	188
	(4.79)	(40.96)	(4.26)	(7.98)	(4.26)	(1.6)	(5.85)	(30.32)	(100)
Maize	17	68	13	21	8	4	6	113	250
	(6.8)	(27.2)	(5.2)	(8.4)	(3.2)	(1.6)	(2.4)	(45.2)	(100)
Pearl millet	3	78	7	9	6	3	6	45	157
	(1.91)	(49.68)	(4.46)	(5.73)	(3.82)	(1.91)	(3.82)	(28.66)	(100)
Pigeon pea	12	88	21	15	16	6	7	53	218
	(5.5)	(40.37)	(9.63)	(6.88)	(7.34)	(2.75)	(3.21)	(24.31)	(100)
Rice	13	110	10	12	24	8	34	63	274
	(4.74)	(40.15)	(3.65)	(4.38)	(8.76)	(2.92)	(12.41)	(22.99)	(100)
Sorghum	6	73	8	14	8	2	7	80	198
	(3.03)	(36.87)	(4.04)	(7.07)	(4.04)	(1.01)	(3.54)	(40.4)	(100)
Soybean	0	24	2	2	6	0	2	5	41
	(0)	(58.54)	(4.88)	(4.88)	(14.63)	(0)	(4.88)	(12.2)	(100)
Total	74	583	84	98	88	29	79	484	1519
	(4.87)	(38.38)	(5.53)	(6.45)	(5.79)	(1.91)	(5.2)	(31.86)	(100)

Note: Row percentages in parenthesis.

3.5 Implications for Rainfall Insurance

3.5.1 Basis Risk

Our findings show that the joint density of yield and rainfall exhibit lower tail dependence, i.e. a stronger association between yield and rainfall when rainfall is abnormally low. This implies that the basis risk varies across the joint distribution of yield and index. This opens up the possibility of designing insurance such that it covers the losses with the least basis risk. Here, we analyze the implications of these findings for the demand and design of index insurance.

Assume that a farmer's yield q is a random variable with distribution function $g(q)$. The payout from one unit of rainfall based insurance contract is given by

$$I = Max\{\hat{R} - R, 0\} \tag{3.17}$$

where R is the rainfall index with distribution function $h(R)$ and $\hat{R}$ is the rainfall threshold set by the insurance selling agency. Lower is the threshold, greater is the deductible in the insurance payouts. The contract trigger's payouts only if actual rainfall falls below $\hat{R}$. The implicit assumption in offering such a contract is that farmers' yield and the rainfall index are correlated such that in periods of low rainfall crop yields will also be lower. The actuarially fair price P of such a contract is just the expectation of I.

$$P = \int_0^{\hat{R}} (\hat{R} - R)h(R)dR \tag{3.18}$$

The net profits of a farmer purchasing a rainfall insurance contract can be written as

$$\pi = q + \alpha(I - mP) \tag{3.19}$$

where α is the number of insurance units purchased and m is the mark-up over actuarially fair insurance. We want to find the optimal value of α that maximizes the expected indirect utility.

$$Max_\alpha \eta(\alpha) \equiv Eu(q + \alpha(I - mP)) \tag{3.20}$$

where $u(.)$ is the utility function of the farmer with $u^{'}(.) > 0$ and $u^{''}(.) < 0$.

Starting from no insurance, the increment to expected utility because of insurance is given by

$$\eta^{'}(\alpha) \mid_{\alpha=0}= Eu^{'}(q)(I - mP) \tag{3.21}$$

Or,

$$\eta^{'}(\alpha) \mid_{\alpha=0}= \iint u^{'}(q)(I - mP)h(R \mid q)g(q)dRdq \tag{3.22}$$

where $h(R \mid q)$ is the density of rainfall conditional on yield. This can be rewritten as

$$\eta^{'}(\alpha) \mid_{\alpha=0} = \int u^{'}(q)[\int (I - mP)h(R \mid q)dR]g(q)dq \tag{3.23}$$

The term inside the square brackets is nothing but $E(I \mid q) - mP$. Hence we have

$$\eta^{'}(\alpha) \mid_{\alpha=0} = Eu'(q)(E(I \mid q) - mP) \tag{3.24}$$

From the above it can be seen that the insurance demand is zero if $E(I \mid q) \leq mP$, for all values of q. This result is a restatement of a theorem in Clarke (2016). Clarke defines

$$\kappa(q) = \frac{E(I \mid q)}{mP} = \frac{\text{Expected claim payment over yield distribution}}{\text{Commercial premium}} \tag{3.25}$$

The ratio basically reflects the average amount a farmer gets back as claims per dollar paid as commercial premium. He shows that if $\kappa(q) \leq 1$ over the entire yield distribution then $\alpha = 0$, for a risk-averse individual. In our model, this result follows from (3.24).

Clarke et al. (2012) use the payout structure of 270 weather based crop insurance products sold to Indian farmers in one state in one year and combine it with historical data to simulate payouts over the period 1999-2007. Their work finds the ratio $\kappa(q)$ to be almost flat over the entire yield distribution.

The ratio is below 1 for most values of q and is barely above 1 for very low levels of q. It follows then that the basis risk in these contracts is so large that it would be optimal not to purchase them. Morsink et al. (2016) proposed that the ratio defined in (3.25) should be used as a measure of reliability of weather insurance contracts and called it the catastrophic performance ratio. They further suggested that the ratio could be used to "improve the quality of products, protect consumers, and reduce reputational risk".

We use the catastrophe performance ratio to examine how tail dependence matters to basis risk. A hypothetical rainfall insurance contract of the form in (3.17) is considered. The payoffs are simulated using 10,000 draws of rainfall and yield from a Gaussian copula and from a copula exhibiting lower tail dependence. The correlation between the two variables is held constant across the two copulas. The comparison of the performance ratio across the two copulas is, then, revealing about the effect of tail dependence.

The exact procedure is as follows. For both these copulas, the marginal distribution of yield and rainfall are assumed to be normal with a mean of 2000 and standard deviation of 300. In the last section, the best fit copula to the joint distribution of rice yields and rainfall was found to be the Clayton copula with a parameter of 0.42. The marginal distributions are combined in a Clayton copula with a parameter of 0.42 to generate 10,000 observations of yield and rainfall. These observations are used to compute the insurance and payoffs. The linear correlation between rainfall and yield draws from the Clayton copula is combined with the assumed marginal distributions to generate another 10,000 observations from a bivariate normal distribution.

Thus, we have two empirical joint distributions such that they share the same marginal distributions and the same correlation between rainfall and yield. The only difference is that yield and rainfall index simulated from Clayton copula exhibit lower tail dependence, while the other does not.

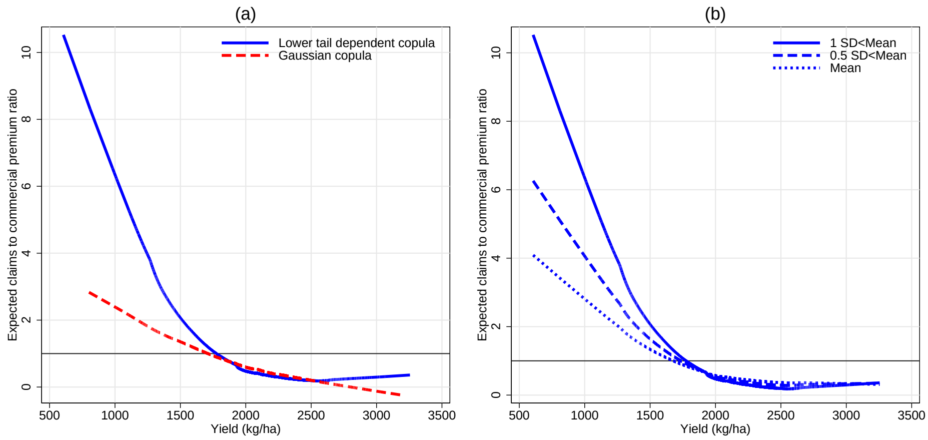


Figure 3.5: Expected Claims to Commercial Premium Ratio: All India

Figure 3.5a plots the nonparametrically estimated relationship between claims to commercial premium ratio and yield from the simulated data, i.e.

$$I(q) = E\left(\frac{Max\{\hat{R} - R, 0\}}{mP} \mid q\right) \tag{3.26}$$

where the insurance contract parameter $\hat{R}$ is assumed to be one standard deviation below the mean rainfall and m is assumed to be 1.56 times the actuarially fair premium.[11] At this premium level, the catastrophic performance ratio is below 1 for the rainfall insurance contracts considered by Clarke et al. (2012). This is not true, however, for the payouts from rainfall contracts in Figure 3.5a The ratio from the normal distribution and from Clayton Copula are above 1 for low output levels. There is, however a substantial divergence between the normal distribution and the Clayton

[11] Clarke (2016) based on 270 weather based crop insurance products sold to Indian farmers report's that a markup greater than 1.56 times the fair premium will lead to no demand for rainfall insurance.

copula at these low output levels. The catastrophic performance ratio is substantially higher for the Clayton copula. Thus, by the measures proposed by Morsink et al. (2016), accounting for tail dependence markedly reduces basis risk.

Figure 3.5b plots the Clayton copula based catastrophic performance ratio for different levels of the deductible. $\hat{R}$ is chosen to be either the mean, or 0.5 standard deviation below the mean or 1 standard deviation below the mean. It can be seen that as the deductible rises (i.e., $\hat{R}$ falls) so does the basis risk. Catastrophic insurance carries the least basis risk.

3.5.2 Optimal Insurance

In figures 3.5a and 3.5b, the Clarke condition that is sufficient to ensure zero insurance demand is not met. $(E(I \mid q) - mP)$ is above 1 for low realizations of output but below 1 for high realizations of output. This does not mean that insurance demand is necessarily positive. That depends on the evaluation of equation (3.24) which depends on the extent of risk aversion. (3.24) can also be written as

$$\eta^{'}(\alpha) \mid_{\alpha=0} = Cov(u^{'}(q), E(I \mid q)) - (m-1)PEu^{'}(q) \tag{3.27}$$

Risk aversion and the expected shape of the regression $E(I \mid q)$ guarantees the first term to be positive. When insurance is actuarially fair, the second term is zero and it is optimal for farmers to buy some insurance. When $m > 1$, the answer would depend on risk aversion and the mark-up over the fair premium.

To investigate these issues, we consider data from two districts in India, Mahabubnagar and Anantapur, that have been heavily researched for the extent of local risk sharing (e.g., Townsend, 1994). These districts are characterized by dependence on rainfed agriculture and vulnerability to droughts. Households in these districts have also been recently surveyed for their risk aversion using Binswanger type lotteries (Binswanger, 1980; Cole et al., 2013) and we use those estimates.

Using the procedures in appendix B.1, a best fit copula model is selected for rice yields and rainfall in each of the two districts. Table 3.7 displays the results. Unlike the exercise that generated figures 3.5a and 3.5b, we do not assume marginal distributions of rainfall and yield to be normal. Instead, we consider various parametric form and choose the best fit functional form (Table 3.7).[12] Rainfall is log-normal in both districts. Yield follows a Weibull distribution in Anantapur and follows a gamma distribution in Mahabubnagar. Plots of estimated parametric distributions against the observations are presented in appendix B.2.

Table 3.7: Best Fit Parametric Marginal Distributions and Copula Models

		Parameter estimates	
(a) *Fitted marginal distribution of cumulative rainfall*			
Anantapur	Log normal	6.06	0.28
Mahabubnagar	Log normal	6.38	0.24
(b) *Fitted marginal distribution of de-trended recentered yield*			
Anantapur	Weibull	2961.8	15.0
Mahabubnagar	Gamma	126.7	21.3
(c) *Copula model of joint distribution*			
Anantapur	Rotated Gumbel	1.187	
Mahabubnagar	Clayton	1.127	

[12]The distributions that were considered were Gamma, Weibull, log-normal and Gumbel. All of these are two-parameter distributions and the parameters were estimated by maximum likelihood procedures. The distribution that maximizes the log likelihood is picked as the marginal distribution.

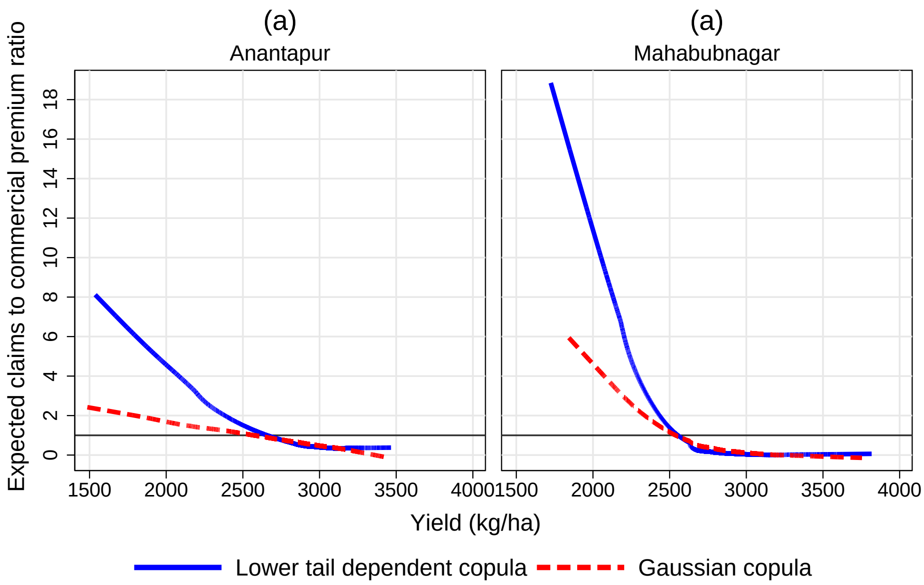
These marginal distributions are combined in the appropriate copula (as in Table 3.7) to generate 10,000 observations of yield and rainfall. These observations are used to compute the insurance and payoffs. The linear correlation between these rainfall and yield draws is combined with the selected marginal distributions to generate another 10,000 observations from a Gaussian copula.

Figures 3.6a and 3.6b show the catastrophe performance ratios for these districts. These pictures are very much like Figures 3.5a and 3.5b. Once again, basis risk is much lower relative to a Gaussian copula. Further, basis risk falls with a larger deductible.

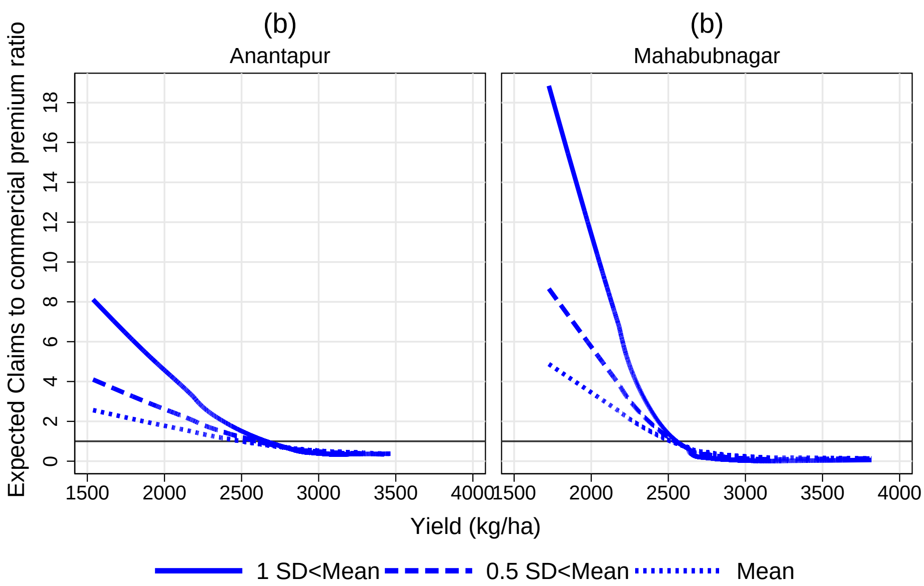
Next we move to an evaluation of equation (3.24). For a constant risk aversion utility function with parameter γ (3.24) becomes

$$\eta^{'}(\alpha) \mid_{\alpha=0} = Eq^{-\gamma}(E(I \mid q) - mP) \tag{3.28}$$

Based on the work of Cole et al. (2013), the risk aversion parameter is assumed to be 0.57. The above equation can be used to compute the mark-up over the actuarially fair premium for which insurance demand is positive. From the results displayed in Figure 3.7, it can be seen that the m that extinguishes insurance demand is higher for a tail-dependent copula as compared to a Gaussian copula. This is simply a reflection of the lower basis risk that comes with lower tail dependence. A second finding of Figure 3.7 is that the maximum mark-up for which insurance demand is positive is higher when the deductible is larger. This again is a reflection of the earlier figure 3.6b that showed the basis risk is lowest in contracts with the smallest rainfall threshold.



(a) Expected Claims to Premium Ratio with and without Tail Dependence



(b) Expected Claims to Premium Ratio with Different Trigger Thresholds

Figure 3.6: Expected Claims to Premium Ratio for Two Districts of Andhra Pradesh

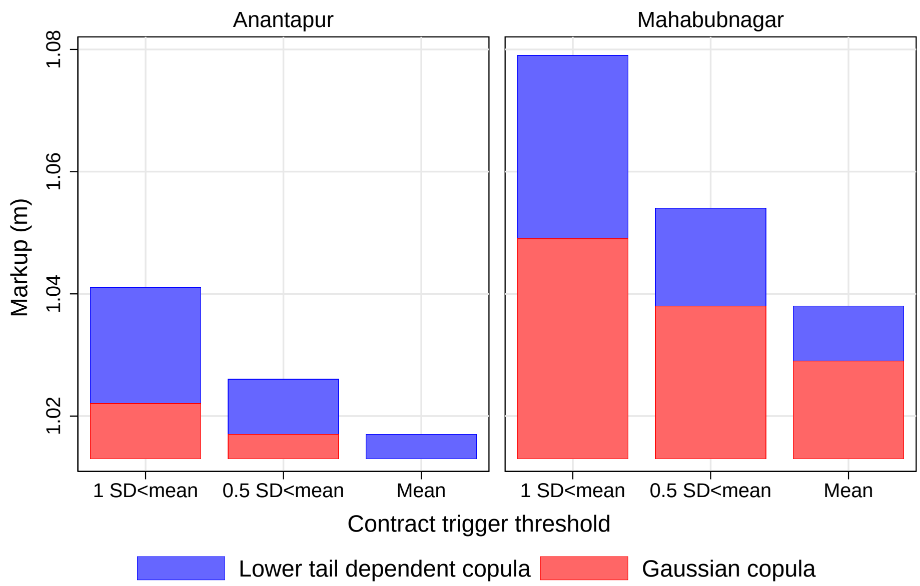


Figure 3.7: Markups at which Demand for Insurance Cover is Zero

For the constant relative risk aversion utility function, the optimal insurance units can be solved from

$$\eta'(\alpha) = E(q + \alpha(I - mP))^{-\gamma}(I - mP) = 0 \tag{3.29}$$

The payouts and the premium that were simulated to compute the catastrophe performance ratios can also be used to evaluate (3.29). We continue to use $\gamma = 0.57$. Optimal insurance cover is computed with and without tail dependent yield and rainfall distribution and for insurance contracts that vary according to the index threshold value that triggers payout. The results are displayed in Figure 3.8 where the computations assume $m = 1$. What is noteworthy about the results is that the optimal insurance cover is much larger with a tail dependent copula than with a Gaussian copula. This is consistent with the lower basis risk with a tail dependent copula.

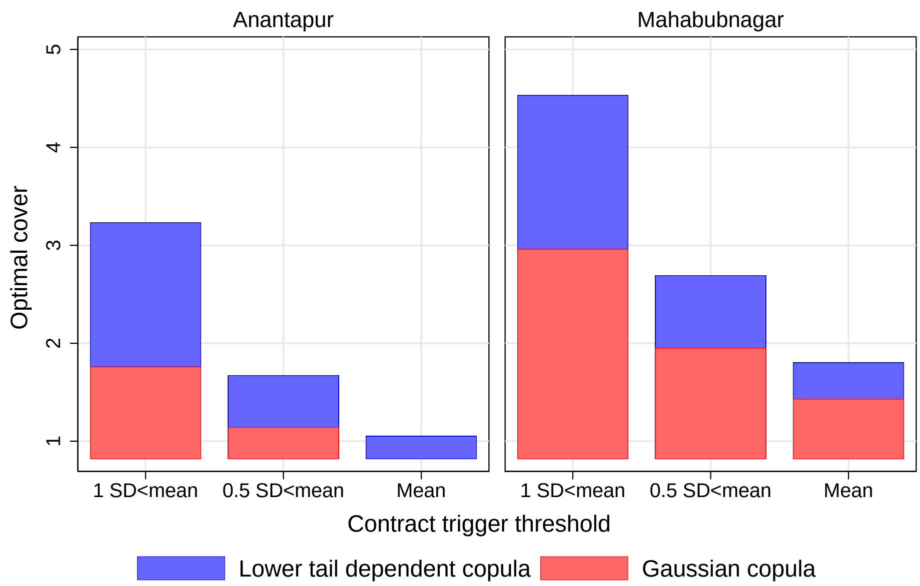


Figure 3.8: Optimal Cover for Actuarially Fair Contract under Different Thresholds

The fact that contracts with the lowest threshold (highest deductible) have the lowest basis risk and the greatest demand for insurance, does not, however, mean that farmers necessarily prefer these contracts to all others. Figure 3.9 evaluates the expected utility for the optimal levels of insurance for actuarially fair premiums. This shows that the optimal threshold is 0.5 standard deviation below the mean for Anantapur while it is the mean yield for Mahabubnagar. For the given risk aversion parameter, it is optimal to accept higher basis risk in exchange for a greater insurance protection. However, if insurance is actuarially unfair, then as Figure 3.8 showed, it is more likely that the contracts with the least basis risk are favored by farmers.

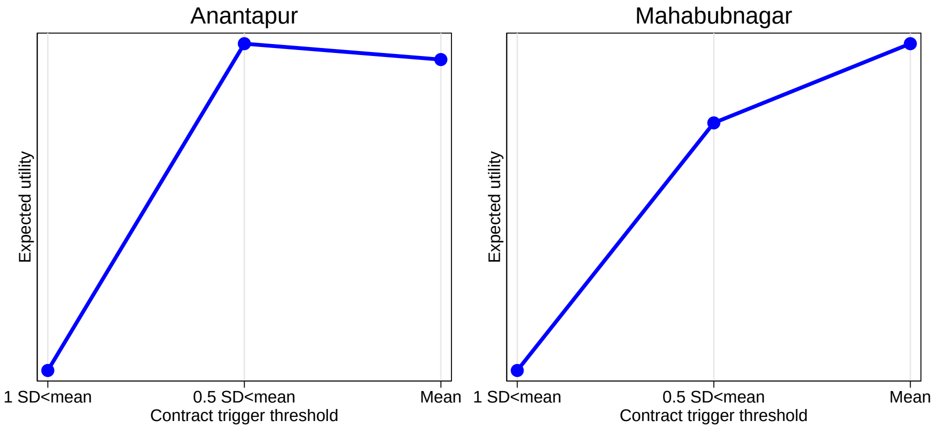


Figure 3.9: Willingness to Pay and Risk Aversion

3.6 Conclusions

Although cost effective and free from moral hazard and adverse selection, the index based crop insurance products have seen poor uptake because of imperfect association between index and crop loss that reduces the value of insurance and therefore its demand.

We find the association between crop yield and rainfall index characterized by the statistical property of 'tail dependence'. This implies that the associations between yield losses and index are stronger for large deviations than for small deviations. The most important implication of our findings is that for farmers the utility of index-based insurance relative to actuarial cost is more during extreme or catastrophic losses than for insurance against all losses. The opens up the issue of evaluating the cost effectiveness of an insurance product that limits itself to compensation against extreme events. Our findings also generates a need to systematically evaluate the basis risk and uptake for index insurance products that differ with respect to the contract threshold.

The idea behind heavily subsidizing insurance premium is that subsidies are essential for widespread uptake of insurance products. If so, the question is: What is the best way to provide subsidy? Our analysis shows that crop losses are widespread during extreme climatic events such as droughts. This implies that a considerable proportion of farmers would benefit from a program that covers their risks during an extreme weather event. In other words, any form of insurance that protects from extreme losses is likely to be favored by a majority of the farmers. The actuarial cost of such an insurance scheme will be lower compared to a normal insurance; hence less burden on government exchequer. Indeed, a policy that completely subsidizes extreme loss insurance could possibly be revenue neutral relative to an insurance program that covers crop losses based on rainfall-deficit.

Extreme loss insurance programs are likely to be more useful to local aggregators of risk such as banks, producer companies, cooperatives, agribusiness firms and local governments. There is a very established protocol for drought relief expenditures by the government. However, its timeliness is often questioned because of many layers of permissions required for such expenditures. On the other hand, an extreme loss insurance program offers the benefits of drought relief but in a timely manner.

We note that farmers may not purchase insurance for other reasons as well including poor understanding of the product, credit constraints, low trust of the insurance seller, and optimism about yields. If these are binding constraints, then again a reduction in basis risk may not impact the demand for insurance.

Finally, we wish to point out that tail dependence is unlikely to be India specific since it flows from the nature of spatial associations of weather.

Therefore, although our results are based on Indian data, the general lessons are available for other countries too.

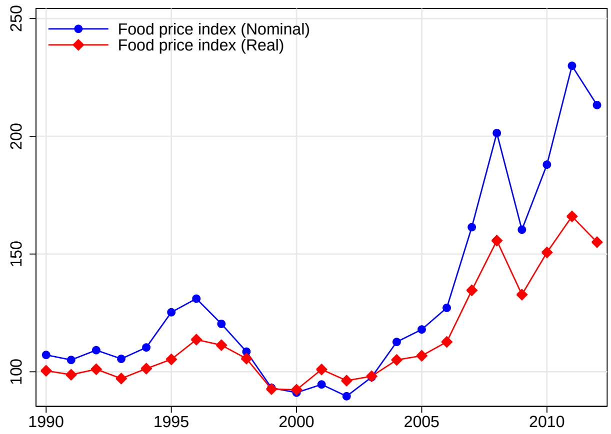
Chapter 4

The Welfare Impacts of High Food Prices: Resource Endowments and Spill-Over Effects

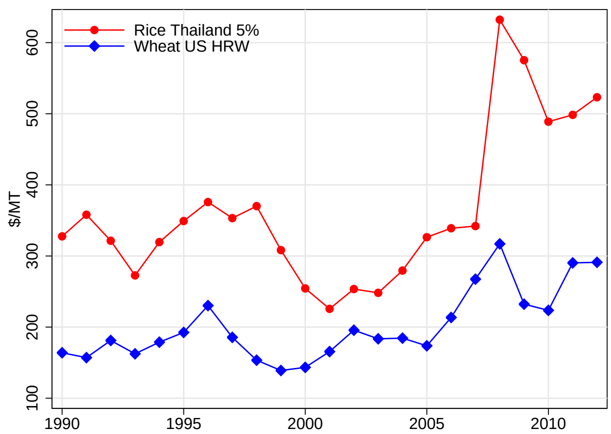
4.1 Introduction

Global food prices have risen dramatically in the recent past. As can be seen from 4.1a, the Food and Agriculture Organization's (FAO) global food price index first surged in June 2008 and then again in 2011, and has not reverted to its previous level. A majority of this surge was driven by equally dramatic increase in prices of staples i.e., rice and wheat in the international markets.

Figure 4.1b shows trends in real prices of rice and wheat for major exporters of the two staple food commodities. This increase in the prices of staples is unprecedented, as in the past, real prices of rice and wheat have either been declining or remained stable.



(a) FAO Global Food Price Index



(b) Rice and Wheat Prices in the International Markets

Figure 4.1: Trends in International Food Prices: 1990-2015

Notes: The food price index (2002-2004=100) is extracted from the Food and Agricultural Organization's database. The international rice and wheat prices at real 2010$ are from World Bank, Global Economic Monitor Commodities price database.

In general, the welfare effects of high food prices would be experienced universally as food is a necessity. The major cause of concern among the academics and policymakers is that, as the exposure to high food prices is proportional to its budget share in a households' consumption expenditure, the worst affected population groups would be the ones placed at the bottom of the income distribution. Therefore, rising food prices have become a matter of serious concern for developing countries, which are home to a majority of the world's poor.

Several studies analyzing the impact of high food prices on household welfare concluded that rising food prices would lead to worsening of poverty in the developing world (Ivanic and Martin, 2008; De Hoyos and Medvedev, 2011; Ivanic et al., 2012). These studies relied on variants of Deaton's (1989) net benefit approach to estimate the impact of food price changes on household welfare and poverty. In this approach, the welfare effect of food price changes is approximated as the net income change from a change in food expenditure and change in earnings from food production.

However, the prediction of rising food prices leading to an increase in global poverty have not fully realized. It is argued that estimates based on the net benefit approach provide good approximations of welfare losses when price changes are marginal, but this approach is not suitable to analyze the welfare effects of large and sustained price changes as witnessed during the global food price crisis (De Janvry and Sadoulet, 2009).

There has been a longstanding belief among scholars that the welfare loss from high food prices will not be uniform across all population groups. This belief stems from the understanding that in the long run high food prices can also stimulate demand for labor and increase wages in the agricultural sector (Gulati and Narayanan, 2003; Ravallion, 1990; Jacoby, 2016; Headey, 2018; Van Campenhout et al., 2018). Greater income in the hands of farmers might increase demand for non-traded goods and therefore increase the local employment and wages. Such effects are welfare enhancing but would be relevant only for those whose earnings are directly or indirectly related to activities in the agricultural sector.

The debate around the short- and long-run welfare impacts of high food prices has led to a few studies re-examining the link between food price changes and household welfare using reduced form empirical approaches. While Deaton's net benefit approach simulates the welfare losses, the reduced form regression of household welfare on food prices directly estimates it. The evidence based on reduced form econometric studies using cross-sectional household level data generally find higher food prices adversely affecting the household welfare (D'Souza and Jolliffe, 2012; D'souza and Jolliffe, 2013). On the contrary, Headey (2018) using country-level panel data finds that rising global food prices between 2005 and 2010 has led to a reduction in global poverty.

Such contradictory findings are probably a reflection of the fact that causal identification of the welfare effects of food price changes is challenging. And this is chiefly on two counts. First, the welfare impacts of food price changes are highly heterogeneous across population groups and it is difficult to capture this heterogeneity empirically as it depends on endogenous household characteristics like budget share of food, production structure and decision to participate in the labor market (Bellemare et al., 2013). Second, there is always the possibility of unobserved omitted variables leading to joint determination of both the price changes and the household welfare outcomes

(Bellemare, 2015; Bellemare et al., 2018).

Though there is an agreement that high food prices may benefit some population groups, empirical evidence is scarce. This study aims to bridge this gap by directly focusing attention on a particular population group which can gain from high food prices, i.e., the rural food producers. The measure of welfare we focus on is the dietary diversity defined as the proportion of calories obtained from starchy staples. As income increases the ratio of calories from staples decreases. Therefore, lower real incomes due to high food prices should be associated with higher proportion of calories from starchy staples. The first contribution of this work is to use a formal econometric identification strategy to test the commonly-held belief that net food producing households stand to gain from high food prices. Our second contribution is to identify labor market impacts of high food prices without relying on any theoretical formulation of agricultural households. And finally, to the best of our knowledge, this is the first study that identifies spill-over effects of price changes on local economy, and thereby gives a flavor of the general equilibrium effects of a rise in food prices.

Our setting is same as in Tandon (2015) who estimates the causal impact of rising staple food prices on nutritional intakes and dietary diversity of households in India. Tandon's identification strategy is based on a difference-in-difference approach that exploits the cross-sectional heterogeneity in budget shares of rice and wheat, two staple foods in India, and differential increase in rice and wheat prices to identify the causal impact of food price changes on welfare.[1] He finds households most exposed to higher food prices have significantly reduced dietary diversity, investment on labor saving productive

[1] Tandon's identification strategy is close to a shift-share design but he defines it as a difference-in-difference and I follow to his terminology while describing his contribution.

assets and schooling of children.

Although Tandon's analysis offers critical insights into the effects of higher prices on welfare outcomes, his identification strategy is designed to captures only the consumption effect of food price changes. But, the households' exposure to food price changes also depends on their production structure. Though an increase in price of staple foods will increase the monetary cost of consumption and consequently reduce welfare, but it would also lead to an increase in income for food-producing households. This possibility of welfare gains from high food prices is ignored by Tandon (2015). The objective of this chapter is therefore to devise an econometric strategy that can capture both the consumption and production effects of price changes.

The main contribution of this study is to design a formal identification strategy to disentangle the consumption and income effects of food price changes on household welfare. To do so, we construct a district-level panel of dietary diversity, defined as the share of calories from rice and wheat in the total calories, and staple food price index constructed as weighted average of state-specific rice and wheat retail prices. The panel structure of the data allows us to control for time invariant differences and aggregate time trends that may be correlated with food price changes and household welfare. Our identification strategy is similar in spirit to Edmonds and Pavcnik (2005) who estimate the impact of changes in rice price on child labor in Vietnam. Edmonds and Pavcnik (2005) capture the consumption and income effects of food price change by allowing the welfare effects of price changes to vary with households' rice production status at the baseline. We add a further innovation to this identification strategy by using spatial variation in natural suitability endowments to identify the food producing regions. We exploit the fact that natural geo-climatic endowments are a major determinant of the types of crops grown in a particular region, and are exogenous to a household's decision problem. This exogenous variation is available in the form of crop suitability indices from the Food and Agricultural Organization's (FAO) Global Agro Ecological Zones (GAEZ) database .

The identification strategy relies on the exogenous cross-sectional variation in the natural suitability for food cultivation to bifurcate rural households into net consumers and net producers of food; thus separating the total effect into consumption and income effect. This is econometrically implemented by interacting the staple food price index with the computed food suitability variable. The interaction allows the food price elasticity of welfare to vary with the natural suitability for food production; hence captures the heterogeneity attributable to income effect. In the final specification, we consider a triple interaction between food price index, food suitability and an indicator variable for rural areas. This strategy compares the difference in food price elasticity of dietary diversity between food and non-food producing districts across rural and urban locations. Finally, to identify how households engaged in different sectors of local economy within the food producing regions are affected by changes in food prices, the consumption and income effects are estimated for different household groups based on their primary occupation.

We find a robust negative consumption effect of high food prices on household welfare and dietary diversity. But this effect is found to be smaller for rural households in the districts suitable for food production. Therefore, the welfare effects of high food prices vary spatially with the natural suitability of food production; with regions highly suitable for food production experiencing lower welfare losses from high food prices. The welfare enhancing income effects are strong for the laborer and cultivator households and almost offset their negative consumption effects. Interestingly, the income effects of high food prices are also present for the households not directly engaged in cultivation and agricultural activities within the food suitable rural regions. This provides for a direct evidence of the spill-over effects and induced general equilibrium responses of high food prices on the local economy.

Rest of the chapter is organized as follows. Next section presents a review of literature studying the welfare impacts of recent food price shocks. Section 4.3 provides details about the data sources and construction of variables. Section 4.4 presents the empirical strategy. Section 4.5 presents the results and establishes their robustness to a variety of controls and different specifications. Conclusions are presented in the last section.

4.2 Literature

A modification of Deaton's (1989) net benefit approach to quantify the welfare impact of an increase in food prices is given by the following expression:

$$\Delta W_i \approx [(Q_i - C_i) + \eta L_i]\Delta p_F \tag{4.1}$$

where, ΔW_i is the welfare change as a proportion of total income for household i , C_i is the share of income spent on food, Q_i is the share of income from food production and sale, η is the wage food price elasticity, L_i is the share of household labor income in total income and Δp_F is the percentage change in food price. The basis for the argument that high food prices may actually benefit some population groups can be examined using equation 4.1. For a net food producer household, the first term in the above expression is positive, and hence it gains from an increase in food prices. A net food buyer household, on the other hand, would experience a welfare loss from such an increase. A higher share of labor income increases the food price elasticity of welfare but the degree of change depends on the wage food price elasticity. Note that, equation 4.1 gives the direct effect of price changes and hence approximates the change in welfare due to small price changes. The indirect or substitution effects of high food prices both in terms of consumption and production are ignored under the assumption that with small price changes these second order effects are infinitesimal.

Deaton (1989) while studying the impact of rice price changes on Thai households assumed the labor market responses of high food prices to be negligible. The induced wage response to high food prices may be marginal when price changes are small or persist for a short duration. Nevertheless, with the extent of food price increase witnessed during the recent global food price surge, the induced wage response may be significant enough to benefit the rural poor even if they are net food consumers (Gulati and Narayanan, 2003; Ravallion, 1990; Headey, 2018; Van Campenhout et al., 2018; Jacoby, 2016).

Studies looking at the immediate impact of 2007-08 food price crisis have primarily relied on Deaton's net benefit approach and have ignored the second order effects of price changes (see, Wodon and Zaman, 2010). For example, Ivanic and Martin (2008) use equation 4.1 to simulate the welfare impacts of 2005-2007 global food price increase for nine low income countries on the assumption of perfect transmission between global and local prices.

They find that high global food prices will in general increase poverty both in rural and urban areas, but the impact would be greater in urban areas. They also conclude that wage adjustment in unskilled labor markets partially offsets the welfare reducing effects of high food prices. Similar findings are also reported by De Hoyos and Medvedev (2011). Improving on their earlier work Ivanic et al. (2012) use data on country level local food price changes to estimate their impact on poverty. This modification builds on the criticism that pass-through rates between global and local prices may vary across countries because of the differences in domestic policies, market structure and transportation costs.

Another set of studies has focused on the long run impacts of high food prices by using the general form of equation 4.1 where both direct and indirect substitution effects are taken into account. Examples of such studies are Minot and Dewina (2013) and Robles et al. (2010) who provide long run estimates either by estimating the cross elasticities or relying on other studies to parametrize their simulations. Attanasio et al. (2013) estimate a Quadratic Almost Ideal Demand System (QAIDS) to account for the possible cross substitution across food commodities due to price increase. The demand system estimation approach is also adopted by Vu and Glewwe (2011) and Friedman and Levinsohn (2002) to estimate the welfare effects of high food prices. Vu and Glewwe (2011) go a step further and allow for differential rate of increase in consumer and producer prices. Ivanic and Martin (2014) add a further layer to the general version of the net benefit approach by accounting for the direct response of output to price changes and the indirect effect through induced change in wages, and the cross effects of price change on the amount of labor sold off farm.

Simulation studies based on Deaton's approach explicitly accommodate the different channels through which price changes influence household welfare. But they assume other variables like prices of other commodities and incomes to be constant that can simultaneously affect household welfare. Further, small errors in estimation of parameters and elasticities can lead to significant bias in the final estimates of household welfare. The true advantage of the simulation based approach lies in the ex-ante prediction of welfare impacts. One such example is the study by Friedman and Levinsohn (2002), which using cross-sectional household data at the baseline, demonstrates the utility of this method in predicting the welfare impacts of an increase in food prices on Indonesian households

An alternative approach is to use reduced form econometric estimation to study the welfare impacts of food price changes. This approach uses observational data to attribute a change in a welfare indicator to food price changes. While the simulation approach uses data to estimate few parameters (e.g., budget shares) necessary to predict the welfare outcome of a given change in food prices, econometric estimations allow the data to directly estimate the impact of such changes in food prices. This chapter is a contribution to the econometric evaluations of the welfare impact of food prices.

A simple reduced form specification to estimate the welfare impact of food price increase can be of the following form

$$W_{it} = \varphi p_{it} + X_{it}\beta + \alpha_i + \mu_t + v_{it} \tag{4.2}$$

where W is the welfare measure of interest which is regressed on food price p conditional on a set of controls in vector X, and individual (α_i) and time fixed effects (μ_t). Adequate controls are important as the dependent variable might be affected by a variety of shocks that are either common to all households or specific to an individual household.

The benchmark specification in 4.2 assumes a price effect that is uniform across all households. However, the objective of analysis is often to assess the impact of food prices on different population groups. Indeed, the simulation analysis points to the fact that impacts may be different across consumers, producers and workers. To allow for such a differential impact, either equation 4.2 must be estimated separately for different population groups or just the price effect should be allowed to differ across population groups.

D'Souza and Jolliffe (2012); D'souza and Jolliffe (2013) estimate a cross-sectional counterpart of equation 4.2 using nationally representative household surveys from Afghanistan and find a large decline in real monthly per capita food consumption and reduction in dietary diversity due to the increase in prices of staple foods. They find welfare loss to be stronger for urban households and for households with no access to agricultural land. Headey (2018), on the other hand, estimates equation 4.2 using country level panel of poverty rates and finds an inverse relationship between food prices and poverty. He argues that, as long as agricultural wages in developing countries are indexed to food prices, rural populations in these countries would be beneficiaries of higher food prices.

A more refined empirical approach can be to focus on just one dimension of heterogeneity in equation 4.1. Tandon (2015) designs his identification strategy such that it focuses on the welfare loss due to the consumption aspect of food price changes. He exploits the differential increase in rice and wheat prices in a difference-in-difference strategy to compare welfare losses of rice vs. wheat consuming regions in India. His identification strategy is based on one of the main insights from the net benefit approach that welfare impact of price change of a particular commodity will be proportional to its share in household consumption. We draw parallel between this identification strategy and equation 4.1.

$$\begin{aligned}\Delta W_R - \Delta W_W = {} & [(Q_R - C_R) + \eta L_R]\Delta p_R \\ & - [(Q_W - C_W) + \eta L_W]\Delta p_W\end{aligned} \tag{4.3}$$

where subscript R and W denote the welfare change for rice and wheat consuming regions. Tandon's simplification is:

$$\Delta W_R - \Delta W_W = C_R \Delta p_R - C_W \Delta p_W \tag{4.4}$$

If, $\Delta p_R > \Delta p_W$, then rice consuming regions would experience greater welfare loss than wheat consuming regions. The assumption required for this simplification is that terms involving food production and labor income shares are either canceled out with the differencing strategy or accounted for using control variables. This seems more convincing for urban areas that are primarily food consumers and hence also independent of the induced labor market response to high food prices but perhaps an oversimplification in case of rural areas. Note that a sound difference-in-difference strategy would also control for other macroeconomic shocks, changing incomes and other commodity prices, which are held constant in Deaton's approach.

This chapter builds on Tandon's analysis by empirically modeling household's exposure to high food prices on consumption and production sides and considers the welfare impacts of this exposure on producers and agricultural workers separately.

4.3 Data

4.3.1 Dietary Diversity as an Indicator of Household Welfare

The study uses dietary diversity as the main measure of household welfare as unlike monetary indicators it captures the food and nutrition security of households (Lele et al., 2016). The dietary diversity is defined as the ratio of calories from rice and wheat in total calories from all food sources. Starchy staples such as rice and wheat are the primary source of dietary energy in India. The rational of using dietary diversity as an indicator of welfare is that with a reduction in real incomes from higher food prices, households' would reduce calories from more nutritious sources to protect their consumption of primary starchy staple foods. This closely correlates with Bennett's Law which states that as real income increases, the proportion of energy from starchy staples decreases (Bennett, 1941). [2] Also, since the poorest households devote highest share of their income on staple foods, their food security and welfare are more sensitive to this measure (Lele et al., 2016). Using nutritional intakes and dietary diversity as indicators of household welfare has an additional advantage that it, unlike income or consumption expenditure, does not require information on price deflators.

[2]This is more an evidence of Bennett's law than Engel's law as Engel's law talks about the relationship between share of food expenditure and incomes whereas Bennett's law is concerned with the share of staples in total food consumption.

To construct the outcome variables we use data from four thick rounds of large scale consumption and expenditure sample surveys of Indian households conducted in years 1999-2000, 2004-2005, 2009-2010 and 2011-2012 (55th, 61st, 66th and 68th rounds).[3] These surveys, conducted by the Government of India's National Sample Survey Organization (NSSO), record in detail a household's consumption in quantity and value for a variety of food and non food items. We use item wise food consumption to convert it into calorie equivalent, and then calculate the per capita per day calorie intake from different food groups for each household. The population multipliers provided by the NSSO are then used as weights to estimate the district level rural and urban average calorie intake from different food groups.

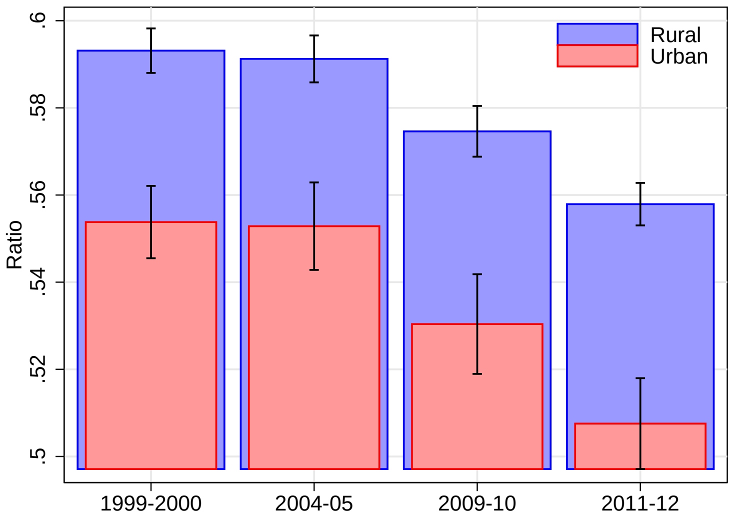


Figure 4.2: Trends in Ratio of Calories from Rice and Wheat in Total Calories

Notes: Authors' estimates based on National Sample Survey Organizations (NSSO) 55th, 61st, 66th and 68th rounds of consumption and expenditure surveys.

Figure 4.2 shows the trends in ratio of calories from rice and wheat

[3] A 'thick' round of the consumption survey is conducted every five years and is called so because of the larger sample size in comparison to the consumption surveys conducted annually.

in total calories for rural and urban households. Rice and wheat provide more that half of the dietary energy for households in our sample. The figure also shows that this measure of welfare is responsive to real income changes. The rural population consumes more calories from rice and wheat i.e. rural diets are less diversified possibly because rural households have lower real incomes than urban. Also dietary diversity shows a declining trend which again can be attributed to the increase in real incomes.

4.3.2 The Natural Suitability for Food Cultivation

The geo climatic conditions of a region are major determinant of the type of crops cultivated in that region. Therefore, this chapter relies on the indicators of natural suitability of a region for rice and wheat cultivation to identify food producing and supplying regions.

Data on indicators of a particular crop's suitability based on the geo climatic conditions are available from the Food and Agriculture Organization (FAO)'s Global Agro-Ecological Zones (GAEZ) 2002 database. The GAEZ dataset was designed to assist governments in crop planning based on agronomic models of crops. The GAEZ dataset provides simulated potential yields and crop suitability indices for a number of crops as grids at a very high spatial resolution. Since the suitability of a crop is simulated from agronomic models where the only inputs are average climatic factors and edaphic conditions, these indices are entirely exogenous and uninfluenced by economic processes. The GAEZ dataset simulates crop suitability for each grid with different scenarios of irrigation and intensity of input use. For this study we use crop suitability based on rainfed conditions and low input use and traditional management practices. More details about the GAEZ dataset can be found in Nunn and Qian (2011).

Several studies utilize the exogenous variation in GAEZ simulated potential yields and suitability indices to devise compelling identification strategies. For example, Nunn and Qian (2011) use the regional variation in suitability of potato cultivation and time variation from introduction of potato to the Old World, to estimate the impact of potatoes on historical world population and urbanization. Similarly, Bustos et al. (2016) use the simulated yields from the GAEZ database as instruments to study the effects of the adoption of new agricultural technologies on structural transformation. Galor and Özak (2015) use simulated potential yields from GAEZ database to construct a Caloric Suitability Index and use it to examine the effect of land productivity on comparative economic development.

The GAEZ dataset provides crop suitability indices in latitude and longitude grids with cells of approximately 100 square kilometers (see, IIASA, 2012). The index varies from zero to 100 where higher number means better suitability or vice versa. The gridded food suitability index is generated as a simple average of suitability index for rice and wheat.

The food suitability grid for India is presented in Figure 4.3. The food suitability grid and geographical district boundaries are used to estimate the proportion of area in a district where the suitability index is higher than the national average. The district level proportion of area suitable for food cultivation is used in the empirical analysis.

Figure 4.4 shows, the actual area under cultivation and the area which is naturally suitable for food crops in India. Areas with higher color intensity correspond to the areas more suitable for and cultivated with rice

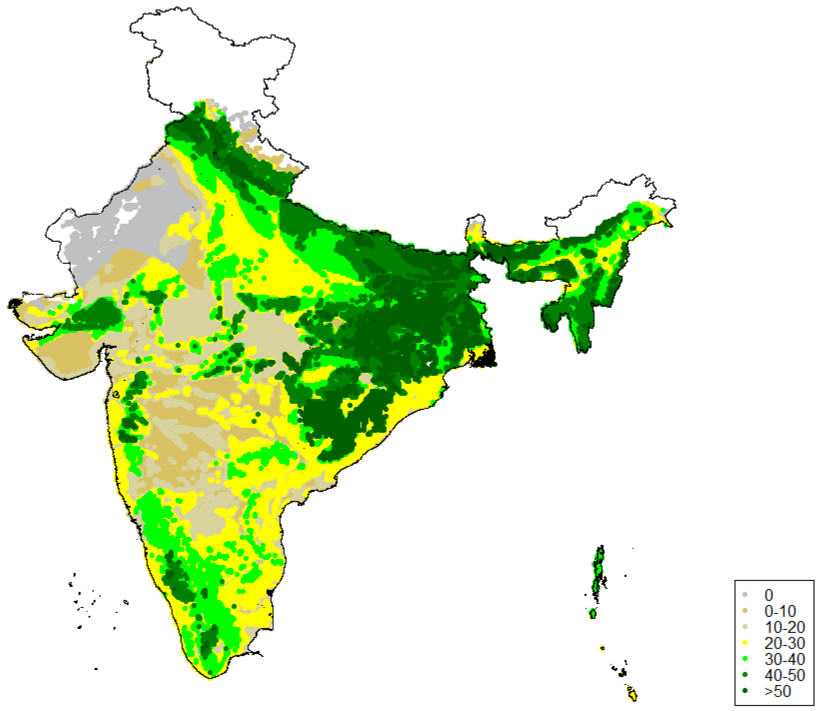


Figure 4.3: Gridded FAO-GAEZ Food Suitability Index

Notes: The food suitability for each grid point is constructed as the simple average of suitability index for rice and wheat. The gridded crop suitability indices are available from FAO GAEZ database.

and wheat. Figure 4.4 shows that natural suitability is a major determinant of a district's area under food cultivation as there is significant overlap in the regions which are naturally suitable and actually cultivate food. For example, the Indo Gangetic plains are highly suitable for food cultivation and also specialize in its production.

Figure 4.5 shows scatter plot of area under food cultivation in 1999-2000 and area suitable for food cultivation. There is a strong positive association between share of land suitable for food cultivation and actual area under cultivation. The correlation coefficient between actual and suitable area is 0.70 and is statistically significant at 1% level.

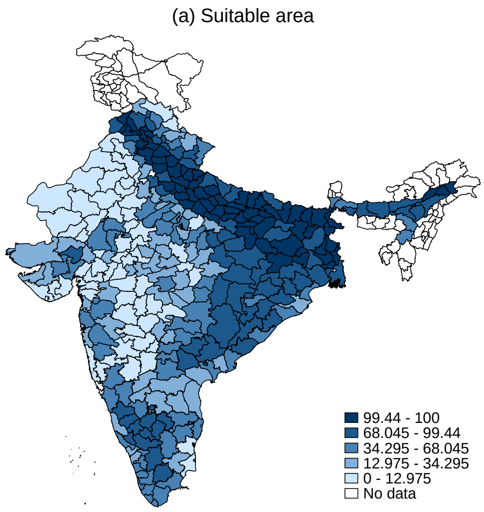


Figure 4.4: Area Cultivated in 1999-2000 and Area Naturally Suitable for Cultivation of Food Crops

4.3.3 Food Prices

Data on government administered producer prices and state wise retail prices of rice and wheat are extracted from the publications of Ministry of Agriculture and Farmers' Welfare, Government of India.

Figure 4.6 shows the trends in consumer prices for rice and wheat and the government administered Minimum Support Prices (MSP). The MSP are price floors maintained by the Government of India in the domestic markets primarily for rice and wheat in order to protect domestic producers from price slumps. With international prices increasing dramatically around 2007 the Indian government was unable to maintain stable price levels with the result that both the administered producer prices and the consumer prices of rice and wheat shot upwards in the domestic market as well.

The food price variable is constructed as a weighted average of state specific average retail prices of rice and wheat where the weights are

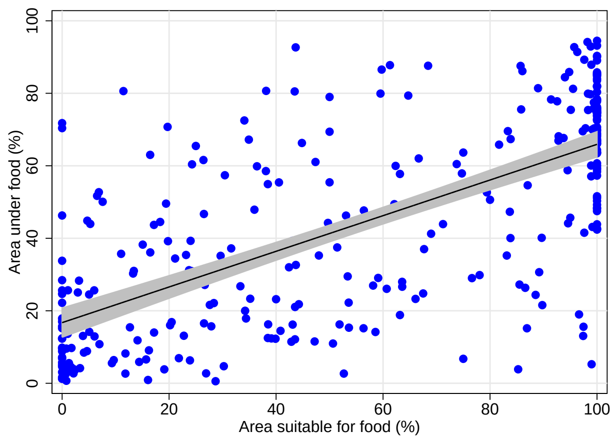


Figure 4.5: Association between Food Suitability and Food Cultivation in 1999-2000

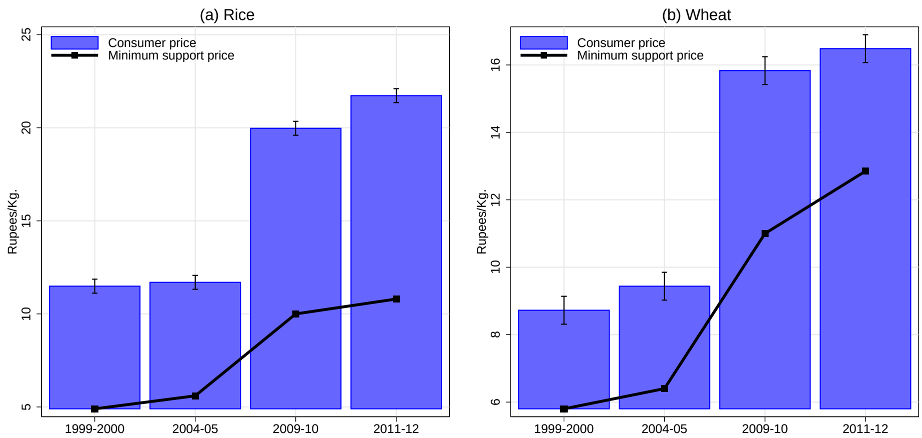


Figure 4.6: Trends in Rice and Wheat Prices

district averages of households' expenditure share of rice and wheat in the total spent on both. These shares are estimated from 1999-2000 consumption expenditure survey and are same for all rounds. There is evidence that increase in rice prices was higher in comparison to wheat in India and therefore rice consuming households lost more compared to wheat consuming households (Tandon, 2015). The weighted food price variable captures a district's exposure to increasing food price based on the preference for a particular staple. The exposure is higher for a household residing in a district having stronger preference for a staple whose relative price increase is higher. Figure 4.7 plots

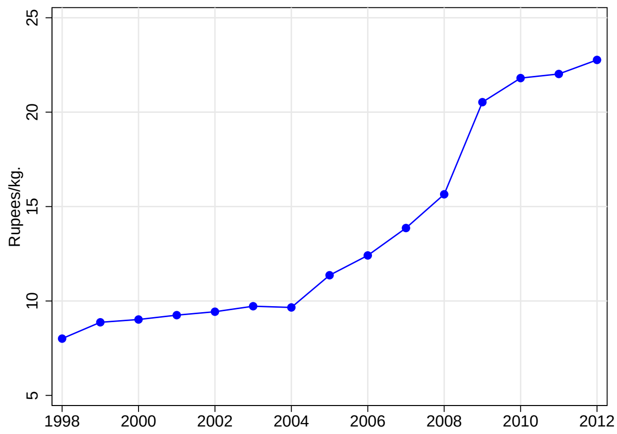


Figure 4.7: Weighted Food Price

the average of food price index for different years. It shows that constructed food price index is capable of capturing the dramatic increase in food prices between 2004 and 2010.

4.3.4 Summary Statistics

Table 4.1 presents the source and summary statistics for the control variables used in this analysis. The variables are divided into two groups, (1) variables for which the information is available for all time periods are the panel variables, and (2) variables for which the information is available for only the initial period are the initial conditions. To maintain consistency and comparability across NSSO survey rounds and other databases we maintain the district boundaries considered in the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)'s Village Dynamics in South Asia (VDSA) meso-level database (see, ICRISAT, 2015).

Table 4.1: Summary Statistics

Control variables	Source	1999-2000	2004-2005	2009-2010	2011-2012
(a) *Panel controls*					
Standardized total rainfall	Indian meteorological department gridded rainfall data	0.16	-0.24	-0.42	0.26
		(0.94)	(0.74)	(0.85)	(1.04)
Proportion of population in rural areas	ICRISAT VDSA database	0.37	0.37	0.36	0.36
		(0.07)	(0.07)	(0.08)	(0.08)
Proportion of literate in total population	ICRISAT VDSA database	0.51	0.56	0.61	0.63
		(0.13)	(0.12)	(0.10)	(0.09)
Proportion of agricultural laborers in total workers	ICRISAT VDSA database	0.27	0.30	0.33	0.34
		(0.15)	(0.16)	(0.17)	(0.17)
Proportion of area irrigated of total cropped	ICRISAT VDSA database	0.42	0.43	0.46	0.49
		(0.28)	(0.29)	(0.30)	(0.31)
Fertilizer use per hectare (kg/ha)	ICRISAT VDSA database	94.51	97.35	136.54	138.18
		(64.00)	(67.66)	(89.01)	(85.41)
Road density (km/1000 persons)	ICRISAT VDSA database	1.97	1.84	2.17	2.24
		(1.63)	(2.41)	(3.10)	(3.38)
Proportion of PDS rice and wheat in total consumed	NSS consumption and expenditure surveys	0.27	0.35	0.38	0.39
		(0.14)	(0.14)	(0.08)	(0.08)
State wise consumer price index	Ministry of Labor and Employment	714.75	824.80	1232.76	1479.22
		(92.8)	(132.26)	(173.94)	(238.96)
Proportion of households with NREGA job card	NSS unemployment and employment surveys	0.00	0.00	0.37	0.39
(b) *Initial conditions*				(0.27)	(0.24)
Percent villages with communication facilities	Census of India, 2001	0.59			
		(0.3)			
Percent villages with banking facilities	Census of India, 2001	0.22			
		(0.17)			
Percent villages with electricity	Census of India, 2001	0.90			
		(0.16)			

Note: Figures in parenthesis are standard errors.

4.4 Empirical Strategy

The benchmark specification is the following

$$Y_{dt} = \varphi Ln(PRICE)_{dt} + X_{dt}\beta + \alpha_d + \mu_t + \varepsilon_{dt} \tag{4.5}$$

where Y_{it} is the share of calories form rice and wheat in total calories consumed in district d at time t and $Ln(PRICE)_{dt}$ is the food price index. Vector X contains control variables described in table 4.1. District fixed effects and time dummies are included to control for district specific time invariant un-observables and aggregate time trends.

Equation 4.5 ignores the heterogeneity based on consumers and producers of food. One classification of consumer and producers of food can be based on rural and urban areas, as most of the agricultural activities are carried out by the rural population and urban households are primarily food consumers. Therefore, we estimate equation 4.5 for subsamples of rural and urban households.

Even within rural regions one would expect the exposure of high food prices to vary across households based on whether they are net food producers or consumers. The main identification strategy of this chapter is designed to incorporate this heterogeneity. In order to identify the net income effect of food price changes on household welfare, we allow coefficient φ in equation 4.5 to vary across districts with the spatial variation in natural suitability of food cultivation. We estimate the following equation

$$
\begin{aligned}
Y_{dt} = {} & \delta Ln(PRICE)_{dt} \times FOOD_d + \eta Ln(PRICE)_{dt} \\
& + X_{dt}\gamma + \alpha_d + \mu_t + \epsilon_{dt}
\end{aligned} \tag{4.6}
$$

where $FOOD_d$ is the proportion of area in a district suitable for food (rice and wheat) cultivation, $Ln(PRICE)_{dt} \times FOOD_d$ is the interaction of food price index with area suitable for food cultivation and other variables are same as equation 4.5. The interaction term allows the food price elasticity of dietary diversity to vary across districts based on their natural suitability for food cultivation. The identification strategy relies on geo climatic endowments to identify districts as net food producing. Conditional on control variables in vector X, the natural suitability for food cultivation is exogenous to the factors associated with changes in dietary diversity between 1999-2012.

The food suitability endowments exogenously separates districts into net food consumers and producers, or separates the total effect into consumption and income effects. Therefore, η captures the consumption effect and δ captures the income effect.

Urban households will experience pure consumption effect, therefore our hypothesis is that $\eta_{URBAN} > 0$ and $\delta_{URBAN} = 0$ or higher food price will unambiguously reduce dietary diversity in urban areas irrespective of suitability endowments of the districts. On the other hand, for rural households there will be an additional income effect based on their food suitability endowments. Hence, for rural regions our hypothesis is that $\eta_{RURAL} > 0$ but $\delta_{RURAL} < 0$.

The third specification combines the distinction between rural and urban regions and food suitability variable in the following manner.

$$
\begin{aligned}
Y_{sdt} = & \theta^1 Ln(PRICE)_{dt} \times RURAL_{sdt} \times FOOD_d \\
& + \theta^2 Ln(PRICE)_{dt} \times RURAL_{sd} \\
& + \theta^3 Ln(PRICE)_{dt} \times FOOD_d \\
& + \theta^4 Ln(PRICE)_{dt} \\
& + \theta^5 RURAL_{sd} \times FOOD_d \\
& + \theta^6 RURAL_{sd} \\
& + X_{sdt}\eta + \alpha_d + \mu_t + v_{sdt}
\end{aligned} \tag{4.7}
$$

where the dependent variable is rural-urban sector specific dietary diversity. This specification expresses the heterogeneity of price effects between rural-urban households and food suitable regions as a triple interaction between food price index, an indicator variable for rural households $(RURAL)$ and the share of area suitable for food cultivation. The coefficient of interest in this equation is θ^1 which is equivalent to $(\delta_{RURAL} - \delta_{URBAN})$ where δ is the coefficient on the interaction term in equation 4.6. Therefore, θ^1 gives the differential impact of food price changes for rural households residing in food suitable districts. Note that if our hypothesis $\delta_{URBAN} = 0$ is true then $\theta^1 = \delta_{RURAL}$.

To assess the labor market effects of food price changes, the analysis is limited to rural areas. Equation 4.6 is re-specified at the individual household level as

$$Y_{idt} = \delta Ln(PRICE)_{dt} \times FOOD_d + \eta Ln(PRICE)_{dt} + Z_{idt}\rho + X_{dt}\gamma + \alpha_d + \mu_t + \epsilon_{idt} \tag{4.8}$$

where the dependent variable is the dietary diversity for an individual household i, residing in rural region of a district d at time t. Use of household level data has the advantage that we can now control for household specific control variables. Vector Z has controls for household characteristics along with district level controls in vector X. To capture the heterogeneity of effects across laborer households, cultivator households and other household, equation 4.8 is estimated for subsamples of rural households based on their primary occupation types.

4.5 Results

4.5.1 Benchmark Specification

Table 4.2 presents the estimated coefficients from equation 4.5. In panel A, where we consider log calories from staple foods as the dependent variable, the coefficient on log food price is statistically insignificant. This suggests that Indian households' demand for calories from staple foods is price insensitive. In comparison, the staple food price elasticity of demand for calories from foods other than staples is negative and statistically significant (table 4.2 panel B). Negative and statistically significant food price elasticity is also found for calories form more nutritious sources like pulses, milk, meat, eggs fruits and vegetables (panel C). This suggest that Indian households cope with high food prices by reducing their consumption of calories from more nutritious sources in order to maintain their consumption of staple foods such as rice and wheat. Therefore, food prices would be positively correlated with the share of calories from staples in total calories. This is indeed the case in panel D where the dependent variable is the share of calories from staples in total calories and the coefficient on food price is positive and statistically significant. These results are robust to addition of controls listed in table 4.2.

Table 4.2: Estimates from Benchmark Specification

A. Log of per capita per day calories from rice and wheat			
$Ln(PRICE)$	0.023	0.021	0.014
	(0.029)	(0.031)	(0.033)
R^2	0.731	0.738	0.739
F	207.666	77.607	57.468
B. Log of per capita per day calories from items other than rice and wheat			
$Ln(PRICE)$	-0.144***	-0.145***	-0.151***
	(0.051)	(0.051)	(0.055)
R^2	0.679	0.683	0.691
F	122.291	46.887	32.907
C. Log of per capita per day calories from pulses, fruits, vegetables and animal sources			
$Ln(PRICE)$	-0.168***	-0.150***	-0.159***
	(0.056)	(0.055)	(0.058)
R^2	0.698	0.706	0.711
F	78.631	30.222	20.928
D. Ratio of calories from rice and wheat in total calories			
$Ln(PRICE)$	0.038***	0.036***	0.038***
	(0.013)	(0.013)	(0.014)
R^2	0.811	0.820	0.822
F	14.303	18.344	13.618
Panel controls	No	Yes	Yes
Initial conditions*Time	No	No	Yes
Observations	2456	2452	2452

Notes: All specifications include district fixed effects, time dummies and rural region dummy. Panel and initial conditions are listed in table 4.1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In terms of magnitude, a one per cent increase in the food price is associated with a 4 percentage point increase in the ratio of calories from staple cereals to total calories. These findings are similar to D'Souza and Jolliffe

(2012) who find that rising food prices in Afghanistan led to households shifting from animal based calorie sources and vegetables toward staple foods. Tandon (2015) also finds similar results for India.

4.5.2 Rural Urban Heterogeneity in Price Effects

The results presented in the previous section are based on pooled sample of rural and urban households. In this section we present the estimates of equation 4.5 for the subsamples of rural and urban households.

Table 4.3: Rural Urban Heterogeneity in Price Effects

	(1)	(2)	(3)	(4)	(5)	(6)
		Rural			Urban	
Dependent variable: ratio of calories from rice and wheat in total calories						
$Ln(PRICE)$	0.034*	0.038**	0.036*	0.043**	0.037**	0.038*
	(0.019)	(0.017)	(0.019)	(0.018)	(0.018)	(0.020)
N	1232	1232	1232	1224	1220	1220
R^2	0.914	0.926	0.927	0.842	0.847	0.849
F	7.165	20.141	13.283	18.326	10.554	7.510
Panel controls	No	Yes	Yes	No	Yes	Yes
Initial conditions*Time	No	No	Yes	No	No	Yes

Notes: Specification 1 to 3 are for rural households and specifications 4 to 5 are for urban households. All specifications include district fixed effects, time dummies and rural region dummy. Panel controls and initial conditions are listed in table 4.1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4.3 presents the results from a regression of share of calories from staples in total calories on log of staple food price index. For both rural and urban households, the coefficient on food price index is positive and statistically significant. Hence higher food prices reduce dietary diversity for both rural and urban households. The comparable price elasticity estimates across rural and urban households points to the fact that this specification is unable to identify the income and consumption effects.

4.5.3 Effects by Food Suitability Endowments

Table 4.4: Heterogeneity of Effects for Rural and Urban Households by Food Suitability Endowments

	(1)	(2)	(3)	(4)	(5)	(6)
		Rural			Urban	
Dependent variable: ratio of calories from rice and wheat in total calories						
$Ln(PRICE)$	0.067***	0.059***	0.058***	0.041**	0.038*	0.039*
	(0.021)	(0.019)	(0.020)	(0.019)	(0.020)	(0.022)
$Ln(PRICE) \times FOOD$	-0.056***	-0.034***	-0.035**	0.004	-0.002	-0.002
	(0.012)	(0.012)	(0.014)	(0.010)	(0.012)	(0.015)
Panel controls	No	Yes	Yes	No	Yes	Yes
Initial conditions*Time	No	No	Yes	No	No	Yes
N	1232	1232	1232	1224	1220	1220
R^2	0.918	0.927	0.928	0.843	0.847	0.849
F	18.813	19.145	13.417	14.589	9.907	7.225

Notes: Specification 1 to 3 are for rural households and specifications 4 to 5 are for urban households. All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 4.1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4.4 presents the estimates of equation 4.6 for rural and urban subsamples. As hypothesized the estimated coefficient η which captures the consumption effect of change in food price is positive and statistically significant for both rural and urban households. The coefficient δ on interaction term ($Ln(PRICE) \times FOOD$) is negative and statistically significant for rural households but is close to zero and statistically insignificant for urban households. This implies that both rural and urban households experience a reduction in dietary diversity as food price increase. But the income effect of high food prices, visible in the negative and statistically significant coefficient on the interaction term for rural regions, mitigates the welfare reducing consumption effect. The absence of income effects for urban subsample is proof that this empirical strategy is capable of identifying the income effect of price changes.

Table 4.5 presents the results from triple interaction specification. Conceptually, the coefficient on triple interaction is just the difference between the interaction coefficients for rural and urban subsamples in table 4.4. Con-

Table 4.5: Triple Interaction Specification

	(1)	(2)	(3)
Dependent variable: ratio of calories from rice and wheat in total calories			
RURAL	-0.130***	-0.124***	-0.124***
	(0.029)	(0.028)	(0.028)
$RURAL \times FOOD$	0.213***	0.200***	0.199***
	(0.037)	(0.037)	(0.037)
$Ln(PRICE)$	0.036**	0.041***	0.039**
	(0.015)	(0.015)	(0.016)
$RURAL \times Ln(PRICE)$	0.036***	0.033***	0.032***
	(0.009)	(0.009)	(0.009)
$FOOD \times Ln(PRICE)$	-0.004	-0.014	-0.007
	(0.010)	(0.010)	(0.011)
$RURAL \times FOOD \times Ln(PRICE)$	-0.045***	-0.041***	-0.041***
	(0.012)	(0.012)	(0.012)
Panel controls	No	Yes	Yes
Initial conditions*Time	No	No	Yes
N	2456	2452	2452
R^2	0.835	0.843	0.844

Notes: All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 4.1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

sidering specification (3) in table 4.5 as the main specification the estimated coefficient on the triple interaction term is -0.04. This estimate is equal to the interaction coefficient from comparable specification (3) in table 4.4. [4] This is so because the income effect in urban areas in negligible hence the coefficient on the triple interaction term in table 4.5 is equal to income effects estimated for rural areas.

4.5.4 Labor Market and Spill-Over Effects

Table 4.6 presents the estimates of equation 4.8 by household types based on main occupation and income source.

The surprising finding from table 4.6 is that the coefficient on the interaction term is negative and statistically significant for all household types.

[4] Increase in consumption of food items sourced from the public distribution system, differential rise in prices of other commodities, procurement of food grains and households substitution to cheap source of calories are some variables which might influence the results. The results have to be interpreted accordingly.

Table 4.6: Labor Market and Spill-Over Effects

	(1)	(2)	(3)	(4)	(5)
	Non agricultural households	Agricultural laborer households	Other laborer households	Cultivator Households	Other households
Dependent variable: ratio of calories from rice and wheat in total calories					
$Ln(PRICE)$	0.043***	0.083***	0.074***	0.046***	0.039**
	(0.014)	(0.020)	(0.023)	(0.016)	(0.016)
$Ln(PRICE) \times FOOD$	-0.030***	-0.073***	-0.067***	-0.038***	-0.019*
	(0.011)	(0.018)	(0.017)	(0.011)	(0.010)
N	50242	39590	28948	73701	36646
R^2	0.583	0.639	0.518	0.596	0.449

Notes: The household types are based on the major source of the household's income during the year preceding the survey. Households under others include regular salaried earners. All specifications include district fixed effects and time dummies. Household controls include land class dummies based on operated area (marginal if operated area in less than 0.01 hectare, small if it is between 0.01 to 1 hectare, medium if it's between 1 to 3 hectare, and large if it is greater than 3 hectare). Asset count of durables (radio, TV, bicycles, electric fan, fridge, air conditioner, cooler, motor cycle, or car). Age of the household head in years. A dummy for sex of the household head. Dummies for religion of the households (Hinduism, Islam, Christianity, Sikhism, Jainism, Buddhism, Zoroastrianism, and other religions). Household size. Household caste dummies for scheduled caste, scheduled tribe, and other castes. Dummies for education of household head (literate with less than primary education; primary education; more than primary but less than secondary; and secondary or higher education). Proportion of household members below 15 years of age. Proportion of subsidized grains (rice and wheat form the Public Distribution System) consumed in total. District level panel controls are rainfall deviations, road density, state specific consumer price indices, and proportion of households with National Rural Employment Guarantee Act (NREGA) job card. Initial conditions are listed in table 4.1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

This we take as an indication of the spill-over effects, as in the absence of spill-overs, the income effect of food price changes should have been limited to cultivator households. For laborer households the income effect can be attributed to the induced wage responses of food price changes. But the presence of statistically significant and negative coefficients on the interaction term for non agricultural and other households is evidence of spill-overs effects of high food prices on other sectors of the local economy.

4.5.5 Robustness Checks

The main identification strategy in this chapter relies on the use of natural suitability endowments as exogenous variation. As shown before natural suitability for food cultivation is highly correlated with actual food production. Our first concern is that the coefficient δ in equation 4.6 may be capturing the fact that districts with higher food suitability experience lower price increases than districts with lower food suitability. We test this empirically by running a regression of the following form

$$Ln(PRICE)_{dt} = \rho FOOD_d \times \mu_t + \mu_t + X_{dt}\pi + \sigma_d + \epsilon_{dt} \tag{4.9}$$

where we interact the proportion of area suitable for food cultivation with time dummies. We want to test the hypothesis that $\rho = 0$. This is to rule out systematic variation between change in food prices and the crop suitability variable $FOOD_d$. Note that this is similar to a parallel trends check that the data has to satisfy for a difference-in-difference identification strategy to work.

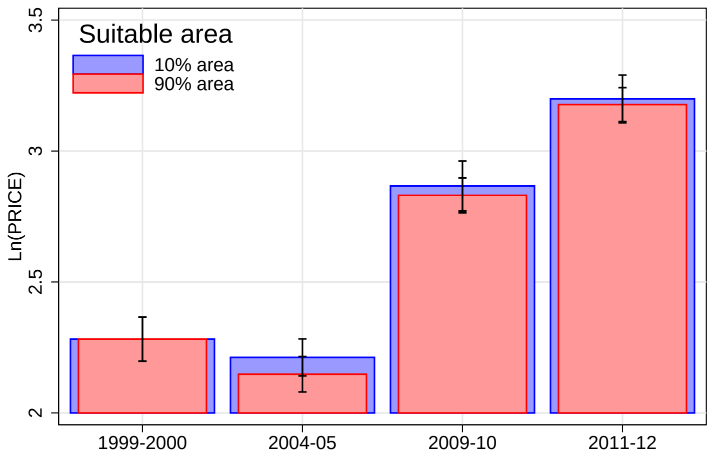


Figure 4.8: Parallel Trends in Food Prices

Figure 4.8 presents the simulated price trends from equation based on 10% area suitable for food cultivation (unsuitable for food cultivation) and 90% area suitable for food cultivation (suitable for food cultivation). Figure 4.8 shows that food prices follow common trends and do not vary systematically with food suitability status.

The second concern relates to the way in which the dietary diversity variable is defined. It is constructed as the ratio of calories from rice and wheat in total calories. As food becomes expensive, households can substitute rice and wheat with cheaper coarse cereals [5]. Although the substitution effect will depend on how strongly households prefer rice and wheat in relation to coarse cereals, it still has the potential to introduce bias in our results. The bias can be introduced in the following sense; since calories from coarse cereals is part of the denominator it is possible that we are capturing households substitution to cheaper cereals rather than diversification of diets. To check the robustness of the results against this bias we reconstruct the dependent variable as ratio of calories from rice and wheat in total calories excluding calories from coarse cereals.

The third exercise is conducted is to check the sensitivity of the results to the construction procedure of the food suitability variable. We generate the food suitability index as the maximum of suitability indices of rice and wheat rather than their average as was done earlier. Using the new food suitability index we recalculate the proportion of area in a district where the suitability index is higher than the national average. Finally, we test for the sensitivity of the results to district specific linear time trends.

Table 4.7 presents the results from the robustness checks based on the triple interaction specification in equation 4.7. The dependent variable in specification 1 is the reconstructed dietary diversity variable. In specification 2 we use the new food suitability variable and specification 3 controls for district specific linear time trends. The coefficients on the triple interaction for all three specifications are negative and statistically significant. Hence our results remain unaffected by these robustness tests.

[5] Coarse cereals include pearl millet, finger millet, Sorghum, barley and maize.

Table 4.7: Robustness Checks

	(1)	(2)	(3)
$RURAL \times FOOD \times Ln(PRICE)$	-0.020**		-0.046***
	(0.010)		(0.014)
$RURAL \times FOOD \times Ln(PRICE)$		-0.022*	
		(0.011)	
District linear time trends	No	No	Yes
N	2452	2452	2456
R^2	0.805	0.815	0.815

Notes: Dependent variable in specification 1 is the ratio of calories from rice and wheat in total calories excluding calories from coarse cereals. Dependent variable in specification 2 and 3 is the ratio of calories form rice and wheat in total calories. Specification 2 uses an alternative procedure to calculate the area suitable for food cultivation in a district. All specifications include district fixed effects and time dummies. Panel controls and initial conditions are listed in table 4.1. Figures in parenthesis are robust standard errors clustered at district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.6 Conclusions

Though several studies using Deaton's (1989) net benefit approach have predicted that rising food prices would lead to worsening of poverty in the developing world, these predictions have not fully realized. In this chapter we take an empirical approach to estimate the welfare impact of food price shocks. Our primary innovation is to use the spatial variability in the natural suitability of food cultivation to disentangle the consumption and income effect of food price changes on household welfare.

We find a statistically significant welfare improving income effect of high food prices for households located in regions suitable for food cultivation. The income effects are present for both laborer and cultivator households and offset the negative consumption effects to a large extent. This finding is especially important in the light of the trade policy responses of countries during global food price shocks. Countries often rely on restrictive trade policy to insulate households from food price shocks on the grounds that high food prices would hurt the poor. Our results show that laborer and cultivator households within food producing regions are completely insured from food price shocks. Therefore, countries with larger share of population engaged in food production either as cultivator or as wage laborer will be least affected by such events. The households most vulnerable to food price shocks are primarily urban or food importer households. Urban households only experience increase in consumption expenditures as food price rise without offsetting increase in income but as long as richer households reside in urban areas the consumption effect may not be of much consequence to them.

Finally, we also find income effects of high food prices for households not directly engaged in food cultivation within food producing regions. These results indicate that different sectors within food producing regions are closely linked and hence the spill-over effects of high food prices are important.

Appendix A

Appendix to Chapter 2

A.1 Non-Separable Utility and Test of Risk Sharing

We assume the same setup as in the main text. The only difference is that now the representative consumer's utility function is non-separable in the two goods.

$$U_i = u_i(x_i, y_i) \tag{A.1}$$

where, $u_i(.)$ is strictly increasing, concave and twice differentiable function. The social planner's problem is

$$Max_{\{(x_{is}, y_{is})_{i=1}^{N}, s \in S\}} \sum_{i=1}^{N} \omega_i E(U_i) \tag{A.2}$$

Subject to following aggregate resource constraints in each state.

$$\sum_{i=1}^{N} x_{is} = \sum_{i=1}^{N} w_{is}^{x} = X_{is}, \forall s \in S \tag{A.3}$$

$$\sum_{i=1}^{N} y_{is} = \sum_{i=1}^{N} w_{is}^{y} = Y_{is}, \forall s \in S \tag{A.4}$$

Resultant Lagrangian is

$$\mathcal{L} = \sum_{i=1}^{N} \omega_i \sum_{s \in S} \pi_s u_i(x_{is}, y_{is}) + \lambda_s^x (X_s - \sum_{i=1}^{N} x_{is}) + \lambda_s^y (Y_s - \sum_{i=1}^{N} y_{is}) \tag{A.5}$$

where λ_s^x and λ_s^y denote the Lagrange multiplier associated with the resource constraints for good x and y in state s respectively, then the first order conditions for individual i with respect to good x is

$$\omega_i \frac{\partial u_i(x_{is}, y_{is})}{\partial x_{is}} = \frac{\lambda_s^x}{\pi_s} = \mu_s^x, s \in S \tag{A.6}$$

$$\omega_i \frac{\partial u_i(x_{is}, y_{is})}{\partial y_{is}} = \frac{\lambda_s^x}{\pi_s} = \mu_s^y, s \in S \tag{A.7}$$

Total differentiating equations A.6 and A.7 we get

$$\omega_i \left(\frac{\partial^2 u_i(x_{is}, y_{is})}{\partial x_{is} \partial x_{is}} dx_{is} + \frac{\partial^2 u_i(x_{is}, y_{is})}{\partial x_{is} \partial y_{is}} dy_{is} \right) = d\mu_s^x \tag{A.8}$$

$$\omega_i\left(\frac{\partial^2 u_i(x_{is},y_{is})}{\partial y_{is}\partial x_{is}}dx_{is}+\frac{\partial^2 u_i(x_{is},y_{is})}{\partial y_{is}\partial y_{is}}dy_{is}\right)=d\mu_s^y \tag{A.9}$$

Dividing equation A.8 and A.9 by A.6 and A.7 respectively we get

$$\frac{u_{i,xx}}{u_{i,x}}dx_{is}+\frac{u_{i,xy}}{u_{i,x}}dy_{is}=\frac{d\mu_s^x}{\mu_s^x} \tag{A.10}$$

$$\frac{u_{i,xy}}{u_{i,y}}dx_{is}+\frac{u_{i,yy}}{u_{i,y}}dy_{is}=\frac{d\mu_s^y}{\mu_s^y} \tag{A.11}$$

Solving the system of two equations in A.10 and A.11 we can see that the change in the allocation of a good is associated with the relative change in the Lagrangian multipliers associated with the aggregate resource constraint of both goods.

$$dx_{is}=\beta_i^x\frac{d\mu_s^x}{\mu_s^x}+\beta_i^y\frac{d\mu_s^y}{\mu_s^y} \tag{A.12}$$

$$dy_{is}=\delta_i^y\frac{d\mu_s^x}{\mu_s^x}+\delta_i^y\frac{d\mu_s^y}{\mu_s^y} \tag{A.13}$$

where, the parameters are associated with the curvature the utility functions with respect to different goods.

A.2 Tests of Unit Root, Serial Correlation and Heteroscedasticity

Table A.1: Unit Root Tests

Variables	Rice	Wheat	Maize	Rice	Wheat	Maize
	Level			First difference		
(A) Maddala and Wu (1999) Panel Unit Root test (MW)						
log of per capita consumption	122.78	149.06***	206.98***	785.86***	605.97***	734.69***
log of per capita production	120.84	129.57***	143.07	761.48***	576.04***	693.48***
(B) Pesaran (2007) Panel Unit Root test (CIPS)						
log of per capita consumption	-0.027	-2.691***	-0.293	-12.835***	-12.572***	-13.781***
log of per capita production	4.511	-2.151**	1.032	-13.836***	-12.176***	-13.230***

Notes: MW test assumes cross-section independence and CIPS test assumes cross-section dependence in the form of a single unobserved common factor. Null for MW and CIPS tests is that series is $I(1)$. The lag length for the CIPS test is set to $T^{\frac{1}{3}} = 4$. MW and CIPS test result reported for without trend specification. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Table A.2: Tests of Serial Correlation and Heteroscedasticity

Tests	Statistic	Probability
Rice		
Wooldridge test for null of no serial correlation in panel-data	$F(1,94) = 61.15$	$Prob. > F = 0.0000$
Modified Wald test for group-wise heteroskedasticity	$\chi^2(95) = 74094.36$	$Prob > \chi^2 = 0.0000$
Wheat		
Wooldridge test for null of no serial correlation in panel-data	$F(1,86) = 12.94$	$Prob. > F = 0.0005$
Modified Wald test for group-wise heteroskedasticity	$\chi^2(87) = 31647.30$	$Prob. > \chi^2 = 0.0000$
Maize		
Wooldridge test for null of no serial correlation in panel-data	$F(1,118) = 9.37$	$Prob. > F = 0.0027$
Modified Wald test for group-wise heteroskedasticity	$\chi^2(120) = 5.9e^{+34}$	$Prob. > \chi^2 = 0.0000$

Note: All tests conducted on a country fixed effects model with time dummies.

A.3 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

$$Y_{it}^{NX} = Y_{it} - NX_{it} \tag{A.14}$$

where

$$NX_{it} = Exports_{it} - Imports_{it} \tag{A.15}$$

is net exports. Consumption (domestic supply) will then equal to sum of production left after trade and change in stocks i.e.,

$$C_{it} = Y_{it}^{NX} + \Delta S_{it} \tag{A.16}$$

Production for country i at time period t can then be expressed as

$$Y_{it} = \frac{Y_{it}}{Y_{it}^{NX}} \times \frac{Y_{it}^{NX}}{C_{it}} \times C_{it} \tag{A.17}$$

Taking logs on both sides

$$lnY_{it} = (lnY_{it} - lnY_{it}^{NX}) + (lnY_{it}^{NX} - lnC_{it}) + lnC_{it} \tag{A.18}$$

First differencing

$$\Delta lnY_{it} = (\Delta lnY_{it} - \Delta lnY_{it}^{NX}) + (\Delta lnY_{it}^{NX} - \Delta lnC_{it}) + \Delta lnC_{it} \tag{A.19}$$

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

$$\begin{aligned} Var(\Delta lnY_{it}) = {} & Cov(\Delta lnY_{it}, \Delta lnY_{it} - \Delta lnY_{it}^{NX}) \\ & + Cov(\Delta lnY_{it}, \Delta lnY_{it}^{NX} - \Delta lnC_{it}) \\ & + Cov(\Delta lnY_{it}, \Delta lnC_{it}) \end{aligned} \tag{A.20}$$

Appendix B

Appendix to Chapter 3

B.1 Copula Estimation

We use copula functions to estimate the joint distribution of yield and rainfall. The copula function provides a flexible way to bind the univariate marginal distributions of random variables to form a multivariate distribution and can accommodate different marginal distributions of the variables (Nelsen (2006); Trivedi and Zimmer (2007)). A two-dimensional copula can be defined as a function $C(u, v) : [\theta, 1]^2 \longrightarrow [0, 1]$ such that

$$F(Y, X) = P[G(Y) \leq G(y), F(X) \leq F(x)] \tag{B.1}$$

$$F(Y, X) = C(G(Y), F(X); \theta) \tag{B.2}$$

Where θ represents the strength of dependence and $G(.)$ and $F(.)$

are the marginal distribution functions of Y and X respectively. The joint probability density function can be expressed as:

$$c(G(Y), F(X); \theta) = \frac{\partial C(G(Y), F(X); \theta)}{\partial G(Y) \partial F(X)} = C(G(Y), F(X); \theta) g(Y) f(X) \quad \text{(B.3)}$$

Sklar (1959) has shown that for a continuous multivariate distribution, the copula representation holds for a unique copula C. This construction allows us to estimate separately the marginal distributions and the joint dependence of the random variables. There are several parametric families of copula available in the literature. The frequently used ones are the elliptical copulas and the Archimedean copulas. Note that the nature of dependence among the random variables will depend on the copula function chosen for estimation. The statistical properties of the copulas that we use in this paper are given in table B.1.

Table B.1: Some Common Copula Models

Copula models	Functional forms	Dependence parameter	Parameter space	Lower tail dependence	Upper tail dependence
Gaussian	$\Phi_{\Sigma}(\Phi^{-1}(u), \Phi^{-1}(v); \rho)$	ρ	$(-1, 1)$	0	0
Clayton	$(u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}}$	θ	$(0, \infty)$	$2^{-\frac{1}{\theta}}$	0
Rotated Clayton	Same as Clayton with $1 - u$ and $1 - v$	θ	$(0, \infty)$	0	$2^{-\frac{1}{\theta}}$
Plackett	$\frac{1+(\theta-1)(u+v)-\sqrt{[1+(\theta-1)(u+v)]^2-4\theta(\theta-1)uv}}{2(\theta-1)}$	θ	$(0, \infty)$	0	0
Frank	$-\frac{1}{\theta}log\left(1 + \frac{(\exp^{-\theta u}-1)(\exp^{-\theta u}-1)}{(\exp^{-\theta}-1)}\right)$	θ	$(-\infty, \infty)$	0	0
Gumbel	$\exp\left\{-(-logu^{\theta} - logv^{\theta})^{\frac{1}{\theta}}\right\}$	θ	$(1, \infty)$	0	$2 - 2^{-\frac{1}{\theta}}$
Rotated Gumbel	Same as Gumbel with $1 - u$ and $1 - v$	θ	$(1, \infty)$	$2 - 2^{-\frac{1}{\theta}}$	0
Student's t	$t_{\nu,\Sigma}(t_{\nu}^{-1}(u), t_{\nu}^{-1}(v); \rho)$	ρ, ν	$(-1, 1) \times (2, \infty)$	$2 \times t_{\nu+1}\left(-\sqrt{(\nu+1)}\frac{\sqrt{(1-\rho)}}{\sqrt{(1+\rho)}}\right)$	$2 \times t_{\nu+1}\left(-\sqrt{(\nu+1)}\frac{\sqrt{(1-\rho)}}{\sqrt{(1+\rho)}}\right)$

Note: Table presents some common parametric copula models with their functional forms, parameter spaces and the expression for tail dependence coefficient implied by the specific copula model.

We use two-step maximum likelihood procedure to estimate the copula function wherein the marginals are estimated in the first step, and the dependence in the second step by substituting the estimated marginal distributions in the selected copula function (Trivedi and Zimmer (2007)). A non parametric estimator is used to estimate the univariate marginal distribution for crop yield deviations and rainfall deviations. This makes the model semi parametric. Estimation of copula using non parametric distribution does not affect the asymptotic distribution of the estimated copula dependence parameter (Chen and Fan (2006)).

A simple maximum likelihood estimator can be used to choose the best fitting copula and estimate the dependence parameter (Patton (2013)). Selection of the copula model can be made based on the Akaike or (Schwarz) Bayesian information criterion (AIC). If all the copulas have equal number of parameters, then the choice of model based on these criteria is equivalent to choosing copula with highest log likelihood (Trivedi and Zimmer (2007)). The log likelihood function of the copula can be written as:

$$L(\theta) = \sum_{i=1}^{N} LnC(\hat{U}_{X_i}, \hat{U}_{Y_i}; \theta) \tag{B.4}$$

Where $\hat{U}_{X_i}$ and $\hat{U}_{Y_i}$ are the nonparametrically estimated marginal distributions. Copula parameter can be estimated by maximizing the likelihood function using numerical methods. This procedure gives the "Inference Functions for Margins" (IFM) estimator as θ is conditional on the model that is used to transform the raw data (Trivedi and Zimmer (2007); Patton (2013)). All copula models and tail dependence statistics are estimated using Patton's (2013) procedure and MATLAB codes.

B.2 Estimated Marginal Densities

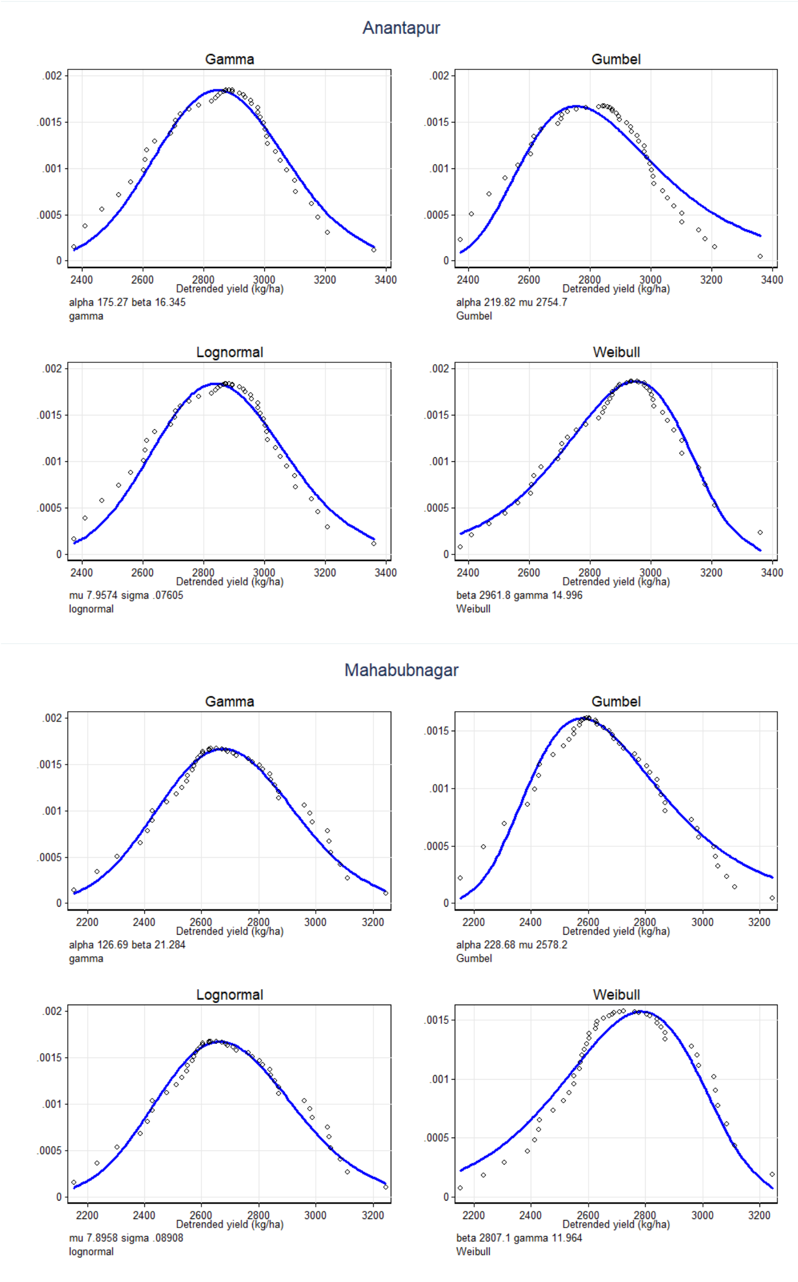


Figure B.1: De-trended Yield

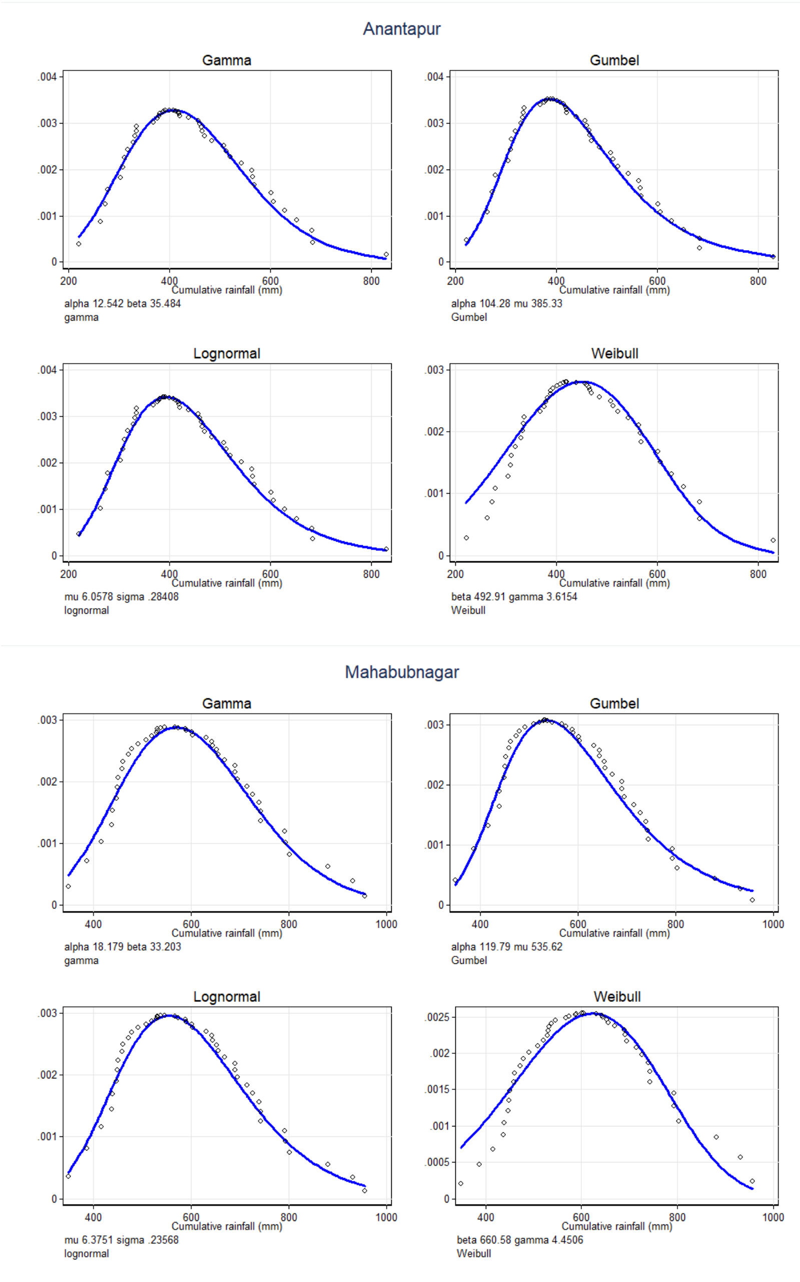


Figure B.2: Cumulative Seasonal Rainfall

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