2015

Three Essays on Food Demand, Land Use Intensity, and Food Crop Portfolio Choice under Weather Risk

Aditya Raj Khanal
Louisiana State University and Agricultural and Mechanical College, akkhanal@gmail.com

THREE ESSAYS ON FOOD DEMAND, LAND USE INTENSITY, AND FOOD CROP PORTFOLIO CHOICE UNDER WEATHER RISK

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Agricultural Economics and Agribusiness

by

Aditya Raj Khanal
B.S., Tribhuvan University, 2006
M.S., Louisiana State University, 2014
M.A., Virginia Tech, 2012
August 2015

I would like to dedicate this dissertation to my parents Mr. Gopi Raj Khanal and Mrs. Laxmi Khanal for their endless love, support, and encouragement.

ACKNOWLEDGEMENTS

This dissertation and a doctoral degree is an important accomplishment in my academic journey. Over the past several years during my educational attainment, I have received support and encouragement from a number of individuals. It is my great pleasure to express my sincere gratitude for all those who have helped me during this journey.

Dr. Ashok K. Mishra, my major advisor, has been a mentor, colleague, and friend. I cannot really express in words about how much his valuable instruction and continuous encouragement matters to me to achieve this. I also like to thank Dr. Mishra for encouraging me to pursue a MS degree in Finance as a dual degree while I pursue a doctoral degree in Agricultural Economics.

I am deeply indebted to Dr. Jeffrey Gillespie for his help and unselfish advice during my academic endeavor at LSU. I like to express my sincere thanks to my dissertation committee members: Dr. James Fannin, Dr. Kelly Pace, and Dr. Costas Busch for their valuable suggestions. I like to give special thanks to Dr. Krishna Paudel and Dr. Gail Cramer for their encouragement to do my best in economics and applied economics. Thanks also goes to Dr. Madhusudan Bhattarai from ICRISAT India for helping me to collect information about data and study area. I am very thankful to Dr. Ji-Chai Lin and Dr. Carlos Slawson in the Department of Finance for helping me while I earn a dual degree in Finance.

Thanks to my family for their love and support. My dad has been an inspiring figure for me. Thank you dad for teaching me to choose right over wrong and to persistently pursue the objectives. Thanks to my loving mom, brothers, sisters, nephew, and nieces for your constant love and support. I owe my thanks to my wife, Geeta, for her love and best wishes. Finally, I am thankful to all my friends who helped me during my stay and study at LSU. Thanks goes to my colleagues and friends Krishna, Arun, Narayan, Madhav, Isaac, Surendra, Saroj, Vikash, Basu, Trina, AEGSA, and Nepalese community at Baton Rouge for their best wishes.

TABLE OF CONTENTS

ABSTRACT

Food security and adaptation to climate change has been an important research and development agenda in most of the development organizations and in the national policy of developing countries. The most vulnerable population from climate change and food security problems are rural and agricultural households in the developing and low income countries. Weather and climatic factors and food security has a direct link with poverty because a large majority of poor live in rural areas and depend on agriculture for their livelihoods.

The primary focus of this dissertation is to analyze consumption and production aspects of the rural agricultural households. On one hand, demand for total food is increasing with increases in population. Failing to meet the demand for food, rural households face malnutrition and chronic hunger. On the other hand, production agriculture is highly affected by weather and climatic factors. In the absence of well-developed irrigation and infrastructures and insurance mechanisms, agricultural households in the rural areas of developing countries need to respond to higher weather risk and combat it through different adaptation strategies. The first essay of this dissertation studies an influence of income, relative prices, and relevant socioeconomic factors on food purchasing behavior, in total and by primary food categories, among rural Indian households with projections being made on future demand. The second essay investigates how intensity of land use and cropping is affected by an increase in weather risk. It analyzes farmers' short- and long- run responses towards weather risk through land utilization for crops while controlling for changes in irrigation and infrastructure, introduction of high yielding varieties, and increased literacy in rural areas. The final essay focuses on farmers' adjustment through risk-based food crop choice combinations when they are subject to higher weather risk in the area.

CHAPTER 1: INTRODUCTION TO THE ESSAYS

This dissertation is comprised of three independent essays but related through a theme of food consumption and production in rural households. Food consumption in rural households is influenced by social, demographic, and economic factors and constitute a significant proportion of the rural household income. On production side, most of the rural households have small scale agricultural production and are highly influenced by variability in weather in the absence of well-developed irrigation and infrastructures. Farmers in rural areas undertake mechanisms of ex-ante and ex-post responses towards weather risks. The three essays draw on the same dataset: a rural district- and household- level dataset from International Crop Research Institute for Semi-arid Tropics (ICRISAT) survey from India. ICRISAT data contains data on two different levels: 1) *Meso* or macro data consists of district-level data on agricultural production, land use, and climatic information dating back to 1966 and 2) *Micro* or household-level panel dataset contains household specific information on different time period windows—named as Generation I (1975-1984, 1989) and Generation II (2001-2007, 2008-2012). The first essay of this dissertation extracts a cross-sectional data related to food consumption from a *Transaction* module of *micro*-level data, the second essay uses *meso*-level data, and the third essay extracts panel data from different modules of *micro*-level data.

The households analyzed in this study are rural households that represent mainly the farm households in a low-income economy. Food expenditure exhibits the greatest share of total expenditures in the rural households and is allocated vis-à-vis income. Rural households rely primarily on various agricultural incomes but also have, to various degrees, non-agricultural or off-farm income. Farm families in rural areas are subject to production and income risks and try to cope with these risks through production and employment decisions, in general. Weather risk may affect agricultural production and crop choice decisions as well as decisions about income diversification through alternative income-generating activities. These issues get considerable attention in the literature. However, there are some limitations or shortcomings in the previous studies that come either from a data, or have narrower scope to generalize, or have limitations in modeling perspective. Each of the three essays in this dissertation brings a unique representation of the problem, appropriate data, model, and a different viewpoint and addition to the literature while overcoming the limitations of previous studies.

The rural population represents a significant proportion of the total population in developing and low-income countries. Therefore, the problem of a high poverty rate among the rural population exacerbates the poverty and inequality status at the national level. Inequalities in income can, as one might expect, culminate in inequalities in consumption. With food expenditures representing a significant portion of disposable income among rural Indian households, an empirical understanding of those factors influencing the expenditures for food in total and by primary food groups (e.g., cereals, pulses, milk and milk products, meats) among this portion of the population represents an important element in the development of appropriate policy related to the mitigation of malnutrition among rural poor household many of whom have incomes insufficient to secure a balanced diet. Food demand in total and by primary food groups at a point of time in the rural areas and projected future demand, influenced by demographic and socio-economic factors, provides an estimate for the direction of agricultural production as well as the status of food surplus or deficits. The first essay in this dissertation focuses on the consumption side of rural households. It examines the influence of income, relative prices, and relevant socioeconomic factors on food purchasing behavior, in total and by primary food categories, among rural Indian households with projections being made on future demand.

On the income side of the rural households, predominantly from small scale agricultural production, weather and climatic conditions play an important role. In particular, it is anticipated that adverse impacts on the agricultural sector will exacerbate the incidence of rural poverty. Impacts on poverty are likely to be especially severe in developing countries where the agricultural sector is an important source of livelihood for a majority of the rural population. Variability and risks associated with climate and weather not only influence farmer decisions on land use and cropping intensity and patterns, but may also influence the decision to farm in the first place. Farmers' short- and long- run responses towards weather risk allows us to investigate these behaviors. The second essay in this dissertation investigates such effects using district level data from 1966 to 2007. Altogether 4,782 district-time observations were used to examine the relationship from 115 districts from Semi-arid tropical regions of India.

It should be of paramount importance to examine both spatial and temporal aspects of land use or cropping responses to weather risk. Utilization of the information in terms of both cross-sectional variation and time variation leads to better insights; panel data modeling approaches offer much better inferences. Previous literature utilizing cross-sectional or time-series studies or even panel studies but with specific small sample or only for limited regions have limitations in drawing meaningful inferences, in that they are not sufficiently generalized. This study uses non-stationary co-integration and dynamic panel approaches, better suitable analyses, to examine the relationship that may represent a better picture for village dynamics.

The long- and short- run responses in cropping and land-use decisions on the district level boils down to the risk responses from household-level (micro level) decisions in crop choice. Moreover, the broader picture about land use intensity and farming decisions should be verified at the micro-level. The third essay of this dissertation investigates household specific responses to weather risk by using household panel data for 5 years from rural households in India. Two aspects are important to consider while analyzing the decision: first, riskiness of the crop and second, how the household manages risk associated with crops by adjusting their food crop portfolio. In response to weather shocks, households may alter crop choices and adjust their portfolios to smooth income from crop production. First, using a single index approach, risk associated with every crop is estimated, referred as "beta coefficients." Then based on the crops that a rural household selected for a particular year, the average risk index for each household is computed. Then, we investigate how a rural household adjusts (or could adjust) its food crop portfolio in response to weather risk.

Each of the three essays is a result of closer examination of common assumptions in the literature and subsequently investigating the assumptions using appropriate empirical methods to answer policy-relevant research questions. The first essay estimates and projects food demand of rural households. It adapts a Quadratic Almost Ideal Demand System, a flexible demand system allowing for non-linear Engel curves, in the rural household's two-stage budgeting approach. The second essay is innovative in using long- and short- run effects of weather risk on land use intensity. The "Large-T and large-N" non-stationary and dynamic heterogeneous panel model is appropriate and innovative in the field of agriculture and land use studies. The third essay provides insights into how rural households adjust their crop portfolios by choosing less-risky and more-risky crops in their portfolios under high weather risk. Estimation of adjustment in food crop portfolios rather than separate regressions for a few major crops captures the interdependency between crops in the case of inter- or mixed- cropping patterns. Note that inter- and mix- cropping is a common feature of subsistence farming in most of the developing countries. Most of the previous studies dealing with crop choice are focused on a few major crops. By combining plot-specific information with household-level data, allowing for mix- and intercropping patterns, and also accounting for adjustment across time and location by using panel data, our third essay provides a better picture of rural households' response to weather risk through crop choice.

CHAPTER 2: HETEROGENEITY IN FOOD DEMAND AMONG RURAL INDIAN HOUSEHOLDS: THE ROLE OF DEMOGRAPHICS

2.1. Introduction

The Indian economy is experiencing a high rate of economic growth and this rate is anticipated to accelerate in the near future. The Indian Planning Commission, while recognizing the benefits of this growth, acknowledges that the growth has failed to be sufficiently inclusive, particularly after the mid-1990s. Specifically, while the economic growth has provided the opportunity for a large portion of the urban population to transition out of poverty status (based on a cost-of-living index), the proportion of the rural population designated as living below the poverty line has been increasing and equaled more than 30% in 2010 (World Bank, 2012). The problem of a high poverty rate among the rural population is compounded by the fact that the rural component represented 70% of the total Indian population in 2010 (World Bank, 2012).

Inequalities in income can, as one might expect, culminate in inequalities in consumption (Cirera and Masset, September 2010) with two recent studies (Deaton and Dreze, 2002, and Jha, 2004) reporting a rise in the consumption inequality among rural Indian households vis-à-vis their urban counterparts. With food expenditures representing a significant portion of disposable income among rural Indian households, an empirical understanding of those factors influencing the expenditures for food in total and by primary food groups (e.g., cereals, pulses, milk and milk products) among this portion of the population represents an important element in the development of appropriate policy related to the mitigation of malnutrition among rural poor households; many of whom have incomes insufficient to secure a balanced diet.

The costs associated with malnutrition are multifaceted (Tanumihardjo et al., 2007; Bronte-Tinkew and DeJong, 2004). First, malnutrition results in lost productivity among the working population which, if large enough, can hamper the rate of economic growth. Second, financial costs imposed on the government (e.g., health care costs, subsidies associated with government programs to feed the malnourished) are undoubtedly directly tied to the proportion of the country's population that is malnourished. Financial outlays being devoted to these activities detract from government expenditures that could otherwise be devoted to other, income generating, activities. Third, malnutrition in infancy can lead to long-term learning deficits which, over time, may result in a reduction in long-run economic growth. Finally, an individual's nutrition level and well-being are inexorably linked. As such, and without going into detail, a well-functioning society is premised on it being a nourished society. It is important to realize, however, that a balanced diet is simply not a matter of caloric intake. Some products, simply put, are more nutritious than others and purchases of these products are a function of income and relative prices. Changes in income or relative prices culminate in changes in purchasing patterns and these changes can lead to a healthier or more malnourished rural population.

While the benefits of a balanced diet – represented by a mixture of carbohydrates, proteins, and minerals - to the welfare of a country are generally recognized, only limited effort has been given to examining the role of income and relative prices in promoting a balanced diet. The overall purpose of this study is to examine the influence of income, relative prices, and relevant socioeconomic factors on food purchasing behavior, in total and by primary food categories, among rural Indian households with projections being made on future demand. This is accomplished based on analysis of a recently collected database that provides detailed information on expenditure patterns among rural Indian households. Furthermore, unlike previous studies (Meenakshi and Ray, 1999; Fashogbon and Oni, 2013) that treated demand for food commodities in a one-step budgeting process, this study considers a two stage budgeting process in food demand. In two-stage budgeting, we assume that the household determines the share of income that will be devoted to food in the first step and, based on the outcome of this first stage, then determines how to allocate food expenditures across the different food categories such as carbohydrate, protein, fats, and mineral related diets.

To accomplish the stated objective, the remainder of this paper is organized as follows. The next section of the paper presents the demand system considered to be appropriate for estimation and the estimation procedure. Then, attention is turned to introducing and discussing the data used to estimate rural household demand for food in total and by primary categories. Results associated with the analysis are presented in Section 4 of the paper focusing on estimated elasticities and generating projected future demand for food in total and by primary categories based on these elasticities and other relevant information. The paper concludes with a summary of findings, the implications of these findings, and avenues for future research on this important research area.

2.2. Conceptual Model and Empirical Framework

The Quadratic Almost Ideal Demand System (QUAIDS) is an extension of the now famous Almost Ideal Demand System (AIDS) originally proposed by Deaton and Muellbauer (1980). This demand system, which is quadratic in expenditures, is considered to be more flexible than the Almost Ideal Demand System (AIDS) in that it allows demand curves to be non-linear in the logarithm of expenditures and, as such exhibit non-linear Engel curves[1]. In particular, it allows a good to be a luxury item at one end of the income distribution but a necessity at the other end (Banks, Blundell, and Lewbel, 1997). Originally proposed by Banks et al. (1997), several studies have employed the QUAIDS model to estimate food demand, by broad category, in both developed (e.g., Abdulai for Switzerland) and developing (e.g., Boysen (2012) for Uganda; Meenakshi and Ray (1999) for India; and Fashogbon and Oni (2013) for Nigeria) countries. The analyses in many of the studies, such as that by Fashogbon and Oni (2013) are augmented to account for differences in demographic factors

[1] For studies discussing the advantages of rank 3 demand systems such as QUAIDS, over other rank 2 demand systems, see Decoster and Vermeulen (1998) and Cranfield et al. (2003)

across households using methods proposed by Poi (2012) and Ray (1983). These studies, in general, support the superiority of the QUAIDS model to the AIDS model in complete food demand system.

Based on the body of literature supporting the superiority of the QUAIDS model to the AIDS model for estimating food demand, this study also employs the Quadratic Almost Ideal Demand System (QUAIDS) for the estimation of food demand among the rural Indian population.[2] The model accounts for differences in socioeconomic conditions across households by augmenting the demographic and household specific variables (e.g., household size) using the method proposed by Ray (1983) and Poi (2012). For purposes of analysis, furthermore, like Boysen (2012) we assume weak separability in the household's two-stage budgeting process wherein the first stage, the household makes a determination as to the percentage of the total budget to be allocated to food items and then in the second stage allocates the food budget among the different food items.[3] As noted by Thompson (2004), elasticities contingent on exogenous total group expenditure in the demand system may be inappropriate when assuming a two-stage allocation process. In this study, we overcome the limitation of single stage and conditional elasticities by computing appropriate unconditional elasticities based on estimations from two demand models in the manner proposed by Edgerton (1993; 1997) and Carpentier and Guyomard (2001).

2.2.1. First-stage Demand Model

The first stage demand system represents the household's decision regarding what proportion of income will be budgeted to food (in total). Following Ecker (2009), we formulated our first-stage model while incorporating demographic variables and a quadratic expenditure term as follows:

---

[2]We also estimated Almost Ideal Demand System (AIDS) for comparison but only QUAIDS results are presented in this paper. We conducted a quadratic specification test, which suggested for a QUAIDS model.

[3] Additionally, the plot of food group shares over household expenditure (figure1and figures 2a to 2f) and a formal test for quadratic specification in demand system analysis suggests the superiority of QUAIDS model over AIDS in our estimation.

$$w_F = \alpha_F' + \sum_{d \epsilon D} \delta_d z_d + \gamma_F lnP_F + \beta_F lnM + \lambda_F (lnM)^2 \quad (1)$$

where w_F represents share of food expenditure in relation to total household expenditures (i.e., all food and non-food items), *z* is the vector of household characteristic and demographic variables, and

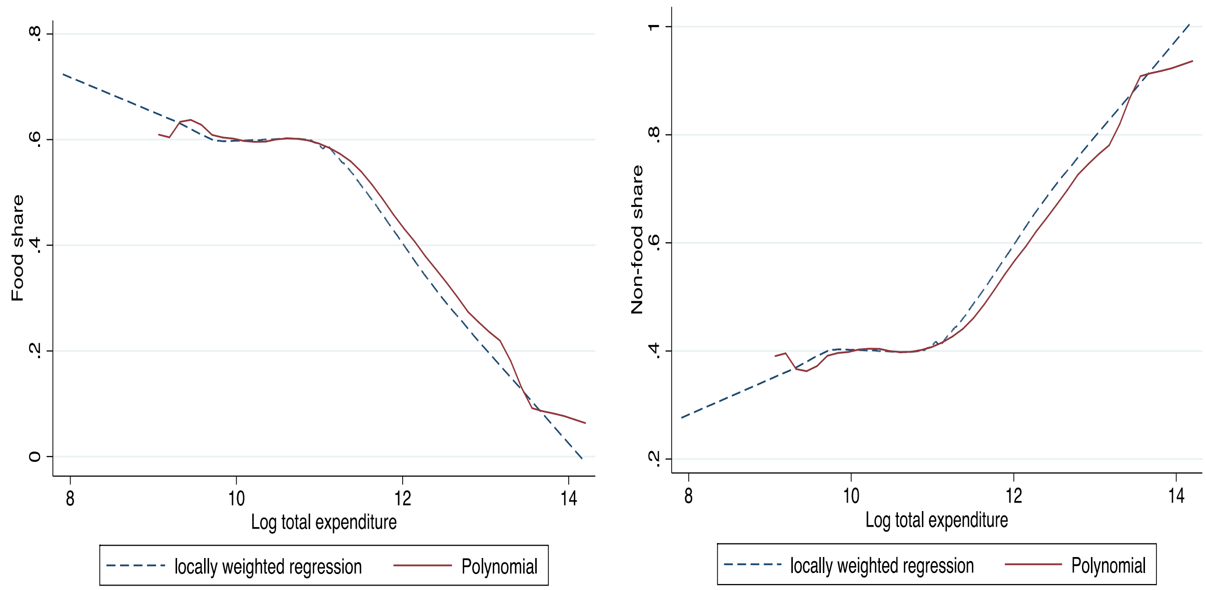
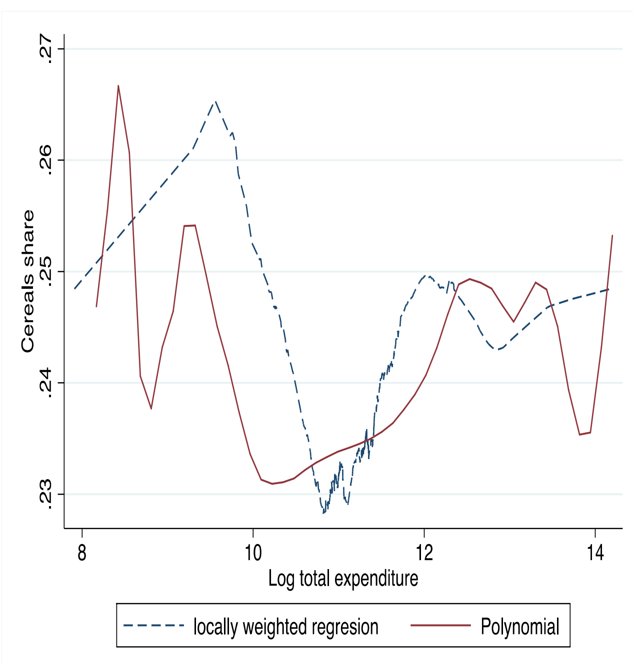


Figure1: Nonparametric Engel curves for total food share (left) and total non-food share (right)



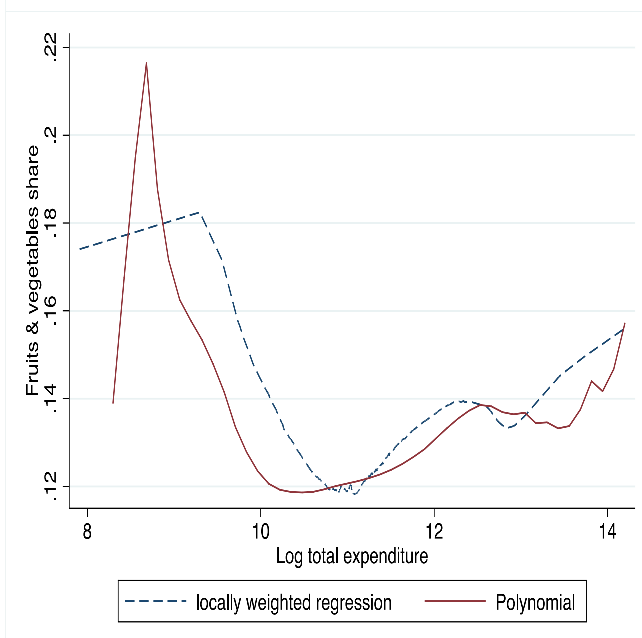
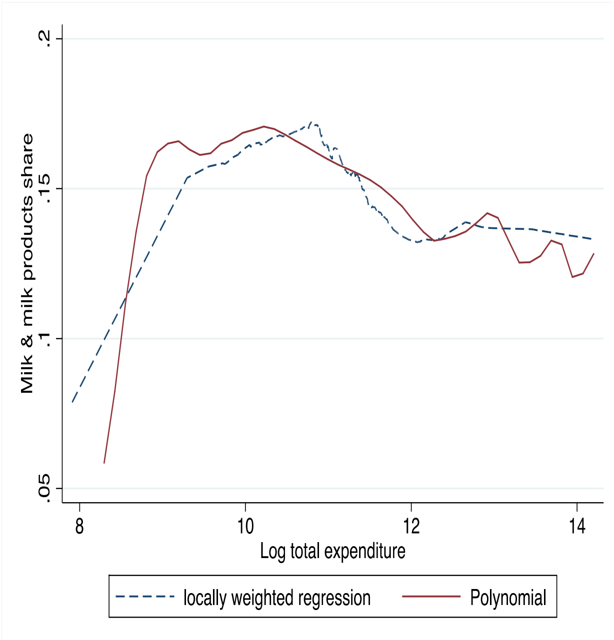


Figure 2a: Nonparametric Engel curve for cereals;Figure 2b: Nonparametric Engel curve for fruits,veg



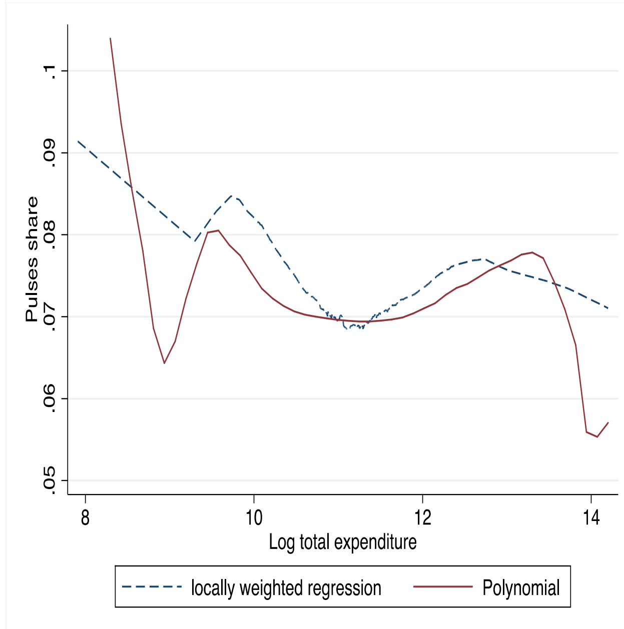
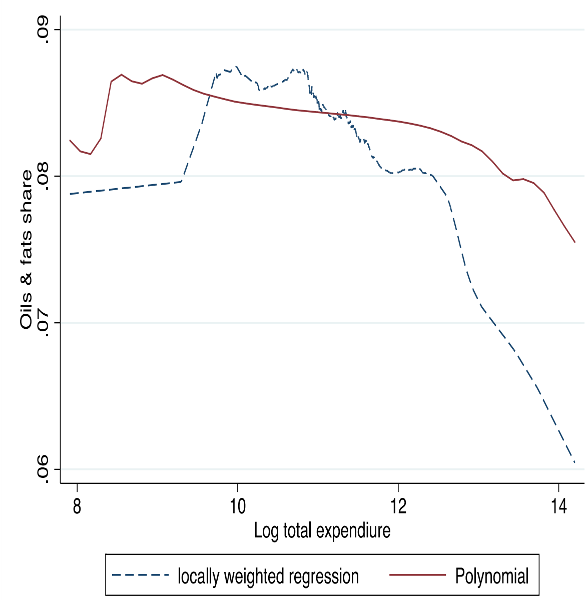


Figure 2c: Nonparametric Engel curve for milk; Figure 2d: Nonparametric Engel curve for pulses



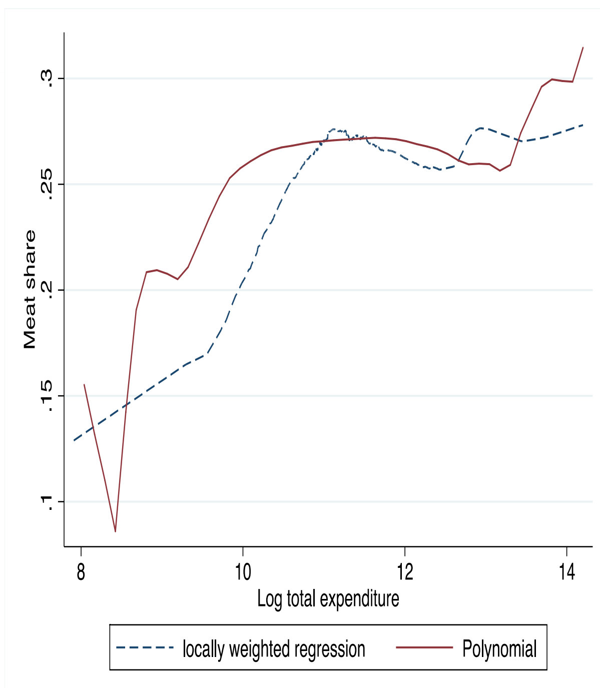


Figure 2e:Nonparametric Engel curve for oils, fats; Figure 2f: Nonparametric Engel curve for meat

M represents total household expenditures. As suggested in Pollak and Wales (1981), we used a demographic and household characteristics translation approach to account for household specific heterogeneity in demand.[4] The variable P_F in Equation 1 represents an aggregate food price index computed based on value weighted aggregation of respective food group prices such that:

$$p_F = \sum_{g=1}^{7} \frac{V_g^F}{V_F} * \overline{p_g} \tag{2}$$

where $\frac{V_g^F}{V_F}$ represents food group g's share on total food expenditure and $\overline{p_g}$ represents price index of food group g computed as described in the data section (equation 20). Also included in the first stage analysis are socio-demographic variables representing the age, education, gender, and marital status of the household head as well as a suite of dummy variables designating the location where the household resides.

Finally, the food expenditure elasticity[5] (η_F), uncompensated (Marshallian) elasticity (ε_F), and compensated (Hicksian) elasticity (ε_F^H), can be derived based on the estimated parameters derived from Equation 1 in conjunction with the Slutsky equation. These three elasticities are presented in Equations 3 through 5:

$$\eta_F = 1 + \frac{\beta_F}{w_F} + \frac{2\lambda_F \, lnM}{w_F} \tag{3}$$

$$\varepsilon_F = -1 + \frac{\gamma_F}{w_F} \tag{4}$$

$$\varepsilon_F^H = \varepsilon_F + \eta_F * w_F. \tag{5}$$

2.2.2. Second-stage Demand System

A system of demand equations of food items aggregated to seven food item groups, as shown in table 2.1, represents the second stage in the two-stage budgeting process. The QUAIDS model,

---

[4] This is obtained by substituting ordinary intercept term α_F, such that: $\alpha_F = \alpha_F' + \sum_{d\epsilon D} \delta_d z_d$.

[5] Since budge share for food and non-food add up to one, the expenditure elasticity of non-food can be calculated as $\eta_{NF} = \frac{1-\eta_F * w_F}{1-w_F}$

which represents the model employed in the second stage of the two-stage budgeting process, is derived from the following indirect utility function (Banks, Blundell, and Lewbel, 1997):

$$lnV(p,M) = \left[\left[\frac{lnm - lna(p)}{b(p)}\right]^{-1} + \lambda(p)\right]^{-1}, \quad (6)$$

where *ln a(p)* is in the following form:

$$lna(p) = \alpha_0 + \sum_{i=1}^{k} \alpha_i lnp_i + \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k} \gamma_{ij} lnp_i ln\, p_j\ , \quad (7)$$

where price of good *i* for *i=1,…k* is represented by p_i; $b(p)$ and $\lambda(p)$ are represented as follows:

$$b(p) = \prod_{i=1}^{k} p_i^{\beta_i} \quad (8)$$

$$\lambda(p) = \sum_{i=1}^{k} \lambda_i\ lnp_i \text{ where } \sum_{i=1}^{k} \lambda_i = 0. \quad (9)$$

When we apply Roy's identity to the indirect function above, the budget shares in the QUAIDS are obtained by:

$$w_i = \alpha_i + \sum_{j=1}^{n} \alpha_{ij} lnp_j + \beta_i ln\left(\frac{m}{a(p)}\right) + \frac{\lambda_i}{b(p)}\left(ln\left(\frac{m}{a(p)}\right)\right)^2, \quad (10)$$

where w_i, p_i, p_j and *m* are budget share and price of food item group i and group j, and total food expenditures, respectively. From this specification, the AIDS model arises as a special case when $\lambda_i = 0$. Additionally, in order to comply with demand system theory, we impose restriction of adding-up, homogeneity, and Slutsky symmetry as follows:

$$\sum_i \alpha_i = 1\, ; \sum_i \beta_i = 0\, ; \sum_i \lambda_i = 0; \sum_i \gamma_{ij} = 0 \text{ for all } j \epsilon \text{ group } i. \quad (11)$$

A sufficient condition for the expenditure shares to be homogenous of degree zero in prices is: $\sum_i \gamma_{ij} = 0$ for equation of group food group *i* (price parameters of same equation). Symmetry condition are imposed by $\gamma_{ij} = \gamma_{ji}$.

In addition to prices and income effects, we are interested in assessing the effect of demographic variables on food demand system. Poi (2002) derived a procedure to augment demographic variables in QUAIDS. Poi (2002) expressed each household's expenditure function of the form specified below with *z* as a vector of *s* characteristics:

$$e(p,z,u) = m_o(p,z,u) * e^{R(p,u)}, \tag{12}$$

where $m_o(p,z,u)$ scales the expenditure function to account for household characteristics. Equation 12 can be decomposed as:

$$m_0(p,z,u) = \overline{m_0}(z) * \emptyset(p,z,u). \tag{13}$$

The first term measures the increase in the household's expenditure as a function of vector z not controlling for any changes in the consumption pattern while the second term controls for changes in relative prices and actual goods consumed. Poi (2012) described parameterization of the above function in QUAIDS as: $\overline{m_0}(z) = 1 + \rho' z$ and $ln\phi(p,z,u) = \frac{\prod_{j=1}^{k} p_j{}^{\beta_j} (\prod_{j=1}^{k} p_j{}^{\eta_j' z} - 1)}{\frac{1}{u} - \sum_{j=1}^{k} \lambda_j ln p_j}$, where η_j represents the j^{th} column of $s * k$ parameter matrix η. It looks complicated but has a nice feature that we can augment and compare with the equation without demographics. The expenditure share equation with demographics now takes the following form, (Poi, 2012):

$$w_i = \alpha_i + \sum_{j=1}^{n} \alpha_{ij} ln p_j + (\beta_i + \eta_i' z) ln\left(\frac{m}{\overline{m_0}(z) a(p)}\right) + \frac{\lambda_i}{b(p)c(p,z)}\left(ln\left(\frac{m}{\overline{m_0}(z)\, a(p)}\right)\right)^2 \tag{14}$$

where $c(p,z) = \prod_{j=1}^{k} p_j{}^{\eta_j' z}$ and imposition of adding-up requires: $\sum_{j=1}^{k} \eta_{rj} = 0$ for *r=1,2,……,s.*

As derived by (Poi (2012), elasticities can be presented as:

Uncompensated price elasticity of good i with respect to changes in the price of good j is given by:

$$\varepsilon_{ij}^{M} = -\delta_{ij} + \frac{1}{w_i}\left(\gamma_{ij} - \left[\beta_i + \eta_i' z + \frac{2\lambda_i}{b(p)c(p,z)} ln\left(\frac{m}{\overline{m_0}(z)\, a(p)}\right)\right] * \left(\alpha_j + \sum_l \gamma_{jl} ln p_l\right) - \frac{(\beta_j + \eta_i' z)\lambda_i}{b(p)c(p,z)}\left(ln\left(\frac{m}{\overline{m_0}(z)\, a(p)}\right)\right)^2\right) \tag{15}$$

where δ_{ij} is defined such that $\delta_{ij} = 0$ for $i = j$ and $\delta_{ij} = 1$ for $i \neq j$

The expenditure (income) elasticity for good *i* is given by:

$$\eta_i = 1 + \frac{1}{w_i}\left[\beta_i + \eta_i' z + \frac{2\lambda_i}{b(p)c(p,z)} ln\left(\frac{m}{\overline{m_0}(z)\, a(p)}\right)\right]. \tag{16}$$

Compensated price elasticities are obtained from the Slutsky equation: $\varepsilon_{ij}^{H} = \varepsilon_{ij}^{M} + \eta_i w_j$.

The second stage elasticities are conditional on the first-stage because allocation among food categories is conditional on allocation of the budget to food. Based on Carpentier and Guyomard (2001) and Boysen (2012), unconditional food group demand elasticities, based on the estimated demand equations associated with total food (Equation 2) and food categories, can be expressed as:

Unconditional expenditure elasticity:

$$\eta_i^{\bar{u}} = \eta_{i|F}\eta_F. \tag{17}$$

Unconditional uncompensated price elasticities are:

$$\varepsilon_{ij}^{\bar{u}} = \varepsilon_{ij} + w_{j|F}\left(\frac{1}{\eta_{j|F}} + \varepsilon_F\right) * \eta_{i|F}\eta_{j|F} + w_F w_{j|F}\eta_F\eta_{i|F} * \left(\eta_{j|F} - 1\right). \tag{18}$$

Unconditional compensated price elasticities:

$$\varepsilon_{ij}^{H,\bar{u}} = \varepsilon_{ij}^{H} + w_{j|F}\, \varepsilon_F^{H}\eta_{i|F}\eta_{j|F}\ , \tag{19}$$

where subscript F represent statistics from the first-stage estimation on total food demand, $\bar{u}$ denotes unconditional elasticities and $i|F$ denotes statistics from the second-stage estimation which are conditional on first stage.

2.3. Estimation Procedure

The first stage demand model is estimated by Ordinary Least Squares (OLS). The second-stage QUAIDS model is estimated with one budget share equation for each food group item. We maintain theoretical assumptions of symmetry, homogeneity, and additivity in QUAIDS model. To estimate the QUAIDS demand system, a non-linear seemingly unrelated regression approach (NLSUR) is employed.[6] To correct for potential biases in the variance covariance matrix of demand system estimation in two stage models, Deis and Hill (1998) and Boysen (2012) propose computing non-parametric bootstrapped standard errors instead of usual asymptotic standard errors. Following this

[6]For QUAIDS estimation, we used Stata software. For more information about estimation, coding and model in Stata, we refer to Poi (2012); Poi (2008).

procedure, we undertook 50 replications with bootstrapped standard errors to obtain valid and consistent standard errors in demand system estimation.[7]

2.4. Data

This study uses cross-sectional data on monthly consumption expenditures among rural Indian households from July 2011 to June 2012. Relevant monthly information including expenditures on food items, total non-food expenditures, and household specific income and demographic variables were collected from 848 households through a survey administered by International Crops Research Institute for Semi-arid Tropics (ICRISAT). Walker and Ryan (1990) argue that a consistent household time-series database on a representative cross-section of Semi-arid tropics (SAT) villages was lacking. They argue that benchmark households and villages could be used by scientists at ICRISAT and cooperating Indian and overseas research institutions to enhance understanding of development in the Indian SAT. The data would allow to test hypotheses on relevant design of technology and policies for the improvement of economic well-being.

The need to collect uniform data across a panel of households over several years arose from three mutually reinforcing considerations centering on the nature of interdisciplinary research at ICRISAT. These include, (1) variability in agricultural production in SAT; (2) potential for complementarities in data collection; and (3) analysis to address a range of research topics. Village studies in three broad production regions were started in 1975. This survey is also known as the Village Dynamics Studies in South Asia (VDSA). Other benchmark village sites—five in West Africa and two more in India and Bangladesh were opened in 1980s. Information in India were collected from villages in East India and SAT India. To collect and manage information, different seven

[7] QUAIDS first approximates $a(p)$ (equation 7) by Stone price index and $b(p)$ (equation 8) by setting all β_k to one. Using the resulting coefficients, it recalculates $a(p)$, and $b(p)$ and reestimates QUAIDS system. This procedure is repeated until the iteration-to-iteration change of the coefficient is very small and the process is converged. As α_0 is difficult to estimate, we choose an arbitrary small value of 10, as practiced in previous such studies (see Deaton and Muellbauer, 1980), page 316; Boysen, 2012).

modules have been developed for the household surveys. The villages involved in the studies of ICRISAT were selected from districts which represented the broad agroclimatic sub regions in India.[8]

A random sample of ten households was selected from each group of farmers including the agricultural labor group so that 40 sample farmers were selected from each village (see Jodha, Asokan, and Ryan, 1977). In particular, 10 households in labor/landless; small farms; medium farms; and large farm households were selected. The VDSA household data included six traditional villages and 12 new villages—original to SAT. This study uses the 'transaction module.' This module is split into four parts. The first part provides the information about the expenditure on broad categories of food and non-food items. The second part provides information on income from the sale of crop and livestock outputs. The third part provides information regarding financial transactions and benefits received by the household through Government welfare and development programs. The fourth part provides information about the sale, and purchase of capital assets. Survey data reports monthly consumption of food items by households; however, we compute average monthly consumption and aggregated under seven food groups, namely cereals; fruits & vegetables; milk & milk products; pulses; oils & fats; meats, fish, & eggs; and other food.[9] The study area is shown in map in figure A1 in appendix (shown by gray color in India map). The study area represents 5 large states (Andhra Pradesh (AP), Madhya Pradesh (MP), Karnataka (KN), Gujarat (GJ), and Maharashtra (MH)), and are located in Semi-arid tropical climates. These states represent around 30% of the total rural and 40% of the total urban population of India (Dyson, Cassen, and Visaria, 2005; India Census, 2011).

[8] The VDSA household survey data included six traditional villages, and 12 new villages—original to SAT. The VDSA household survey consist of seven modules. Modules for household survey includes: (1) Household Census Schedule; (2) Plot List and Cropping Pattern Module; (3) Employment Module; (4) Transaction Module; (5) Monthly Price Module; (6) Cultivation Module; (7) Livestock Module.

[9] The cereal group consists of rice, wheat, maize, barley, and sorghum; fruits and vegetables consists of different fruits and vegetables consumed; the pulses group mainly consists of legumes, green and black beans, etc; oils & fats group comprises of groundnut oils, palm oils, mustard and sesame oils; milk & milk products group includes milk, milk-made and associated products such as sweets; other foods group mainly includes spices, sugar, tea and coffee, etc.

A price of each food group was computed using a price index based on the additive value weighted share of each of the food items on the group and then multiplying with their unit prices. In some of the commodities, unit prices are not directly reported in the data set. In such cases, we computed our price index as follows:

$$\overline{p_g} = \sum_{i=1}^{k} \frac{V_i^g}{V_g} * \left(\frac{V_i^g}{q_i^g}\right), \qquad (20)$$

where $\overline{p_g}$ represents price index for food group *g, g=1,2,….,6,7* $\frac{V_i^g}{V_g}$ represents value weighted share of food item *i* on group *g*, and $\left(\frac{V_i^g}{q_i^g}\right)$ represents unit price of item *i*. We collected household specific socio-demographic information, such as total annual expenditures, total non-food expenditures, operator characteristics, location variables from general information module of the ICRISAT data and matched those with household identification number in the micro module of the ICRISAT data.

Relevant information on annual household income and food expenditures across quantile are given in table 2.1. For the first quantile, average income is around 53,571 Rupees (Rs.) while the fourth quantile average income is Rs. 146,796—with average being 89,000 Rupees. However, this average is slightly higher than reported by the National Sample Survey (NSS, 2011) office—about 79,000 Rupees. Table 2.1 shows that a significant share, 60% and 47% of average income is dedicated to food for first and fourth quantile, respectively. Approximately 55% of total household expenditures, on average, is allocated to food. The NSS (2001) report shows that approximately 57% of the total expenditures, on average, is allocated to food items. Food share between first and fourth quantile of income ranges from 47% to 60%. As indicated by the information in Table 2.1, relatively poor households allocated a higher share of total expenditures on food. When it comes to different food group shares, we notice some heterogeneity with respect to income.

Table 2.1: Food expenditures of rural households, by income quantiles

	First	Second	Third	Fourth	Mean
Items	*Income and shares*				
Annual household income (in Indian Rupees)	53,571	68,984	99,124	146,980	88,724
Food share	0.598	0.610	0.561	0.468	0.547
	(0.113)	(0.108)	(0.117)	(0.143)	(0.148)
Non-food share	0.402	0.389	0.440	0.531	0.452
	(0.114)	(0.108)	(0.117)	(0.143)	(0.148)
Share of food groups					
Cereals	0.238	0.221	0.236	0.252	0.236
	(0.128)	(0.130)	(0.130)	(0.123)	(0.129)
Fruits and vegetables	0.122	0.113	0.124	0.141	0.125
	(0.066)	(0.557)	(0.065)	(0.071)	(0.065)
Milk and Milk Products	0.164	0.179	0.147	0.122	0.156
	(0.110)	(0.131)	(0.124)	(0.106)	(0.119)
Oils and Fats	0.085	0.090	0.080	0.083	0.084
	(0.071)	(0.044)	(0.041)	(0.043)	(0.051)
Meat, Fish, Eggs	0.258	0.268	0.282	0.265	0.273
	(0.198)	(0.192)	(0.198)	(0.229)	(0.204)
Other food	0.060	0.061	0.063	0.064	0.062
	(0.042)	(0.047)	(0.046)	(0.050)	(0.044)

Note: Standard deviations are in parentheses, 1 USD=Indian Rs. 64
Source: Author's compilation

Descriptive statistics pertaining to demographic variables used in the analysis are presented in Table 2.2. The average age of the household head was around 49 years. Formal education among heads of households in the sample approximated 5 years with most of them being males (92%) and married. Compared to the National Sample Survey (NSS), conducted by the Ministry of Program Implementation, our sample statistics are very close. For example, NSS report (2011) reports that a majority of the households (90%) in the rural area are headed by males and the average age of the head of household is about 50 years. [10] Region wise, the sample covers 32% households from *Maharashtra* (MH), around 20% each from Andhra Pradesh (AP), Gujarat (GJ) and Karnataka (KT), and 10% of households from Madhya Pradesh (MP).

[10] The NSS (2011) report notes that the average household size in rural areas is about 5.83.

Table 2.2: Summary statistics of demographic variables included in the model

Variables	Mean	Std. Dev
Age of head of household (years)	48.87	12.47
Annual household expenditure (in Rupees)	88,724	84,176
Educational attainment of head of household (years)	4.85	4.73
Gender of head of household (1=Female, 0= Male)	0.08	0.27
Marital status of head of household (1=married, 0=else)	0.91	0.28
Family Size	5.63	3.01
Location		
Andhra Pradesh (AP)	0.19	0.39
Madhya Pradesh (MP)	0.09	0.29
Maharashtra (MH)	0.32	0.46
Gujarat (GJ)	0.19	0.39
Karnataka (KN)	0.20	0.40

2.5. Results and Discussion

2.5.1. Determinants of Total Food Demand

Parameter estimates associated with the total food demand model are presented in Table 2.3. In addition to an aggregate price index for total food (computed based on equation 2) and income variables, the model is augmented to include those socio-demographic and household characteristics (e.g., age, education level, gender, and location variables) hypothesized to influence food demand. Results suggest that the demand for food is, as expected, negatively related to its own price (index) and positively related to total household expenditures. Additionally, we found a significant gender effect on total food headed households. This may be the result of lower opportunity costs among female head of households vis-à-vis their male counterparts (Alderman et al., 1995) and, hence, the purchase of less value-added food items. It is interesting to note that in our sample total household income of female headed household is about 65,090 Rupees, while those headed by males is about 90,864 Rupees.

Estimated expenditure and price elasticities are presented in table 2.4. Elasticities suggest that a 10% increase in total household income increases total food consumption (expenditure) by almost 8%. Price elasticities (uncompensated price elasticity: -1% and compensated price elasticity: -0.58%)

Table 2.3: Parameter estimates of determinants of food demand

Variables	Mean	Std. Dev.
Constant	-3.485*	1.187
Aggregate price index of food, in log (*lnP_F*)	-0.032*	0.012
Age of the head of the household, in log	-0.025	0.022
Years of education of the household head, in log	-0.002	0.009
Total expenditure, in log	0.863*	0.203
Total expenditure squared, in log	-0.044*	0.009
Female (=1 if household head is female)	-0.069*	0.033
Married (=1 if household head is married)	0.022	0.029
Location		
Andhra Pradesh (AP)	0.064*	0.017
Madhya Pradesh (MP)	0.0002	0.02
Maharashtra (MH)	0.044*	0.015
Gujarat (GJ)	0.078*	0.017
Adjusted R^2	0.3964	

Dependent variable: share of food expenditure on total household expenditures;
*indicates statistical significance at 10% or higher
Source: Author's computation

indicate that total food demand is heavily influenced by its own price with a 1% increase in the aggregate food price resulting in a 0.6% decrease in food expenditures. Coefficients of total household income and squared income suggest that consumption increases at a decreasing rate with respect to an increase in income. This result is consistent with theory suggesting a non-linear relationship between income and food expenditures.

Table 2.4: Total food demand elasticities

	Expenditure elasticity (η_F)	Uncompensated price elasticity (ε_F)	Compensated price elasticity (ε_F^H)
Total food demand elasticities	0.794	-1.053	-0.579

Source: Author's computation

2.5.2. QUAIDS Demand Parameter Estimates

Own- and cross- price and expenditure parameters associated with the food demand system are presented in Table 2.A1.[11] Support for the quadratic term of food expenditure is indicated in all but

[11] Parameter estimates of the QUAIDS model are presented in Table 2.A1 in the appendix. Because symmetry was imposed such that $\gamma_{ij}=\gamma_{ji}$, we do not present the lower cross diagonal elements. The standard errors presented in parentheses below the parameter estimates are bootstrapped standard errors with 50 replications.

one equation (fruits and vegetable) based on the statistical significance of the quadratic term in each of the equations. In the cereal equation, for example, the coefficient associated with the linear term of food expenditure is positive while the squared term is negative implying that cereal consumption initially increases with income but at a decreasing rate and beyond some point will begin to fall. With a combination of coefficients on demographic parameters and their scale estimates, we can observe the significance of the inclusion of demographic variables such as characteristics of head of household and location variables in the demand system estimation. Coefficients on regional variables show significant regional differences in consumption of food items in the demand system. Additionally, a formal test of joint significance of specific demographic variable on the demand system highlights the importance of controlling for demographic variables, which we present in the "econometric tests" section, below.

2.5.3. Income and Price Elasticities

Expenditure and uncompensated and compensated price elasticities computed using parameter estimates from table 2.A1 are presented in table 2.4. Overall expenditure elasticities suggest that cereals, milk & milk products, pulses, fruits & vegetables, and oils & fats are normal goods; consumption of cereals and oils & fats is relatively inelastic in expenditure; pulses are borderline necessary-luxury; consumption of meats, fish, and eggs and milk & milk products are luxuries. For example, a 1% rise in food expenditure leads to around a 0.8% increase in consumption expenditure of cereals and fruits and vegetables. A 1% increase in food expenditure leads to a 0.7% increase in oils and fats expenditure while the same increase leads to about a 1% increase in pulses expenditure. A plausible explanation for the relatively inelastic expenditure elasticity estimate associated with oil and fats, while controlling for other factors, is that increases in income are also associated with an increased awareness of the adverse health effects associated with 'excessive' consumption of oils and fats. Interestingly, a 1% increase in total food expenditure leads to a 1.4% and 1.2% increase in expenditure in milk & milk products as well as meat products (i.e., meat, fish, and eggs) indicating that these products are considered luxury goods among rural Indian households. Products made from milk are considered superior and are also importantly served in special social gatherings, festivals, and religious holidays. In combination, this may also suggest that additional income may accompany diversification in food habits from more traditional meals.

Columns 3-16 in table 2.5 present uncompensated and compensated price elasticities for respective food groups. Own-price elasticities are negative for all food groups, consistent with economic theory. Results of uncompensated elasticities suggest that own price elasticities range between -0.87 to -0.3. Uncompensated own price elasticities indicate that a uniform (1%) decrease in prices of all commodities would elicit a respective percentage increase in quantity of consumption of that food group. The own-price elasticity is lowest (in absolute terms) for pulses and other food followed by cereals reflecting their status as staple food groups. Not surprising, fruits & vegetables, milk & milk products, and meat products have relatively higher own-price elasticities.

The compensated price elasticities provide a more accurate picture of cross price substitution between commodity groups, as they have purely substitution effects, net of income. In compensated price elasticities matrix, notice that own price effects are relatively larger and negative than the cross price elasticities (table 2.5). Importantly notice that the signs of cross elasticities are not always the same as that of the matrix of uncompensated elasticities. This finding reemphasizes that the expenditure effects are significant and remarkable in influencing the demand for food. A positive cross price elasticity indicates that the food groups are substitutes for their respective food groups. Among food groups, the largest substitution possibilities with higher magnitude are between fruits & vegetables with other food (0.48), pulses with milk and milk products (0.36), fruits & vegetables with oils and fats (0.29) and meat, fish and eggs with milk and milk products (0.21). Elasticities suggest that a 1% increase in the price of commodities in the oil and fats category increases expenditures on

Table 2.5: Expenditure and price elasticities computed based on QUAIDS model

Food items	Expen elasticity (η_i)	Price elasticities Cereals		Fruits & Vegetables		Milk & milk products		Oils & Fats		Pulses		Meats, fish, eggs		Other food	
		Uncom (ε_{ij})	Comp (ε_{ij}^{H})	Uncom (ε_{ij})	Comp (ε_{ij}^{H})	Uncom (ε_{ij})	Comp (ε_{ij}^{H})	Uncom (ε_{ij})	Comp (ε_{ij}^{H})	Unco (ε_{ij})	Comp (ε_{ij}^{H})	Uncom (ε_{ij})	Comp (ε_{ij}^{H})	Unco (ε_{ij})	Com (ε_{ij}^{H})
Cereals	0.843*	-0.569*	-0.358*	-0.007*	0.104*	-0.020	0.118*	-0.092*	-0.017*	-0.09*	-0.03*	-0.075*	0.163*	-0.04*	0.018
	(0.035)	(0.021)	(0.017)	(0.014)	(0.013)	(0.016)	(0.017)	(0.008)	(0.007)	(0.009)	(0.01)	(0.008)	(0.010)	(0.008)	(0.013)
Fruits	0.852*	-0.001	0.200*	-0.870*	-0.764*	-0.111*	0.021*	0.127*	0.198*	-0.06*	-0.00	-0.109*	0.118*	0.174*	0.226*
& Veg.	(0.032)	(0.029)	(0.024)	(0.080)	(0.080)	(0.024)	(0.026)	(0.021)	(0.020)	(0.033)	(0.03)	(0.009)	(0.013)	(0.009)	(0.060)
Milk &	1.472*	-0.198*	0.150*	-0.182*	0.001*	-0.710*	-0.481*	-0.064*	0.059*	0.044*	0.148*	-0.181*	0.213*	-0.18*	-0.09*
milkpro	(0.061)	(0.036)	(0.028)	(0.024)	(0.022)	(0.041)	(0.048)	(0.016)	(0.014)	(0.016)	(0.01)	(0.022)	(0.025)	(0.023)	(0.025)
Oils &	0.758*	-0.225*	-0.046*	0.197*	0.291*	0.028	0.146*	-0.611*	-0.547*	-0.07*	-0.02*	-0.048*	0.154*	-0.03*	0.018*
Fats	(0.043)	(0.025)	(0.020)	(0.030)	(0.029)	(0.022)	(0.024)	(0.021)	(0.020)	(0.019)	(0.02)	(0.011)	(0.015)	(0.011)	(0.028)
Pulses	1.066*	-0.368*	-0.116*	-0.144*	-0.012*	0.201*	0.367*	-0.125*	-0.036*	-0.44*	-0.36*	-0.045*	0.0240*	-0.15*	-0.08*
	(0.064)	(0.038)	(0.032)	(0.060)	(0.059)	(0.033)	(0.035)	(0.024)	(0.023)	(0.045)	(0.05)	(0.017)	(0.021)	(0.017)	(0.051)
Meats,	1.194*	-0.30*	0.153*	-0.084*	0.064*	-0.122*	0.064*	-0.043*	0.052*	-0.03*	0.052*	-0.733*	-0.413*	-0.05*	0.024*
fish,egg	(0.035)	(0.011)	(0.007)	(0.006)	(0.004)	(0.012)	(0.010)	(0.005)	(0.003)	(0.004)	(0.003	(0.015)	(0.014)	(0.015)	(0.004)
Other	-0.081	0.142*	0.123*	0.487*	0.478*	-0.167*	-0.180*	0.064*	-0.046*	-0.04*	-0.045	-0.075*	-0.096*	-0.33*	-0.34*
food	(0.085)	(0.060)	(0.052)	(0.119)	(0.012)	(0.057)	(0.060)	(0.040)	(0.039)	(0.058)	(0.058	(0.045)	(0.048)	(0.044)	(0.013)

*indicates statistical significance at 10% or higher; numbers in parentheses indicate standard errors
Source: Author's Computations

Table 2.6: Unconditional expenditure and price elasticities

Food items	Uncond Expend. elasitity ($\eta_i^{\bar{u}}$)	Unconditional price elasticities Cereals		Fruits & Vegetables		Milk & milk products		Oils & Fats		Pulses		Meats, fish, eggs		Other food	
		Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)	Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)	Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)	Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)	Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)	Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)	Uncom ($\varepsilon_{ij}^{\bar{u}}$)	Comp ($\varepsilon_{ij}^{H,\bar{u}}$)
Cereals	0.669	-0.562	-0.455	-0.666	0.052	-1.166	0.006	-0.703	-0.048	-0.978	-0.067	-0.884	0.491	0.061	0.020
Fruits & Vegetable	0.677	0.002	0.102	-1.536	-0.817	-1.270	-0.092	-0.490	0.167	-0.954	-0.037	-0.927	0.450	0.272	0.228
Milk & milk prod.	1.170	-0.273	-0.019	-1.332	-0.090	-2.712	-0.677	-1.130	0.005	-1.501	0.084	-1.594	0.786	-0.012	-0.086
Oils & Fat	0.602	-0.219	-0.133	-0.395	0.244	-1.003	0.045	-1.160	-0.575	-0.868	-0.053	-0.775	0.449	0.060	0.020
Pulses	0.847	-0.375	-0.239	-0.977	-0.078	-1.249	0.225	-0.897	-0.075	-1.557	-0.407	-1.068	0.439	-0.022	-0.077
Meats	0.948	-0.354	0.016	-1.017	-0.010	-1.746	-0.095	-0.908	0.008	-1.285	0.000	-1.879	-0.052	0.089	0.027
Other food	-0.064	0.139	0.132	0.550	0.483	-0.057	-0.169	0.123	-0.043	0.046	-0.041	0.003	-0.128	-0.341	-0.340

Source: Author's Computation

fruits and vegetables by 0.3%. Similarly, a 1% price increase in commodities in the milk and milk product category results in a 0.2% increase in expenditures on meats, fish, and eggs. We can also think about some other substitutions as indicated by positive cross elasticities. However, their low magnitudes suggest quite limited substitution possibilities. On the other hand, negative cross price elasticities indicate complementary relationships. For example, among food groups, complementarity is likely between cereals with pulses. This makes sense because pulses are indispensable component of most of the cereal-based food (for example, rice, chapatti, bread are eaten together with grain legumes, beans, peas etc.) in India.

Elasticities presented in table 2.5 are conditional elasticities because they are calculated based on demand system of share equations of seven food items in QUAIDS and are conditional on the household's budget allocation to total food. Table 2.6 presents unconditional -expenditure and -uncompensated and compensated price elasticities. Unconditioning allows one to examine the pure price and expenditure effects pertaining to a particular food item. All expenditure elasticities, with the exception of the 'other food' category which was not found to be statistically significant, are positive. Expenditure elasticities ($\eta_i^{\bar{u}}$) range from 0.6 (oils & fats) to 1.17 (milk and milk products), indicating that food items used in this study are necessity to nearly unitary-elastic normal goods.

All own-price elasticities are negative. When unconditioned, the-own price effect is substantially higher in most of the food items. Own price effects from uncompensated elasticities can be further analyzed by extracting the pure price or substitution effects by computing compensated or Hicksian price elasticities. While singling out the pure price effects, compensated elasticities allow one to identify whether foods are substitutes and complements. Consistent with the findings from conditional compensated price elasticities, unconditional elasticities also suggest a substitution possibility between meat, fish, and eggs with milk & milk products, fruits & vegetables, oils & fats, and pulses. Similarly, a substitution possibility between milk & milk products and pulses is also suggested by unconditional elasticities. On the other hand, a complementary relationship between cereals and pulses and cereals and oils & fats was found.

2.5.4. Econometric Tests

Table 2.7 shows a summary of various tests conducted, null hypothesis, test-statistics, and decision of the test. For example, we conducted a test to check whether quadratic specification (QUAIDS) is better than linear specification (AIDS) of the model. From the two log likelihoods of demand models, we computed Likelihood Ratio (LR) statistics, which has the asymptotically chi-square distribution. Log likelihood of AIDS model (restricted, model under null) was 5431.968, while that of QUAIDS model (unrestricted, model under alternative) was 5489.025.

$$LR = 2(loglikelihood_{unres.} - loglikelihood_{res.}) = 2(8637.029 - 8591.028) = 92.002$$

LR-statistics of 114.11 is compared with chi-square statistics with 6 degrees of freedom ($DF_{unres.} - DF_{res.}$), thereby rejecting the null. This suggests the superiority of using QUAIDS model in our demand estimation compared to the AIDS model.[12]

Additionally, to test for demographic effects in the demand system parameters, we conducted separate Wald tests for joint significance of gender effect, marital status effect, age effect, education effects, and regional effects (table 2.7). Though we could not find a significant effect of gender and marital status of the household head on food consumption system, we found a significant effect of the age and level of education of the household head on food consumption at the 10% level of significance. Additionally, we found strong significance of regional effects on the food consumption system. These findings underscore the importance of inclusion of socio-demographic variables in the estimation of demand systems. Since these variables have significant effects on household

[12] As one reviewer point out that QUAIDS is flexible functional form, which means the estimated system may violate negativity and monotonicity. Therefore, we test for these two assumption and found that with the exception of 9, monotonicity and negativity are satisfied at all points of the data. Recall, our sample includes rural Indian households and very few data points have high income that violate negativity, which are excluded from the post-estimation.

Table 2.7: Summary of econometric and specification tests

Tests	Null hypothesis	Test statistics	Decision on test and conclusion
Quadratic Specification test	Linear model (AIDS) is better over quadratic (QUAIDS)	LR stat=114.1	Reject null; QUAIDS model is better model than AIDS
Tests for demographic and household specific effects in the demand system			
Marital status effects	Marital status of the household head has no effect on food consumption system	chi^2 (7) = 7.79 p> chi^2 =0.351	Fail to reject null
Gender effect	Gender of the household head has no effect on food consumption system	chi^2 (7) = 8.19 p>chi^2 = 0.216	Fail to reject null
Education effect	Education level of the household head has no effect on food consumption system	chi^2(7)= 17.86 p> chi^2 =0.081	Reject null (at 10% significance), Household head's education level has significant effect on food consumption system
Age effect	Age of the household head has no effect on food consumption system	chi^2(7)=15.57 p> chi^2 =0.088	Reject null (at 10% significance), Household head's age has significant effect on food consumption system
Location effects			
Andhra Pradesh	Food consumption in Andhra Pradesh is not significantly different from that of Karnataka (base)	chi^2(7) =105.6 p> chi^2 =0.000	Reject null, Household being in *Andhra Pradesh* significantly influence food consumption system
Gujarat	Food consumption in Gujarat is not significantly different from that of Karnataka (base)	chi^2(7)=95.66 p> chi^2= 0.000	Reject null, Household being in *Gujarat* significantly influence food consumption system
Madhya Pradesh	Food consumption in Madhya Pradesh is not significantly different from that of Karnataka (base)	chi^2(7)=102.81 p> chi^2 =0.000	Reject null, Household being in *Madhya Pradesh* significantly influence food consumption system
Maharashtra	Food consumption in Maharashtra is not significantly different from that of Karnataka (base)	chi^2(7)=60.11 p> chi^2 =0.000	Reject null, Household being in *Maharashtra* significantly influence food consumption system

Source: Author's computations

consumption behavior, failing to control for these effects would have led to biased price and expenditure effects and biased demand elasticities.

2.5.5. Food Demand Projections

With some assumptions about population and income growth and using our estimates of unconditional expenditure elasticities, we project food demand for rural Indian households. Population projection is presented in table 2.8. The estimates are obtained from Health, Nutrition, and Population statistics (HNPstat, 2013) and maintained by the World Bank. Projection on income growth rate was derived from the Indian economic surveys and those adapted from previous studies (Kumar, Joshi, and Birthal, 2009). We assumed income growth rates under two alternative scenarios: (a) low economic growth rate in GDP of 5% and (b) a high economic growth rate in GDP of 7%.

Table 2.8: Population projection and economic growth assumptions, India 2015-2030

Year	Growth rate assumption		Rural population projection
	Low (GDP 5%)	High (GDP 7%)	(million)
2015	3.43	4.96	862.34
2020	3.56	5.09	881.96
2025	3.69	5.22	891.5
2030	3.82	5.35	889.3

Source: Author's Compilation from various sources and previous studies

Table 2.9 presents food demand projections for respective food groups. We used expected food demand in 2016 for respective food groups as a base year demand as reported in agricultural statistics book (Pocket Book on Agricultural Statistics) recently published by the Ministry of Agriculture, Government of India (Agristat, 2013) after adjusting for the rural population share.[13] Demand projection for year t is computed using formula: $D_t = d_0\, N_t(1 + y * e)^t$, where D_t represents demand for year t, d_0 represents base year demand, N_t represent population projected for year t, y represent expected income growth during the period, and e represents expenditure

[13] The Agricultural statistics book only presents expected demand for the total Indian population. Indian population census of 2011 suggests that rural population account for 69% of total population. Based on this, we roughly estimated rural demand for the base year as 69% of the expected food demand for overall India.

elasticities. In projecting demand, we used population and income growth presented in table 2.8 and unconditional expenditure elasticities reported in the first column of table 2.9. Table 2.10 reports projected per capita food consumption by rural Indian households.

Cereals demand is projected to grow from between 156-163 million metric tons in 2020 and 157-164 million metric tons in 2030. Annual per capita consumption of cereals is projected to be around 175 to 184 kilogram (kg). Our projection for total cereal demand is slightly higher than previous studies. One of the reasons is that our expenditure elasticity for cereals is higher than previous studies

Table 2.9: Projected food demand in rural India

Food group	Unconditional Expenditure Elasticity	Projected food demand (million metric tons)						
		2016 (base)	2020		2025		2030	
			Low	High	Low	High	Low	High
Cereals	0.669	162.15	156.59	162.96	156.59	164.72	157.90	164.31
Pulses	0.847	15.18	21.76	22.88	22.75	24.22	22.82	24.29
Milk & milk products	1.17	97.29	145.55	155.83	154.15	167.86	154.90	168.65
Oils & fats	0.602	40.71	56.47	58.53	40.35	42.20	58.56	61.25

Source: Author's computations

(for example, Kumar, Joshi, and Birthal, 2009). However, note that unlike our data specific to rural households, Kumar, Joshi, and Birthal (2009) used national survey data in 2004-2005. Moreover, previous studies have also documented higher cereal expenditure elasticities in rural areas than urban. Thus the higher expenditure elasticity for cereals in our estimation may amount to our sample specific to rural village households. Table 2.10 reports that per capita consumption of pulses among rural households is projected to be fairly stable at approximately 24 to 27 kg in 2020 and 2030. Per capita consumption of milk and milk products is projected to be increasing over the next 15 years, while the per capita demand of oils and fats is projected to be relatively lower in 2025 but increasing slightly in 2030. Our study provides a more updated projection based on the rural household demand pattern. Increasing demands for cereals and milk & milk products suggest that the scope of production for these food groups will also increase in the future. Consumption of pulses and oils &

Table 2.10: Projected food consumption per capita for rural households

Food group	Projected per capita consumption (in Kilograms)					
	2020		2025		2030	
	Low	High	Low	High	Low	High
Cereals	177.55	184.77	175.65	184.77	177.55	184.77
Pulses	24.67	25.94	25.52	27.17	25.66	27.31
Milk & milk products	165.03	176.69	172.91	188.29	174.18	189.65
Oils & fats	64.03	66.37	45.26	47.34	65.85	68.87

Source: Author's computations

fats seem to be relatively stable. These estimates may provide insight for agricultural production and supply side policies. Our study suggests that there is a scope of supporting production policies in cereals and dairy industry or their food substitutes in India.

2.6. Summary and Conclusions

This study adds to the limited literature on food demand research in India, particularly in relation to its rural population. This study utilizes a novel data set collected by International Crops Research Center for Semi-arid Tropics (ICRISAT) and contributes to the literature in several ways. First, it examines rural household food demand in a large country, India, where the majority of the population lives in a rural setting. Rural households allocate a large portion of their resources for food production, so as to guarantee income sources for consumption, be it on food or on other commodities and services. Second, the study estimates a total food demand model in the first stage, accounts for two stage budgeting decision, and appropriately computes unconditional elasticities. Third, the study uses more appropriate QUAIDS in modeling food demand system that allows for more flexible and realistic functional form consistent with economic theory. Finally, unlike previous studies, this study includes demographic factors that could have an impact on food demand among rural households.

This study examined the food demand system by allocating the food expenditure shares to seven major food groups and augmenting socio-demographic characteristics. The study found that consumption expenditure share varies across food groups, and more importantly along and across income. Own-price elasticities for each food group were negative but with varying range from inelastic to relatively elastic. Expenditure elasticities for food items are positive. Milk and milk products, and different meats are necessary-luxury while cereals and pulses are basic necessity goods. Matrices of compensated and uncompensated price elasticities suggested the significant income (expenditure) effect on food consumption. We also find a number of significant substitution and complementary relationships between food groups. Among food groups, complementarity was between cereals with pulses and cereals with oils & fats. Findings from this study suggested substitutability in consumption between milk & milk products with meats, oils & fats with meats. Finally, this study found a significant impact of demographic attributes, such as characteristics of household head, and regional variables on household food consumption behavior.

Using our unconditional elasticities, we projected demand for four food groups in India for next two decades. Demand projection from our study provides an updated picture of projection using recent data and rural consumption pattern. Particularly, our projection suggests that per capita demand of cereals and milk & milk products will be slightly increasing in the future while those for pulses and oils & fats are relatively stable. This finding provides a good insight for agricultural crop and dairy production planning and policies. Further research while overcoming limitations from this study could focus on, for example, but not be limited to, differentiating demand system for more specific disaggregated food items that account for heterogeneity in quality.

2.7. References

Abdulai, A. 2008. Household demand for food in Switzerland. A quadratic almost ideal demand system. *Swiss Journal of Economics and Statistics* (SJES) 138:1-18.

Agristat. 2013. Pocket Book on Agricultural Statistics. Ministry of Agriculture, Department of Agricultural and Cooperation, India.

Alderman, H., J. Hoddinott, L. Haddad, and C. Udry. 1995. *Gender Differentials in Farm Productivity: Implications for Household Efficiency and Agricultural Policy*. Food and Consumption Division Discussion Paper 7. International Food Policy Research Institute, Washington DC.

Banks, J., R. Blundell, and A. Lewbel. 1997. Quadratic Engel curves and consumer demand. *Review of Economics and Statistics* 79:527-539.

Blundell, R., J.M. Robin, et al. 1999. Estimation in Large and Disaggregated Demand Systems: An Estimator for Conditionally Linear Systems. *Journal of Applied Econometrics* 14:209-232.

Boysen, O. 2012. A Food Demand System Estimation for Uganda. Working paper, The Institute for International Integration Studies.

Bronte-Tinkew J, and DeJong G. 2004. Children's nutrition in Jamaica: Do household structure and household economic resources matter? *Soc. Sci Med*. 58:499-514.

Cameron, A.C., and P.K. Trivedi. 2005. *Microeconometrics: methods and applications*. Cambridge university press.

Carpentier, A., & Guyomard, H. 2001. Unconditional elasticities in two-stage demand systems: an approximate solution. *American Journal of Agricultural Economics*, *83*(1), 222-229.

Cirera, X., & Masset, E. (2010). Income distribution trends and future food demand. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1554), 2821-2834.

Cranfield, J.A., J.S. Eales, T.W. Hertel, and P.V. Preckel. 2003. Model selection when esti-mating and predicting consumer demands using international, cross section data. Empirical Economics 28:353-364.

Deaton, A., and J. Muellbauer. 1980. An almost ideal demand system. The *American Economic Review* 70:312-326.

Decoster, A., and F. Vermeulen. 1998. Evaluation of the empirical performance of two-stage budgeting AIDS, QUAIDS and Rotterdam models based on weak separability. Katholieke Universiteit Leuven, Department of Economics, Center for Economic Studies.

Deis, D.R., and R.C. Hill. 1998. An Application of the Boostrap Method to the Simultaneous Equations Model of the Demand and Supply of Audit Services. Contemporary Accounting Research 15:83-99.

Dyson, T., R. Cassen, and L. Visaria. 2005. Twenty-first century India: population, economy, human development, and the environment. OUP Catalogue, Oxford University Press.

Edgerton, David. 1993. On the estimation of Separable Demand Models. *Journal of Agricultural and Resource Economics* 18(2): 141-146.

Edgerton, David. 1997. Weak separability and the estimation of elasticities in multistage demand systems. *American Journal of Agricultural Economics* 79(1): 62-−-79.

Fashogbon, A.E., and O.A. Oni. 2013. Heterogeneity in Rural Household Food Demand and Its Determinants in Ondo State, Nigeria: An Application of Quadratic Almost Ideal Demand System. *Journal of Agricultural Science* 5: p169.

GOI. 2009. Report of the Expert Group to Review the Methodology for Estimation of Poverty. Working paper, Government of India, http://planningcommission.nic.in/reports/genrep/rep_pov.pdf

HNPstat. 2013. Health, Nutrition, and Population Statistics. World Bank, http://datatopics.worldbank.org/hnp/.

Jodha, N. S., M. Asokan, and J. G. Ryan. 1977. 'Village Study Methodology and Resource Endowments of the Selected Villages in ICRISAT's Village Level Studies'. Economics Programme Occasional Paper 16. Hyderabad: ICRISAT.

Kumar, P., P. Joshi, and P.S. Birthal. 2009. Demand Projections for Food grains in India. *Agricultural Economics Research Review* 22.

Meenakshi, J., and R. Ray. 1999. Regional differences in India's food expenditure pattern: a complete demand systems approach. *Journal of International Development* 11:47-74.

Murphy, K.M., and R.H. Topel. 2002. Estimation and inference in two-step econometric models." *Journal of Business & Economic Statistics* 20:88-97.

National Sample Survey Office (NSS). 2011. Level and Pattern of Consumer Expenditure, 2009-2010. Report Number 538. Ministry of Statistics and Programme Implementation, Government of India, New Delhi.

Poi, B.P. 2008. Demand-system estimation: Update. *The Stata Journal* 8:554-556.

Poi, B.P. 2012. Easy demand-system estimation with QUAIDS. *The Stata Journal* 12:433-446.

Poi, B. P. 2002. Dairy policy and consumer welfare. In *Three Essays in Applied Econometrics*, Chapter II, Doctoral thesis. Department of Economics, University of Michigan.

Ray, R. 1983. Measuring the costs of children: an alternative approach. *Journal of Public Economics* 22:89-102.

Tanumihardjo, C. Anderson, M. Kaufer-Horowitz, L. Bode, N. Emenaker, A. Haqq, J. Satia, H. Silvers, D. Stadler. 2007. Poverty, Obesity, and Malnutrition: An International Perspective Recognizing the Paradox. *Journal of the American Dietetic Association* 107(11): 1966-1971.

Thompson, W. 2004. Using elasticities from an almost ideal demand system? Watch out for group expenditure! *American Journal of Agricultural Economics* 86:1108-1116.

Walker TS and Ryan JG. 1990. Village and household economies in India's Semi-arid tropics. Baltimore and London: The Johns Hopkins University Press.

Wooldridge, J.M. 2009. *Introductory econometrics: a modern approach.* South-Western Pub.

World Bank. 2010. Development Indicators. http://data.worldbank.org/indicator. The World Bank. Washington DC

CHAPTER 3: IMPACT OF WEATHER RISK ON LAND USE INTENSITY: A NON-STATIONARY AND DYNAMIC PANEL MODELING APPROACH

3.1. Introduction

There are several common factors that affect the agricultural sector around the world. These include market price fluctuations, changes in domestic and agricultural policies, credit markets and facilities, and management practices, to name a few. However, because of its inherent link to natural resources, agricultural production is also affected by variations in climate (or weather risk), which in turn influences agricultural productivity and patterns of land use. Weather risk (also referred to as weather variability) not only impacts human settlements but also places greater pressure on agricultural land and production agriculture. As the population of our planet continues to grow, it is expected that an increase in human encroachment on uncultivated fallow and forest lands and a subsequent shifting of agriculture in developing countries—which is where the majority of the population resides. For many low-income rural households in developing countries, their most important source of income is farm production. Take the case of India where crop production dominates and agricultural returns for most farming households is most important source of income. Weather risk, then, may lead to undesirable variability in agricultural output and subsistence farming in India as well as in other developing countries where rural households cultivate smaller holdings, primarily farming to raise crops for household consumption and income.

To further understand the difficulties posed by weather risk (or climate variability), it is important to note that farmers in developing countries are classified as risk-averse agents (Rosenzweig and Binswanger 1992; Lamb 2002). In the absence of crop insurance and well-functioning credit markets, farmers undertake ex-ante or ex-post activities to self-insure income or to smooth consumption. There is a growing consensus among policymakers and research scientists that weather risk influences the performance of agricultural firms, so farmers need to adopt strategies to minimize their losses (Whinston et al., 1981; Rosenzweig and Perry 1994; Seo and Mendelson 2008; Taraz 2012). This is especially true for developing countries where agricultural production depends highly on rainfall and the ability of the farmers to adapt is considerably low. Thus, weather risk appears to impact the agricultural sector to such an extent that many are concerned with the future of global food production (Bindi and Olesen, 2000)[14] and its impact on income uncertainties.

Finally, weather risk is important to consider given the link between the agricultural sector and poverty. In particular, it is anticipated that adverse impacts on the agricultural sector will exacerbate the incidence of rural poverty. Impacts on poverty are likely to be especially severe in developing countries where the agricultural sector is an important source of livelihood for a majority of the rural population. Farmer's behavior is affected by weather outcomes; they directly impact cropping decisions. Farmers in Semi-arid regions like India and poor countries rely solely on rainfall as a source of moisture for crops; therefore, annual and seasonal rainfall patterns influence their food crop portfolio (Bezabih and Falco, 2012). For example, subject to the expectation of high or low rainfall, farmers may alter the types of crops or change the amount of land they cultivate. Additionally, weather risk could push farmers away from farming, inducing occupational shifts or migration to other areas. However, in most of the rural villages in India and other developing countries, fewer opportunities exist for other income generating activities. In this situation, weather risk may induce farmers to allocate even more land area for a variety of crops with the objective of loss minimization.

In other words, if rainfall is more likely to be erratic, farmers may diversify crops by planting more area with different crops; this minimizes income risk by ensuring a positive overall return from

[14] Declines in aggregate production are anticipated in most of Africa and South and East Asia. For example, Murdiyarso (2000) highlights that rice production in Asia may decline by 3.8 percent of production levels of 2000.

non-sensitive crops while compensating for losses in sensitive crops. This raises an important issue of how to measure land allocation among different crops and how much land is available (total cropped area and cultivable fallow) to the farmers. Recall Townsend (1994) reported that one of the important self-insurance mechanisms for income risk among rural households in India is through diversification of a given farmer's land holdings into various spatially separated plots and into various crops.

Land use, adaptation to weather risk and changes in agricultural productivity have been previously studied in several developing countries (Masvaya, Mupangwa and Twomlow, 2008; Graef and Heigis, 2001). However, the literature falls short in assessing the impact of weather risk on land use intensity (defined, in this study, as the ratio of total (net) cropped area to total cultivable area[15]). Additionally, the literature has failed to account for the spatial or temporal nature of weather risk on land use intensity.[16] It should be of paramount importance to analyze the effect of spatial and temporal phenomena (for example, weather risk over time, population growth, rural literacy, irrigation availability, availability of improved varieties, etc.), both short and long run, on land use intensity. Utilization of the information in terms of both cross-sectional variation and time variation leads to better insights; panel data modeling approaches offer much better inferences. Moreover, policymakers may be interested in designing policy incentives that may mitigate farmer's exposure to weather risk and enhance agricultural production and income of farm families under weather adversities.

Therefore, the objective of this study is to assess the impact of weather risk[17] on land use intensity. In particular, we use a different class of non-stationary and panel data modeling techniques to examine the short-run and long-run relationships between weather risk and land use intensity. To

---

[15] Cultivable area includes gross cropped area and cultivable fallow area.

[16] Also used interchangeably as cropping intensity.

[17] Weather risk in this study is measured by variability in rainfall, a major source of weather risk.

accomplish our objective we use district-level data compiled by the International Crops Research Institute for the Semi-arid-Tropics (ICRISAT[18]) based on agricultural production and climatic information gathered from the years 1966 to 2007 in rural Indian villages. Further, to test the robustness of findings we also estimate our empirical model for various agro-ecological zones, within the Semi-arid Tropics region of India during the pre-market reform period—1966-1990 and post-market reform (after 1990) period.

This paper contributes to the literature in several ways. First, the study uses panel data gathered over a significantly long time period which included several significant changes in production agriculture, policies, and weather conditions. Panel analysis provides inferences for both short-run and long-run estimates of weather risk on land use intensity. For example, inferences from short-run analysis may serve as a base for further studies on crop-portfolio choices, and income generation and management by farming households. Farmers and policymakers, and bankers, who are involved in the agricultural sector may wish to decrease the sensitivity to short-run weather risks on production levels and hence prices of important agricultural commodities. This will become even more important as global warming is expected to increase short-run weather variations not only in India but across much of the world. Inferences from the long-run analysis contribute to the literature by adding further insights in farmers' adaptation to mitigate weather risk, an issue that has garnered a significant attention in the recent literature (Rosenberg and Perry, 1994; Mendelsohn and Dinar, 1999; Macous, Premand and Vakis, 2012). Second, this paper fills a gap by offering empirical evidence of long-run consequences of weather risk on land use intensity.

[18] The International Crops Research Institute for the Semi-arid Tropics (ICRISAT) is a non-profit agricultural research organization headquartered in Patancheru (Hyderabad, Andhra Pradesh, India) with several regional centers (Niamey, Niger and Nairobi, Kenya) and research stations (Bamako, Mali and Bulawayo, Zimbabwe. It was founded in 1972 by a consortium of organizations convened by the Ford and Rockefeller Foundations. Its charter was signed by the FAO and the UNDP.

3.1.1 Monsoons and Indian Agriculture

Most of the annual rainfall in India occurs from June to September during what is referred to as the summer monsoon or southwest monsoon.[19] Though rainfall during this season may be a regular occurrence, it also lends to irregular variations in the amount of seasonal mean rainfall from one year to the other. There are many instances of years with either flooding (strong monsoon) or drought (weak monsoon) during which India as a whole receives excess or deficient seasonal rainfall, respectively. Even within a season, there is considerable variations in the rainfall over India, both in space and time. The Indian monsoon exhibits large variations on intraseasonal to interannual and interdecadal time scales (Krishnamurthy and Shukla, 2000). Although the summer monsoon over India occurs regularly from June to September, the year-to-year variation of the seasonal mean monsoon is considerable and has a major impact on agriculture in India. The interannual variability of the seasonal monsoon is nonperiodic.[20] The spatial structure of the interannual variations of the Indian rainfall reveals that central India and the Western Ghats have large variability (Krishnamurthy and Shukla, 2000; Prasanna and Yasunari, 2009). In addition, Gadgil (1996) and Webster et al. (1986) note that interannual variability shows a large impact on agricultural production and gross domestic product of India.[21]

Nearly 70% of the working population of India depends on agricultural activities for its livelihood, and the majority of the population as a whole depends on wheat, rice, sorghum and pulses for personal consumption. Summer monsoons provide the main source of water for the country's

[19] The winter monsoon or the northeast monsoon brings rainfall to the southeastern part of India through northeasterlies from October to December and contributes a small percentage to the annual Indian rainfall.

[20] For more discussion on the processes involved in monsoon variability, see Shukla 1987.

[21] Dinar et al. (1998), note that in India a 2^0C rise in mean temperature and a 7 percent increase in the mean precipitation would create a 12 percent reduction in net revenues for the country.

agricultural production during two crop seasons, Kharif (summer) and Rabi (winter). Thus, variations in rainfall during the monsoons affect the total food grain yield of India and also the country's economy (Krishna et al., 2004). Krishna et al. (2004) point out that more than 60% of the cropped area in India still depends solely on monsoon rainfall, with the poorest farmers practicing rainfed agriculture. Although there has been substantial growth in agricultural production, there is also substantial variability in the trend. Weather variability is regarded as the primary cause of year-to-year fluctuations in crop yields. Finally, Krishna et al. (2004) concluded that crop response to monsoon rainfall does have some predictability. A difference in rainfall or temperature from normal conditions reduces yield and ultimately net income of farmers and their households.

3.2. Literature Review

Broadly, major investigations in the literature on climatic conditions and production agriculture can be classified under three major areas: (1) the impact of weather conditions on crop production and yield; (2) the impact of weather (short-run) and climatic (long-run) factors on crop choices; and (3) ex-post income diversification activities as a response to weather risk. Income diversification activities include off-farm work and/or adaptation through management practices, such as crop portfolio choices. A plethora of studies in crop sciences and agronomy, development economics, and agricultural economics have discussed the issue of weather and climatic conditions and its impact on production agriculture (for example, Rosenzweig and Parry, 1994; Seo and Mendelsohn, 2008; Taraz, 2012; Bezabih and Falco, 2012; Traore et al., 2013; Graef and Haigis, 2001).

In a recent study, Traore et al. (2013) investigated the effect of climate and weather on production of cotton, soybean and groundnut using long-term experimental data (1965-2005) from Southern Mali. The authors found a negative impact of maximum temperature and total seasonal rainfall on cotton yield, while corn yield was positively correlated with total season rainfall in relatively drier locations. In another agronomic study, Graef and Haigis (2001) found that rainfall variability resulted in a significant yield loss for millet in Semi-arid areas of Niger. They reported two major strategies to mitigate rainfall variability at the farm-level, which were to cultivate fields in different locations within the village district and to plant as much area as possible.

From a global perspective, Rosenzweig and Parry (1994) sought to understand the potential impact of climate change on world food supply. They concluded that vulnerability to changes in weather and climate differs between developed and developing countries. They went on to suggest interdisciplinary research on biophysical and socioeconomic aspects to explore the sensitivity towards and mitigation of climate change. Literature regarding the impact of weather and climatic factors influencing crop choices is rather limited (Lamb, 2002; Bezabih and Falco, 2012). Lamb (2002) investigated the impact of weather risk[22] on crop choices (allocation of land across crops) in three villages in India and found that crop choices were influenced by weather risk in two of the three villages. However, there are several weaknesses of Lamb's (2002) study. First, the study focused on the impact of wealth on crop mix. Second, the study ignored inter-land use. Third, the study neglected to use the panel dynamics technique. Finally, it used a short time period (1957-1984) to analyze wealth effect as well as a small dataset—three villages which included only a small number of farms.

Recall that variability in rainfall is an important source of uncertainty in agricultural production decisions. Households mostly rely on crop choice diversification to hedge against weather risk (Kurukulasuriya and Mendelsohn, 2006; Rosenzweig and Parry, 1994). For example, Bezabie and Falco (2011) used household and plot-specific longitudinal data (2000, 2002, 2005, and 2007) from the Amhara National State of Ethiopia to analyze riskiness of crops and how the household's choice of

[22] Weather risk is measured by variability in the start date of monsoon season, with at least 20 millimeters of rainfall after June 1st.

crops affected its crop portfolio riskiness. They found that level of riskiness of crop portfolios was partly motivated by both annual and seasonal rainfall variability and moisture-sensitive crops. Household behavior suggested that farm households chose less moisture-sensitive crops in times of rainfall shortages and combined risky and less-risky crops in places with greater variability in rainfall. Therefore, one can conclude that in response to rainfall variability, farmers are more likely to select less risky crops with lower return; crop selection and crop management practices are ex-ante practices aimed towards mitigating rainfall risk (Bezabih and Falco, 2012).

Finally, Seo and Mendelsohn (2008) investigated adaptation to changing climate of 949 South American farmers in seven different countries.[23] Analyzing the crop choice among seven of the most popular crops under different environmental conditions across the landscape, they concluded that both temperature and precipitation affected crop choices. Additionally, through simulation modeling, the authors concluded that crop switching is a possibility for the future. However, it should be noted that the study has several weaknesses. The cross-sectional nature of the data on crop choice is limiting. The authors assume that in forecasting climate change impacts, the only thing that changes in the future is climate, but, due to the cross-sectional nature of the data, they were not able to capture technological advances, population, and institutional changes. In addition, climate data (temperature and rainfall) were interpolated from the World Meteorological Organization (satellite-based) and the cross-sectional data did not capture crop switching over time. Our study improves on these weaknesses by using panel data and providing robust estimates of the empirical model.

While crop choices, crop mix, and production diversifications are ex-ante risk management, income diversification through off-farm labor supply is explained as major ex-post adjustment. Some studies relate crop production and weather risk with household-specific behavior, human capital, and

[23] Includes Argentina, Brazil, Chile, Columbia, Ecuador, Uruguay, and Venezuela.

household economic conditions. For example, Dercon (1996) examined poor households' use of risk-management and risk-coping strategies and crop choices in Tanzania. Choosing a less risky crop portfolio, which is the mostly likely behavior of poor households, may lead to substantial low income resulting from low returns to crop portfolio. Even with low returns, farm households choose low-risk crops because they are not able to find jobs in nonfarm sectors (Dercon 1996). In another study, in Tanzania and Ethiopia, Dercon and Krishnan (1996) found that income diversification in nonagricultural wage employment was restricted to people even with education. Lastly, Dercon (2002) used cross-country surveys to examine strategies that farm households use to cope with risk and found that entry constraints, like lack of education, limit a poor household's income diversification opportunities. It should be noted that Dercon (2002) did not specifically address the issue of weather risk and ex-post use of risk management tools. Our paper addresses this important issue by including a variable (share of rural literates)[24] in the empirical model.

Though the aspects of weather risk, climate change, agricultural production and adaptation has been discussed in a variety of disciplines, concrete evidence based on responses through farming behavior requires careful attention. Additionally, most of the studies mentioned above use cross-sectional or aggregate level data. Note that cross-sectional studies and/or aggregate state-level time-series studies which are focused on specific regions may lack generalization. The literature is missing solid evidence to support theory and strong empirical study to provide a different perspective on weather risk, crop choice, and land use intensity. In addition, the above studies have not investigated cropping intensity (cropped area/total cultivable area). Another important consideration to better understand farmer's adjustment behavior in response to weather risk is its short- and long-run effects

[24] Unfortunately, schooling variable at the district level is not available in our dataset, but a good proxy at the district level aggregation—rural literate population—is available.

on land use intensity. In that respect, the literature falls short of concrete empirical evidence that can be generalized. Moreover, due to possibilities of multi-dimensional factors such as agricultural system, behavioral responses, and constraints due to weather and other dimensions of risk, the adjustments to weather risk is more of an empirical question that requires careful attention. Our study aims to fill this gap in empirical literature by providing evidence of short- and long-run responses to weather risk and farmer's adjustment behavior using a panel data that accounts for temporal and spatial aspects. The data are taken from the 1966-2007 period and for 115 districts in rural India. We further test the robustness of the impact of weather risk on land use intensity for agro-ecological zones and during the pre-market reform period—1966-1990 and post-market reform (after 1990) period.

3.3. Conceptual Model

We consider a model of land allocation for the cropping decision (acreage decision) of a farm household. Consider a simple income-leisure utility function of a farm household. The farm household maximizes utility subject to production and time constraints, where utility is a function of farming household's total income (I) and leisure (l). Specifically,

$$U = U(I, l) \tag{1}$$

However, total income of the farm household (I) is composed of income from farm (π) and off-farm sources (O_I), $I = \pi + O_I$. We further assume that education (E) is the major determinant of off-farm work decisions and $\frac{\partial O_I(.)}{\partial E} > 0$; *i.e.*, farm households with more educated members in the household are more likely to choose off-farm work in rural areas over farming. Therefore, equation (1) can be written as:

$$U = U\left(I\left(\pi + O_I(E)\right), l\right). \tag{2}$$

The fm household's profit function from agriculture is defined as

$$\pi = P * Q(A, L^F, K, \phi) - C(Q, r), \tag{3}$$

where *C(.)* represents the cost function and *Q(.)* represents a concave production function of a farm household. *P* is a vector of farm output prices and *r* is a vector of input prices. Labor and capital inputs for production are represented as L^F and *K*, respectively. Labor on the farm, L^F, is allocated on the basis of total time, $T = L^F + L^o + l$, where *T* represents total time; L^F is labor provided for farm production; and L^o and *l* represent off-farm labor supply and leisure of farm households, respectively. Land acreage allocated for various crop production is represented by A, with the possibility of acreage allocation for crops enterprise $i = 1, 2, \dots . j$, such that $A = \sum_i A_i$. Note that *A* is a subset of total cultivable area available to the farmer (*G*). Specifically, *G* is the sum of total cropped area and total cultivable fallow (land that is available for cultivation, either in the same location or in another location across the village). This is consistent with the concept of Jodha, Singh, and Bantilan (2012) who document that the villages in the district have significant fallow land and the allocation varies across years and districts. ϕ represents a vector of other exogenous variables influencing farm production. For fixed capital and labor inputs (usually for the short-run), land allocation is a major input for total crop production. However, in the long-run there could be adjustments in factors of production.

Weather is another important factor that affects land allocation to crops. However, as established in the literature, it is the variability or riskiness in weather conditions (such as rainfall and temperature) that may alter land allocation decisions. Let us now introduce weather riskiness (measured as a coefficient of variation), CV_w, that influences total land allocation decisions for crops in the above equation (3). Specifically,

$$\pi = P * Q(A(CV_w), L^F, K, \phi) - C(Q, r) \quad (4)$$

Assuming G, the total cultivable (total land available) land, we define land use intensity (total cropped area over total cultivable area) as $S_A = \frac{A(A_i)}{G}$. Now we can represent the weather risk augmented model in equation (4) as:

$$\pi = P * Q(S_A(CV_w), L^F, K, \phi) - C(Q, r) \tag{5}$$

In response to weather risk, the farmer could perform two tasks. First, the farmer could increase the intensity of cropping, $\frac{\partial(S_A(CV_W))}{\partial CV_W} > 0$, *i.e.*, allocate more acreage under crops, diversifying the crop portfolio, and perhaps including more acreage under less risky crops, as noted by Bezabie and Falco (2011). Alternatively, the farmer could decrease the intensity of cropping, $\frac{\partial(S_A(CV_W))}{\partial CV_W} < 0$, *i.e.*, allocate less acreage under agricultural crops. This may imply that the farmer moves away from cropping or planting crops altogether. We can assume that the farm household with a higher potential for off-farm opportunities may move away from farming when weather risk increases. It is likely that in farm households with educated members, $\frac{\partial L^F(CV_W)}{\partial CV_W} < 0$ in equation (5) and $\frac{\partial I(O_I(E))}{\partial CV_W} > 0$ in equation (2).

3.4. Econometric Method

Equation (5) can be transformed to derive the empirical model. Empirically, we estimate the short-run and long-run sensitivity of land use intensity to weather risk (measured by variability in rainfall) as

$$S_{A_{i,t}} = \Gamma CV_{W_{i,t}} + \beta X_{it} + \alpha_i + \varepsilon_{it} \tag{6}$$

where $S_{A_{i,t}}$ represents land use intensity in district *i* and year *t*. Our main variable of interest, weather risk in district *i* and year *t*, is represented by $CV_{W_{i,t}}$. X_{it} includes exogenous control variables that may affect land use intensity. These include the share of rural literates in the district, a proxy for education; share of cultivators (ratio of number of cultivators to total rural population in the district); share of planted land in a high yielding variety; availability of agricultural labor (total agricultural labor over total rural population in the district); and share of irrigated area (net irrigated area over gross cropped area). Finally, α_i controls district-level fixed effects.

Equation (6) is estimated using panel data. Broadly, two types of panel data models have been discussed in the literature. The first are models with large cross-sectional units but a small time-span (*large N* and *smaller or fixed T*). These panel models require pooling individual groups and allowing only the intercepts to differ across the groups. To this end, we can estimate the fixed effects model in which the time series data for each group are pooled and only the intercepts are allowed to differ across the groups.[25] However, if the slope coefficients are not identical, these estimators could result in misleading inferences. Previous studies have found that the assumption of homogeneity of parameters across groups is often inappropriate (Phillips and Moon, 2000; Baltagi, 2005; Pesaran, Shin, and Smith, 1999).

The second option is to use a model with larger cross-sectional units and large time span (*larger N* and *larger T*). In recent years, there has been a growing interest in such cases, such as sets of countries, regions or industries, where there are fairly long time-series' for a *large* N. This second approach can be utilized in estimation of non-stationary or co-integrated panel models where heterogeneity in parameters is allowed across groups (see Narayan et al., 2010; Mark and Sul, 2003; Costantini and Martini, 2009). This approach will be used in our study.

Techniques to estimate non-stationary dynamic panels in which the parameters are heterogeneous across groups—the mean-group (*MG*) and pooled mean group (*PMG*) estimators—has been presented by Pesaran, Shin, and Smith (1997, 1999). With the MG estimator, the intercepts, slope coefficients, and error variances are all allowed to differ across groups. The PMG estimator, on

[25] For a detailed description of panel data models, we refer to Baltagi (2005).

the other hand, combines both pooling and averaging. This allows the intercept, short-run coefficients, and error variances to differ across the groups but constrains the long-run coefficients to be the same across groups. Applying the assumption of these models, representing our empirical model as an autoregressive distributive lag (ARDL) $(p, q_1, q_2, \dots \dots q_k)$ dynamic panel specification, we have the following form:

$$S_{A_{i,t}} = \sum_{j=1}^{p} \lambda_{ij}\, S_{A_{i,t-j}} + \sum_{j=0}^{q} \tau'_{ij}\, X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{7}$$

where $i = 1, 2, \dots N$ and $j = 1,2, \dots T$ represent number of groups (in our case, districts) and the time periods (in our case, years), respectively. X_{it} is a $k \times 1$ vector of explanatory variables; τ_{ij} are the $k \times 1$ coefficient vectors; and λ_{ij} are scalars; and μ_i is the group specific effect. Note that all explanatory variables in the equation (6), including CV_W are now included and expressed as vector X in equation (7) for notational convenience. The inherent assumption is that when variables in equation (7), for example $I(1)$ and cointegrated, the error term is an $I(0)$ process for all i. Cointegrated variables are responsive to any long run equilibrium and are expressed in the error correction model where short-run dynamics of the variables in the system are influenced by the deviation from equilibrium. Therefore, our empirical model in equation (6) and specification in equation (7) is parameterized into following error correction equation (Blackburne and Frank, 2007) and estimated:

$$\Delta S_{A_{i,t}} = \emptyset_i\left(S_{A_{i,t-1}} - \tau'_i X_{it}\right) + \sum_{j=1}^{p-1} \lambda^*_{ij}\, \Delta S_{A_{i,t-j}} + \sum_{j=0}^{q-1} \delta'^*_{ij}\, \Delta X_{i,t-j} + \mu_i + \varepsilon_{it}, \tag{8}$$

where parameter ϕ_i is the error-correcting speed of adjustment term. If $\phi_i = 0$, then there would be no evidence for long-run equilibrium. Particular interest is the vector τ'_i which contains the long run relationship between the variables while δ'^*_{ij} contains short run relationship.

Asymptotic of *large T* and *large N* dynamic panel models is different from the traditional *large N and small T* dynamic panel model (Baltagi, 2005). With increase in time observations which are inherent in a *large N* and *large T* dynamic panel, non-stationarity arises and must be addressed.

Therefore, we need to test for non-stationarity using stationary, unit root, and cointegration tests. Since these tests confirmed coinegration and our data has both large N and large T components, we present only the results of the cointegrated models.

There are many options for panel stationary and unit root tests. Hardi (2000) has developed several residual-based Lagrange multiplier tests for heteroskedastic and serially dependent error processes with a null hypothesis of trend stationarity. We use Hardi's (2000) test to test for non-stationarity. Thereafter, we present results applying dynamic OLS (DOLS) model, dynamic fixed effects (*DFE*) model, and MG and PMG models. Specifically, MG and PMG models are estimated to assess the short-run and long-run effects of weather risk on land use intensity.

3.5. Data

This study uses survey data collected by the International Crop Research Institute for Semi-arid Tropics (ICRISAT) in India. Specifically, we use the *meso*-level data. This data is useful in identifying priority target areas to track poverty in the Village Dynamics Studies (VDS). The *meso* data acts as a link between the country/state/district level macro/meso-data and household-level micro data. Our sample includes data for 115 districts from 1966 to 2007 in five states (Andhra Pradesh (AP), Madhya Pradesh (MP), Maharashtra (MH), Karnataka (KT), and Haryana (HR)). Figure A1 in appendix shows the five states and their locations on the Indian map.

The meso-level dataset contains data pertaining to the performance, structure and behavior of a national or regional economy at a disaggregated district, state, or province level in India. District-level data for the 19 states indicated in the map is available from 1966 onwards for core and additional variables such as area and production (crop-wise), irrigation, land use, wages and prices, input use,

Table 3.1: Description and summary statistics of the variables, 1966 to 2007

Variable definition	Mean	Standard Deviation
Land use intensity (*total (net) cropped area over total cultivable land area*[1])	0.750	0.115
Weather risk [*Share of unexpected rainfall (total annual rainfall-total rainfall in June, July, and August) to total annual rainfall*[2]]	0.342	0.217
Cultivator share (*share of total cultivators (farmers) in total rural population, district level*)	0.226	0.119
Agricultural labor availability (*total agricultural labor population over total rural population, in the district*)	0.170	0.105
Rural literate share (*rural literate population over total rural population, in the district level*)	0.392	0.289
HYV production share (*area under high yielding varieties over gross cropped area*)	0.228	0.181
Irrigated area share (*total irrigated area (net) over gross cropped area*)	0.190	0.145
Agro-ecological Zones (AEZ)[4]		
AEZ 1	0.200	0.400
AEZ 2	0.123	0.328
AEZ 3	0.641	0.479
AEZ 4	0.036	0.186
Total observations	4,782	

[1] cultivable area includes total hectare available for cultivation (gross cropped area and cultivable fallow area).
[2] weather risk = $\frac{Total\ annual\ rainfall - total\ June,\ July,\ August\ rainfall}{Total\ annual\ rainfall}$
[3] includes total literates in urban and rural areas of the district.
[4] Agro-ecological zones are classification of districts under different zones based on weather, climatic conditions, and agriculture. This classification is based on National Agricultural Innovation Project (NAIP) code of Indian Govt. as recommended by Indian Council of Agricultural Research (ICAR).
Source: Author's compilation based on ICRISAT meso-data, 1966-2007.

census data (human population and livestock population), infrastructure (roads, markets, banks and veterinary institutions) and climatic variables. Meso-level dataset of ICRISAT has compiled district-level information on different climatic and land-use variables such as annual and June-July rainfall, soil-type, irrigated acreage, and high yielding varieties production area. Additionally, information on rural and urban population, farming population, rural and urban agricultural labor, and number of literates in the rural population are available through different modules of the ICRISAT meso-level dataset.

Table 3.1 presents variable definitions and summary statistics in raw form (*i.e,* summary of district-time data points). In total we have 4,782 district time observations (panel) that are used in our analysis. The total cultivable area in a district, on average, is about 719,000 hectares out of which the total cropped area is about 635,000 hectares; however, a small area (119,000 hectares) is irrigated land. On average, 84,288 hectares in a district, on average, is left fallow. The average district comprises of 1.5 million people living in rural areas and of which 250,000 are agricultural workers. About 39% (572,000) of the rural population, in the average district, can read and write. Finally, on average, 151,000 hectares in a district has been devoted to high yielding varieties of crops. We calculated district-level land use intensity as the ratio of total cropped area to total available area for cultivation (this includes gross cropped area and cultivable fallow areas; excludes area for non-agricultural uses, buildings, permanent fallow areas). Average land use intensity is 0.750 with standard deviations of 0.115. This indicates that around 75% of the total cultivable area, in a district, has been allocated for agricultural production (for crops). Overall, we find an increasing land use intensity trend in most of the districts over time. Recall that during the months of June, July and August, India experiences a monsoon season; much of it is expected rainfall that farmers have come to realize over the years. However, we are interested in measuring the off-season variability in rainfall that is unexpected. This variability in rainfall, an indicator for weather risk, is measured by the ratio of the difference between total annual rainfall and rainfall in the months of June, July, and August to total annual rainfall, in each district, in a year. Share of this off-season rainfall is about 0.34 with standard deviation of 0.22.

Our data suggests that only 22.6% of the rural population in the district are farmers or cultivators as indicated by share of cultivators (defined as the ratio of total cultivators (farmers) to total rural population in the district). This also could be referred as the intensity of farmers. On the other hand, data indicates that share of agricultural labor availability (ratio of total agricultural labor available to total rural population, in the district level) is about 17% with a standard deviation of 0.11. Another variable of interest is the literacy rate in the rural areas. Rural literacy (share of rural literate population to total rural population, in the district), is a proxy for educated individuals in the rural area; is about 39%. Indicator of irrigation facility and production of high yielding varieties (HYV) are captured by two variables: namely, the share of irrigated cropped area (defined as the ratio of net irrigated area to gross cropped area); share of area under HYV (defined as the ratio of total area under HYV to gross cropped area). The share of irrigation variable suggests that only 19% of the gross cropped area in the district, on average, is irrigated; share of area under HYV indicates that only 23% of gross cropped area in the district, on average, is used for HYV crops.

Additionally, to provide robustness of our findings in different regions, we estimated our equation across different agro-ecological zones (AEZ). The classification of AEZs is based on National Agricultural Innovation Project (NAIP) code of Indian Government as recommended by the Indian Council of Agricultural Research (ICAR). Gulati and Kelley (1999) have used a slightly modified version of the agro-ecological region (AER) classification system used by the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) of the Indian Council of Agricultural Research (ICAR). The AEZ identifies areas based on ecological and agricultural factors which take a comprehensive view of suitable crop potentials and the basis for a cropping pattern which can exploit the resources of the area to the maximum. Since better rainfed crop production is dependent on the selection of suitable land use pattern at a region, delineation of agro-ecological zones forms a useful basis. The methodology used in the delineating of agro-ecological region includes: (1) mean monthly temperature, higher than 18 degrees Celsius; (2) mean monthly precipitation; (3) type of soil; and (4) length of growing period, LGP, (Subramaniam, 1983). In our case, the AEZs are defined into four categories (based on ICRISAT's database): namely AEZ1 to AEZ4 and AEZs are represented as regional dummies. Humid region (LGP >180 days) represents AEZ1. Semi-arid Temperate (LGP: 75-179 days and Temp: <18^0C) is represented by AEZ2. Semi-arid Tropic (LGP: 75-179 days and Temp: >18^0C) region is represented by AEZ3. Finally, Tropic region (LGP: 0-74 days) is represented by AEZ4—crops include wheat and rice.

3.6. Results and Discussion

First, we will discuss the panel non-stationary, unit root, and cointegration tests. The results of this analysis are presented in Table 3.2. Test results show the evidence that variables of interest in our study are non-stationary in levels form but stationary in the first difference form (see table 3.2, upper panel). With respect to the null hypothesis, no cointegration (table 3.2, lower panel), we use both Pedroni (2004) and Kao (1999) tests for panel data because the Pedroni (2004) test is based on a pooled data type of test, while the Kao (1999) test is based on an augmented Dicky-Fuller (ADF) type of test. Based on these tests, results show a rejection of the null hypothesis based on both the Pedroni (2004) and the Kao (1999) tests, concluding that the variables of interest in our study are cointegrated, implying that one should use a non-stationary dynamic panel modeling approach.[26] Next, using cointegrating regressions suitable for non-stationary dynamic panel models—assume both *N* and *T* approach infinity asymptotically, we estimated the short-run and long-run association between land use intensity, weather risk, and other factors of interest.

Table 3.3 presents results of the non-stationary dynamic panel models.[27] The second column, (table 3.3), presents the dynamic fixed effects regression (DFE) and the results suggest that there is a

[26] Recall that the analysis is performed on district level data and endogeneity may not be an issue. Secondly, to further test for endogeneity we performed a regression based test, to test for possible factors (share of irrigated acres, and share of HYV) that could be endogenous. In both cases we fail to reject the null hypothesis (H_0: the variable is exogenous).

[27] Based on a reviewer's comment, appendix table A1 reports the effect of individual variable without control variables. We also test for causality and using Granger causality test (pairwise test) we rejected the null hypothesis.

long-run association between land use intensity and weather risk, share of rural literates, share of HYV cropped area, and the share of irrigated area. Based on the model fit and test, we adjusted the model by including appropriate lags in the dynamic model. The effects of all these variables are significantly different from zero at the 5% level of significance. A coefficient of 0.015 on the weather risk (in our DFE model) result suggests that a 10% increase in weather risk increases land use

Table 3.2: Stationary, unit root and co-integration tests for panel data

Stationarity tests for Panel Data	Hardi z-statistic	Heteroskedastic consistent z-statistic
Stationary test on variables[1] in **level** form		
H_0: weather risk is stationary	19.18**	9.30**
H_0: land use intensity is stationary	53.71**	44.60**
H_0: rural literate share is stationary	16.57**	14.54**
H_0: rural cultivators share is stationary	16.34**	14.69**
H_0: high yielding variety production per cultivable area is stationary	36.78**	34.66**
H_0: availability of agricultural rural labor is stationary	16.16**	12.45**
H_0: share of irrigated area is stationary	38.39**	29.39**
Stationary test on variables in **first difference** form		
H_0: first difference of weather risk is stationary	-5.60 (*p=0.99*)	-5.54 (*p=0.99*)
H_0: first difference of land use intensity is stationary	-4.77 (*p= 0.99*)	-3.53 (*p=0.98*)

Co-integration Tests[2]	Pedroni (1995)	Kao (1999)
H_0: No integration, H_a: Common AR coefficient (within dimension)		
Panel v-statistic	-0.59 (*p=0.72*)	
Panel rho-statistic	-3.89** (*p<0.000*)	
Panel PP statistic	-18.88** (*p<0.000*)	
Panel ADF statistic	-5.81** (*p<0.000*)	3.64** (*p<0.000*)
H_0: No integration, H_a: Individual AR coefficient (between dimension)		
Group rho statistic	1.45 (*p<0.92*)	
Group PP-statistic	-21.40** (*p<0.000*)	
Group ADF statistic	-3.93** (*p<0.000*)	

Single and double asterisks (*, **) indicate significance at the 10%, and 5% level or above.
[1] we also conducted stationary test for the log of each of the variables and obtained test results with same conclusions.
[2]we also conducted co-integration test of the variables each transformed in log form. The test results suggested same conclusion, even more strongly. For example, statistic from Kao test: -15.51 (*p< 0.000*).
Source: Author's computations

intensity by approximately 0.2%. On the other hand, the long-run effect of a 10% increase in the share of rural literates decreases land use intensity by about 0.4%. Similarly, a 10% increase in the share of

HYV cropped area and the share of irrigated area decreases land use intensity by about 0.2% and 0.4%, respectively.

Table 3.3: Long-run and short-run effects of weather risk: non-stationary panel models for large N and large T (dependent variable: land use intensity, in logs)

	Dynamic FE	Mean Group (MG) regression	Pooled Mean Group (PMG) regression
Long-run coefficients			
Weather risk[a]	0.015**	0.041**	0.017*
	(2.45)	(1.96)	(1.75)
Ag. labor availability[a]	-0.015	0.190	0.029*
	(-0.72)	(1.53)	(1.82)
Rural literate share[a]	-0.044**	-0.187	-0.060**
	(-2.72)	(-3.23)	(-3.95)
Cultivator share[a]	0.022	0.319**	0.065**
	(0.84)	(2.07)	(3.07)
HYV production[a]	-0.021**	-0.012	-0.001*
	(-3.15)	(-1.00)	(-1.78)
Irrigated area share[a]	-0.046**	-0.0754	-0.055**
	(-4.20)	(1.25)	(-4.53)
Short-run coefficients			
D.Weather risk[a]	-0.003**	0.0002	-0.011**
	(-1.49)	(0.40)	(-2.01)
D.Ag. labor availability[a]	-0.010	-0.053	-0.074
	(-1.29)	(-0.38)	(-0.74)
D.Rural literate share[a]	0.014**	-0.018	-0.017*
	(2.38)	(-1.50)	(-1.65)
D.Cultivator share[a]	-0.014*	-0.113	-0.118
	(-1.70)	(-0.63)	(-0.92)
D.HYV production[a]	0.004**	0.021	0.012
	(2.00)	(1.52)	(1.10)
D.Irrigated area share[a]	0.013*	0.110*	0.103**
	(0.83)	(2.64)	(3.15)
Constant	0.135**	0.104	0.120**
	(7.72)	(0.72)	(8.59)
Adjustment factor (∅)[b]	0.329**	0.686**	0.330**
	(10.42)	(17.57)	(9.90)
N		1,812	1,812

[a] Variables are in log*; D.* refers to first difference; *t* statistics in parentheses; single and double asterisks (*, **) indicate significance at the 10%, and 5% level or above, respectively.
[b] Also known as error-correction factor.
Source: Author's computation

Allowing for the heterogeneity of parameters across groups, we estimated and present results for the mean group (MG) and pooled mean group (PMG) estimates[28] (column 3 and 4 of table 3.3). Incidentally, the MG results suggest that a 10% increase in weather risk increases land use intensity by about 0.4%, while the PMG estimator suggests an increase in land use intensity by about 0.2%. These results are much higher than the estimates obtained by DFE model. The PMG result suggests a positive long-run effect of agricultural labor availability and share of cultivators on land use intensity. For instance, a 10% increase in the availability of agricultural labor increases land use intensity by about 0.3% while a same percentage increase in the share of cultivators (farmers) in the district increases land use intensity by about 0.7%. Additionally, results suggest a negative long-run impact of the share of rural literates, the share of HYV cropped area, and the share of irrigated area on land use intensity, in the district. For example, coefficient suggests that a 10% increase in the share of rural literates, in the district, reduces land use intensity by about 0.6%. Findings here may suggest that as the share of literates in the rural population, in the district, a proxy for educational attainment, may lead to increased opportunities for off-farm employment, especially in the presence of weather risk. The adjustment factor (ϕ), also referred as the error-correction factor, in error-correction models for cointegrated economic variables are commonly interpreted as the speed of adjustment towards a long-run relationship. For example, a zero adjustment factor, $(\phi = 0)$ would indicate an evidence for no long-run relationship; however, findings in table 3.3 indicate a significant adjustment factor across all models. For instance, $\phi = 0.33$ (column 4, table 3.3) indicates a 33% adjustment in error-correction model towards long-run equilibrium model.

[28] The MG estimator relies on estimating N time series regressions and averaging the coefficients, whereas the PMG estimator relies on a combination of pooling and averaging the coefficients (Pesaran and Smith, 1995; Pesaran, Shin, and Smith, 1999).

Table 3.4: Hausman test results for model choice between Dynamic FE, MG, and PMG models

Hausman test	Hypothesis	Chi-square Statistics	Conclusion
Comparison between MG and Dynamic FE	MG estimator is consistent under null and alternative Dynamic FE is inconsistent under alternative, efficient under null	0.01 (*p* $>chi^2$ *=0.99*)	Dynamic FE model, efficient under null, is preferred over MG model
Comparison between MG and PMG regression	MG estimator is consistent under null and alternative PMG estimator is inconsistent under alternative, efficient under null	6.29 (*p* $> chi^2$ *=0.39*)	PMG estimator, the efficient estimator under the null hypothesis, is preferred

Source: Author's computations

Finally, we conducted a Hausman test to compare which model is more suitable (among DFE, MG, and PMG) in explaining land use intensity; results are presented in table 3.4. The two sets of Hausman test suggests that the DFE model is preferred over the MG model and the PMG model is preferred over the MG model. Overall, the DFE and the PMG model estimates suggest a long-run positive impact of weather risk, a negative effect of the share of rural literates, and a positive effect of a share of irrigated area on land use intensity, respectively. A positive effect of weather risk on land use intensity may suggest crop mix diversification behavior by farmers and an increase in total cropped area (perhaps, more area allocated to less risky crops). Reardon et al. (1994) supported this idea with the finding that farm households in West Africa fragmented their land holdings into many plots and grew different crops on them—intensification.

This may seem dubious at first glance because it seems more likely that farmers would move away from farming to diversify income through alternative off-farm jobs; the negative coefficient of weather risk on land use intensity (lower half, table 3.3) may provide indirect evidence that in the short-run farmers may not be able to alter land use or cropping intensity—by perhaps working off the farm—but in the long-run farmers may be able to increase land use intensity as a result of weather risk. Further, farmers with low or no outside opportunities respond to weather risks by cultivating more land in different locations and with different crops (crop mix)—self-insurance mechanism, an argument that is consistent with Graef and Haigis (2001). Recall that land use intensity is defined as the ratio of total net cropped area to total cultivable land area. Finally, our findings are consistent with Townsend (1994) who found that one of the important self-insurance mechanisms for income risk among rural households in India is through diversification of a given farmer's land holdings into various spatially separated plots and into various crops.

Recall total cultivable land includes gross cropped land and cultivable fallow land. A plausible mechanism for a positive relationship between weather risk and land use intensity is that when farmers are subject to extreme conditions of weather, they are more likely to utilize cultivable fallow land to plant crops. Jodha, Singh and Bantilan (2012) have reported practices such as fallowing, crop mix, crop rotation for enhanced land use intensity in response to weather and climatic changes in Indian villages. Additionally, focus group discussions with farmers reveals a positive correlation between weather risk and land use intensity. For example, farmers revealed that when there is more rainfall, more than the average, and if it is in the early part of June and July, then it is likely that it leads to higher cultivation acreage in Kharif season. Further, if there is more than adequate water in irrigation reservoirs, farmers have better access to irrigation water in the following Rabi season. This ex-ante knowledge of the probability of getting more and scheduled canal water in the subsequent season would motivate farmers to increase crop acreage in the following Rabi season.

On the other hand, if there is a shortfall in rainfall, less than the average, then farmers respond by increasing crop acreage in the following Rabi season in order to compensate for the loss of crop yield in the preceding Kharif season. Additionally, farmers who leave the village for seasonal migration—usually before Kharif season, tend to hand over the land to other fellow farmers who are likely to grow crops in more acreage in the following Rabi season. Thus, in practice, the crop productivity may be negatively affected by higher fluctuations in rainfall in a year, than the normal rainfall, but the net crop acreage is likely to increase due to various economic incentives related to the factors as noted above (GOI, 1989; Jodha, Singh, Bantilan, 2012; Rao, Anand, and Bantilan, 2009; Rao et. al., 2004).

Moreover, a reduction in fallow land and the increase in total cropped acreage increases our land use intensity measure. To provide external validity of our district-level findings, we tested this mechanism in village level dataset. Based on the village level data from 2001 to 2011, we found a negative correlation of absolute deviation in normal rainfall in the village with percentage of fallow land in the village. For example, we present this relationship in appendix A1 for Dokur village, a negative correlation of 0.50 and figure A1 suggests that during years of higher deviations of rainfall from normal, less fallow lands were left in the village—consistent with our findings that higher weather risk leads to higher land use intensity.[29]

A negative effect of the share of rural literate in rural population, within the district, on land use intensity could be explained through the relationship of education and off-farm labor supply that has been established in farm household literature (Mishra et al., 2002). Increase in human capital (*i.e.*, more education) in rural areas increases the opportunities for off-farm work, thereby inducing farmers (presumably educated farmers or spouses) to move away from farming. Therefore, it is not surprising to observe that as the share of rural literates in the rural population increases, intensity for land use decreases. Increase in the share of HYV cropped acreage—an indication of adoption of improved varieties and progressive farming—decreases land use intensity. A plausible explanation is that increased planting in higher yielding crops, which are usually intensive in nature, increases returns to farming and thus may result in less cropped acreage to receive same output level. Lastly, as expected,

[29] Additionally, we also plot relationship between total cropped area and rainfall deviation, and total rainfall amount and percentage fallow land in the village. The plots suggested that cultivation in the village are rainfall dependent and the intensity of land use increases with higher use of fallow lands.

results show a negative effect of the share of irrigated acreage on land use intensity. Districts with higher share of irrigated acreage are less dependent on rainfall and tend to utilize all possible cultivable land by expanding cropping area and exploiting economies of scale. Thus, in the irrigated areas, relatively less land is available for additional utilization for crops.

Table 3.5: Impact of weather risk on land use intensity, by agro-ecological regions

	AEZ1	AEZ2	AEZ3	AEZ4
Long-run coefficients				
Weather risk[a]	0.0376*	0.0254**	0.0098*	-0.0102
	(1.80)	(1.97)	(1.65)	(-0.43)
Ag. labor availability[a]	-0.0724*	-0.0114	0.0401	-0.0430
	(-1.85)	(-0.27)	(1.41)	(-0.62)
Rural literate share[a]	0.0384	-0.0506**	-0.0872**	-0.0577
	(1.64)	(-2.39)	(-3.85)	(-0.66)
Cultivator share[a]	0.0634*	0.0296	0.0572**	-0.00275
	(1.66)	(0.54)	(2.13)	(-0.03)
HYV production[a]	-0.00335	0.00681	-0.0278**	-0.0791**
	(-0.36)	(0.30)	(-3.19)	(-2.48)
Irrigated area share[a]	-0.0288*	-0.0471	-0.0383**	-0.0826*
	(-1.92)	(-1.21)	(-2.48)	(-1.72)
Short-run coefficients				
D.Weather risk[a]	-0.00522	0.00890*	-0.00634**	-0.00566
	(-1.03)	(1.77)	(-2.66)	(-0.43)
D.Ag. labor availability[a]	-0.0235*	0.00780	-0.00893	0.0388
	(-1.94)	(0.67)	(-0.74)	(0.40)
D.Rural literate share[a]	0.0237**	0.00789	0.0141	-0.0649
	(2.50)	(0.83)	(1.61)	(-0.58)
D.Cultivator share[a]	0.000238	-0.00957	-0.00929	0.0646
	(0.02)	(-0.78)	(-1.23)	(0.71)
D.HYV production[a]	0.00585*	0.00413	0.00300	-0.00990
	(1.71)	(0.45)	(1.31)	(-0.56)
D.Irrigated area share[a]	0.0528**	0.0728*	-0.0125	0.00467
	(2.23)	(1.85)	(-0.82)	(0.03)
Constant	0.103**	0.119**	0.109**	0.485**
	(4.37)	(3.43)	(4.59)	(4.15)
Adjustment factor (∅)	0.323**	0.303**	0.332**	0.633**
	(6.33)	(2.83)	(9.00)	(4.32)

[a] Variables are in log; *t* statistics in parentheses; single and double asterisks (*, **) indicate significance at the 10% and 5%, level, respectively.
Source: Author's computations.

Next, in order to test the robustness of our findings across regions, we use region-wise regressions. Since land use and agriculture in a region tends to vary more distinctly by agro-ecological features, we estimated the empirical model across different agro-ecological zones (AEZ). Recall

AEZ's are described above in this study. Table 3.5 presents the estimates of AEZ region-wise regressions. Our results suggest that the effect of weather risk on land use intensity is positive and consistently significant across AEZ1, AEZ2 and AEZ3 agro-ecological regions; the magnitude is highest in AEZ1 followed by AEZ2 and AEZ3. Recall that, AEZ1 agro-ecological region is humid region (LGP >180 days) and farmers depend on rainfall for their crops. At the same time we also find that irrigated acreage (share of irrigated acreage) has a negative impact on land use intensity. Although the impact of weather risk on land use intensity is not significant for AEZ4, the effects of share of HYV acreage and share of irrigated acreage is negative and the magnitude of the coefficients are highest. A negative effect of education (share or rural literates) on land use intensity is significantly different from zero in the AEZ2 and AEZ3 agro-ecological zones.

Table 3.6: Effect of weather risk on land use intensity: before and after market reform

Dep. Var.: land use intensity	*Before 1990* Period	*After 1990* Period
Weather risk[a]	0.0098**	0.0133
	(2.25)	(1.10)
Ag. labor availability[a]	-0.0119	-0.0534
	(-0.70)	(-0.94)
Rural literate share[a]	0.00854	-0.166**
	(0.74)	(-5.14)
Cultivator share[a]	-0.0112	0.00952
	(-0.66)	(0.12)
HYV production[a]	-0.0131**	-0.00129
	(-3.22)	(-0.19)
Irrigated area share[a]	-0.0250**	-0.0591**
	(-2.80)	(-2.13)

[a] Variables are in log*;* *t* statistics in parentheses; single and double asterisks (*, **) indicate significance at the 10% and 5%, level, respectively.
Source: Author's computations

Finally, we extend our model to test the effects in two periods: a) *before 1990,* which represents the periods of incidence and expansion of early Green Revolution; b) *after 1990,* which represents periods of matured Green Revolution and liberalized Indian economy that promoted investment in infrastructure and irrigation facilities, globalized markets, and increased commercialization of the agricultural sector. Our results suggest that the effect of weather risk and share of HYV acreage on land use intensity was higher in magnitude in the *before 1990* period than the *after 1990* period (Table 3.6). On the other hand, the effect of irrigation (share of irrigated acreage) and education (share of rural literates) were significant and higher in magnitude for the *after 1990* period (columns 3, table 3.6).

3.7. Summary and Conclusion

Weather and climatic conditions play an important role in agricultural production. Variability and risks associated with climate and weather not only influence farmers' decision on crop choice but also on land use intensity; additionally, they may also influence a farmer's or farm household's decision to farm in the first place. This paper presents empirical evidence on a relationship between weather risk and land use intensity using a panel of 115 districts in India from 1966 to 2007 period. We tested for cointegration and used a non-stationary dynamic panel model to estimate the empirical model. Results indicate a positive long-run effect of weather risk on land use intensity. The positive relationship is quite strong and robust among all estimated panel models—dynamic FE, mean group (MG), and pooled mean group (PMG) estimation techniques. The findings are significant and consistent even with the inclusion of additional regressors. Additionally, our results suggest that as the share of educated individuals in the district rises, land use intensity decreases—presumably, in the presence of weather risk, these individuals taking advantage of off-farm opportunities. Finally, results from our study indicates that the impact of weather risk is diminished in the post-market reform period (1990) in India. This period has been marked with implementation of market oriented policies in agriculture, input markets, and infrastructure and irrigation development.

With an opportunity to choose alternative income generating activities such as off-farm jobs, a positive effect of weather risk on land use intensity may first seem dubious. However, the scenario of peasant households in rural areas and subsistence farmers could be different, in that they have fewer off-farm opportunities and hence less likely to find off-farm jobs. Instead, in this case a response towards weather risk would be to diversify crop mix and increase land allocation for less risky crops with the intended objective to stabilize quantity of food produced. This latter behavior results in an increase in land use intensity. Note that we have not tested for crop-specific area allocations in this study; this warrants further investigation. Another limitation of this study may come from the use of district-level aggregate data. Micro-level, crop-specific data on land use intensity and cropping patterns may be more helpful in validating the above findings. Finally, land quality and land type variables may also help in providing better insights.

3.8. References

Baltagi, Badi. 2005. *Econometric Analysis of Panel Data*. Wiley Publication, New York, NY.

Bangake, C. and J.C. Eggoh. 2011. " The Feldstein–Horioka puzzle in African countries: A panel cointegration analysis." *Economic Modelling* 28: 939–947

Bezabih, M. and S. Di Falco. 2012. "Rainfall variability and food crop portfolio choice: evidence from Ethiopia." *Food Security* 4(4): 557-567.

Bezabih, M., and S. D. Falco and M. Yesuf. 2011. Farmer's Response to Rainfall Variability and Crop Portfolio Choice: Evidence from Ethiopia. Discussion paper, Environment for Development. EFD DP 11-10. http://www.rff.org/RFF/Documents/EfD-DP-11-10.pdf

Bindi, M. and J. E. Olesen. 2000. "Agriculture." In M. L. Parry ed. Assessment of Potential Effects and Adaptations for Climate Change in Europe: The Europe ACACIA Project. Norwich, United Kingdom: Jackson Environment Institute, University of East Anglia.

Blackburne III, E. F., and M.W. Frank. 2007. "Estimation of Nonstationary Heterogeneous Panels." *Stata Journal* 7(2): 197-208.

Cameron, A. C., and P. K. Trivedi. 2009. *Microeconometrics Using Stata*. Vol. 5. College Station, TX: Stata Press.

Costantini, V. and C. Martini. 2010. "The Causality between Energy Consumption and Economic Growth: a Multi-sectoral Analysis Using Non-stationary Cointegrated Panel Data." *Energy Economics* 32(3): 591-603.

Dercon, S. 1996. "Risk, crop choice, and savings: Evidence from Tanzania." *Economic Development and Cultural Change*, 44(3): 485-514.

Dercon, S., and P. Krishnan. 1996. "Income Portfolios in Rural Ethiopia and Tanzania: Choices and Constraints." *Journal of Development Studies* 32(6):850-75.

Dercon, S. 2002. “Income Risk, Coping Strategies, and Safety Nets.” *The World Bank Research Observer*, 17(2): 141-166.

Dinar, A., R. Mendelsohn, R. Evenson, J. Parikh, A. Sanghi, K. Kumar, J. McKinsey, and S. Lonergan. 1998. “Measuring the imapct of climate change on Indian agriculture.” Technical Paper 402. World Bank, Washington, D.C.

Gadgil. S. 1996 Climate change and agriculture–an Indian perspective; In: Climate Variability and Agriculture (eds) Abrol Y R, Gadgil S and Pant G B. New Delhi, India.

Government of India (GOI). 1989. Agro-climatic regional planning (an overview), New Delhi, India: Planning commission, Government of India.

Graef, F., and Haigis, J. 2001. "Spatial and Temporal Rainfall Variability in the Sahel and its Effects on Farmers' Management Strategies." *J. of Arid Environments* 48(2): 221-231.

Gulati A and T. Kelley. 1999. Trade Liberalization and Indian Agriculture. New Delhi, India: Oxford University Press. Pp 15-36.

Hadri, K. 2000. "Testing for Stationarity in Heterogeneous Panel Data." *The Econometrics Journal* 3(2): 148-161.

Jodha NS, Singh NP and Bantilan MCS. 2012. Enhancing Farmers’ Adaptation to Climate Change in Arid and Semi-arid Agriculture of India: Evidences from Indigenous Practices: Developing International Public Goods from Development-oriented Projects.Working Paper Series no. 32. International Crops Research Institute for the Semi-arid Tropics, Patancheru, India.

Kao, C. 1999. “Spurious regression and residual-based tests for cointegration in panel data.” *Journal of Econometrics* 90(1):1-44.

Krishna, K. K., Rupa, K. K., Ashrit, R., Deshpande, N. R., and Hansen, J. W. 2004. Climate impacts on Indian agriculture; *Int. J. Climatol*. 24: 1375–1393.

Krishnamurthy, V., and J. Shukla, 2000: Intraseasonal and interannual variability of rainfall over India. *J. Climate,* 13, 4366-4377.

Kurukulasuriya, P., and Mendelsohn, R., 2007. Crop selection: adapting to climate change in Africa. World Bank Working Paper 4307. Washington DC.

Lamb, R. L. 2002. Weather Risk, Crop Mix and Wealth in the Semi-arid Tropics. *Department of Agricultural and Resource Economics Report No, 25*. Raleigh, NC.

Macours, K., Premand, P., and Vakis, R. 2012. “Transfers, Diversification, and Household Risk Strategies," Policy Research Working Paper 6053, the World Bank.

Masvaya, E., W. Mupangwa, and S. Twomlow. 2008. Rainfall Variability Impacts on Farmers' Management Strategies and Crop Yields. Paper presented at the 9th Water Net/WARFSA/GWP-SA Annual Symposium, Johannesburg, South Africa, 29-31 October 2008. Amsterdam, Netherlands: WaterNet.

Mendelsohn, R. and A. Dinar. 1999. "Climate change, agriculture, and developing countries: does adaptation matter?" *The World Bank Research Observer* 14(2): 277-293.

Mishra, A., M. Morehart, H. El-Osta, J. Johnson, and J. Hopkins. 2002. Income, wealth, and well-being of farm operator households. Agricultural Economics Report # 812, Economic Research Service, U.S. Department of Agriculture, Washington, D.C.

Murdiyarso, D. 2000. "Adaptation to Climatic Variability and Change: Asian Perspectives on Agriculture and Food Security." Environmental Monitoring and Assessment 61(1):123-131.

Narayan, P. K., S. Narayan, A. Prasad, and B.C. Prasad. 2010. "Tourism and Economic Growth: A Panel Data Analysis for Pacific Island Countries." *Tourism economics*, 16(1):169-83.

Rao, P., Birthal, P. S., Dharmendra, K., Wickramaratne, S. H. G., & Shrestha, H. R. 2004. Increasing livestock productivity in mixed crop–livestock systems in South Asia. *Project report. National Centre for Agricultural Economics and Policy Research & ICRISAT (International Crops Research Institute for the Semi-arid Tropics), Patancheru, India*.

Rao N.G.D , Anand, B.P, and Bantilan M.C.S. 2009. Dynamics and development pathways in the Semi-arid Tropics: Dokur village profile. Research Bulletin no 23. ICRISAT, Patancheru, India.

Prasanna, V., and Yasunari, T. 2009. Time-space characteristics of seasonal and interannual variations of atmospheric water balance over south Asia. *Journal of the Meteorological Society of Japan*, Vol. 87(2): 263—287.

Pesaran, M. H. and R. Smith. 1995. "Estimating Long-run Relationships from Dynamic Heterogeneous Panels." *Journal of Econometrics* 68(1): 79-113.

Pesaran, M. H., Y. Shin, and R. P. Smith. 1999. "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels." *J. of the American Stat. Assoc.* 94(446): 621-634.

Pedroni, P. 1999. "Critical values for cointegration tests in heterogeneous panels with multiple regressors." *Oxford Bulletin of Economics and statistics* 61(S1): 653-670.

Phillips, P.C.B. and H. R. Moon. 2000. "Nonstationary Panel Data Analysis: An Overview of Some Recent Developments." *Econometric Reviews* 19(3): 263-286.

Rao, GD Nageswara, P. Anand Babu, and C. S. Bantilan. 2009. *Dynamics and Development Pathways in the Semi-arid Tropics: Dokur Village Profile. Research Bulletin no. 23*. International Crops Research Institute for the Semi-arid Tropics, Patancheru, India.

Reardon, T., A. A. Fall, V. Kelly, C. Delgado, P. Matlon, J. Hopkins, and O. Badiane. 1994. “Is Income Diversification Agriculture-Led in the West African Semi-arid Tropics?” In A. Atsain, S. Wangwe, and A. G. Drabek, eds., Economic Policy Experience in Africa: What Have We Learned. Nairobi: African Economic Research Consortium.

Rosenzweig, M. R. and H. P. Binswanger. 1992. “Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments,” Policy Research Working Paper Series 1055, The World Bank.

Rosenzweig, C. and M. L. Parry. 1994. "Potential impact of climate change on world food supply." *Nature* 367: 133-138.

Seo, N. S. and R. Mendelsohn. 2008. "An analysis of crop choice: Adapting to climate change in South American farms." *Ecological Economics* 67(1): 109-116.

Shukla, J., 1987. Interannual variability of monsoons. Monsoons, J. S. Fein, and P. L. Stephens, Eds.,Wiley and Sons, pp: 399-463.

Subramaniam, A. R. 1983. Agro-ecological zones of India. Arch. Met. *Geophys. Bioclim. Ser. Bull.*, 32: 329–333.

Taraz, Vis. “Adaption to Climate Change: Historical Evidence from the Indian Monsoon” 2012. http://www.econ.yale.edu/_vt48/Vis Taraz jmp.pdf.

Traore, B., M. Corbeels, M. T., van Wijk, M. C. Rufino, and K.E. Giller. 2013. “Effects of Climate Variability and Climate Change on Crop Production in Southern Mali” *European Journal of Agronomy*, 49: 115-125.

Townsend, R.M., 1994. “Risk and insurance in Village India.” *Econometrica* 62 (3):539-591.

Webster, P. J., Magana, V. O., Palmer, T. N., Shukla, J., Thomas, R. A., Yanai, M., and Yasunari, T. 1998. Monsoons: Processes, predictability and the prospects of prediction; *J. Geophys. Res.* 103 14,451–14,510.

Whitson, R. E., et al. 1981. “Machinery and crop selection with weather risk.” *Transactions of the ASAE, American Society of Agricultural Engineers* 24 (2): 288-291.

CHAPTER 4. WEATHER RISK AND FOOD CROP PORTFOLIO CHOICE

4.1. Introduction

Although there have been significant improvements in overall agricultural productivity in recent decades, the agricultural sector still faces tremendous challenges in food production and distribution, especially when it comes to developing countries. The Food and Agriculture Organization (FAO) of the United Nations states that "there is sufficient capacity in the world to produce enough food to feed everyone; nevertheless, in spite of progress made over the last two decades, 805 million people still suffer from chronic hunger" (FAO, 2014). Most of the rural households in developing and low income countries depend, to a significant extent, on agriculture for their livelihoods. Additionally, small farm households represent a significant proportion of agricultural production in developing countries. Finally, the availability (and access) of food, major component of food security, depends on the agricultural productivity of these farm households. To this end, farm households face significant challenges in generating a stable income from agriculture. Farm households need to embrace agricultural and non-agricultural activities to manage agricultural production and price risks.

Weather and climatic variability is one of the important factors affecting agricultural production and land allocation (Lobell and Field, 2007; Stige et al. 2006; Tao et al. 2008). Additionally, weather and climate induced changes in agriculture affect the livelihood of agricultural households because they likely affect both incomes earned and food prices faced by poor households (Burke and Lobell, 2010; Morton 2007). To cope with fluctuating weather, farm households need to manage their farm activities and investments. As a self-insurance mechanism in the presence of pervasive risk, farm households are likely to undertake ex-ante risk coping mechanism. Previous studies have indicated that rural farm households in the low-income countries are likely to behave sub-optimally under such risks rather than a profit maximizing agents (Rosenzweig and Binswanger 1993;

Yesuf and Bluffstone, 2009). Hence, in anticipation of different degrees of weather and production risks, farm households may choose to diversify their crops by growing less profitable but less risky crops (Benin et al., 2004) to hedge risk rather than undertaking investments with higher expected returns.

A number of studies have discussed the nature of crop riskiness and its relation to weather and market uncertainties (Dercon 1996; Haile 2007; Lamb 2002). However, previous studies have some limitations. These include: (1) Most of the studies are based on subjective assessment of the riskiness associated with crops; (2) the studies only deal with major crops while ignoring the nature of multicropping. An exception to previous studies is the study by Bezabih and Di Falco (2012) in Ethiopia. The authors presented an objective way of estimating the riskiness of individual crops and then aggregating them to build a crop risk portfolio using a single-index approach. Additionally, they assessed the effect of rainfall variability on crop risk portfolios of Ethiopian farm households[30].

To the best of our knowledge, none of the previous studies has assessed the impact of weather risk on a farmers' risk based crop portfolio index in South Asia. There are several differences in the nature of crops grown and the structure of farm households between Sub-Saharan Africa and Semi-arid tropical regions in South Asia, which is the focus of this study. For example, cash crops and some cereals such as coffee, pulses, oil seeds, teff, and corn are the major components of Ethiopian agriculture. However, in South Asia, the sub-tropical region of India in particular, cereal crops such as rice and wheat are the main staples and intercropping of legumes and multicropping with corn, potato, sugarcane, and oil seeds on the same plot is a common occurrence. It should be noted that intercropping and multicropping is a common feature of subsistence farming in India. Therefore, the objective measure of crop riskiness may lead to better insights than subjective measures. When it

[30] The survey households were in two zones (South Wollo and East Amhara) of the Amhara National Regional State, part of North and Central highlands of Ethiopia. Survey was done from same households for the years 2000, 2002, 2005, and 2007 crop seasons; rainfall data was from Meteorological stations from 1976-2006.

comes to exogenous shocks, Kochar (1995) found that small farm households in India are able to mitigate some effects of crop shocks through increased off-farm labor supply. In that, off-farm labor supply is expected to increase the risk bearing capacity in the food crop portfolio. While this possibility of risk adjustment through off-farm labor supply is lacking in Bezabih and Di Falco (2012), we capture this prospect by including a control variable representing the household head's off-farm job or service activities in the model.

With regard to crop choice in response to weather risk, Taraz (2014) studied farmers' adaptation to multi-decadal rainfall regimes in Indian monsoon and found that farmers are likely to adapt through adjustments in crop portfolio and investment in irrigation facilities. Another study with regard to crop mix and weather risk is by Lamb (2002). By regressing profits against measures of crop share and rainfall uncertainty, Lamb (2002) found that farmers' choices of crop mix are affected by weather risk. However, Lamb (2002) was based only on production data in three villages in India and with only major crops, while ignoring intercropping and multicropping.

Therefore, it is important to know about risk responses and farmer's crop choices, especially in developing countries. Farmers' response to weather risk through adjustments in the crop portfolio helps in understanding how well the farmers are able to mitigate non-systematic components of risk through crop diversification. Diversification through crop portfolio provides helpful information for both private and public sectors including policy-makers, for example, by providing insights into a crop insurance program and quantifying risk premiums.

Two aspects are important in the household-level crop choice decision: first, riskiness of each crop and second, risk management of crop by choosing appropriate crops in their portfolio. The objective of this study is twofold: first, to investigate how crop choices make up food crop portfolio based on the riskiness of crops and second, to assess the relation of crop portfolio choice in presence of variability in weather (weather risk). This study uses household-level panel data for five years

(2008 to 2012) collected by International Crop Research Institute for Semi-arid Tropics (ICRISAT) from 18 different villages in the Semi-arid tropical region of India.

4.2. Literature Review

The effect of weather and climatic variations in agricultural production gets considerable attention in agronomic, geographic, environmental, and development economic literature. In the absence of well functioning insurance and credit markets, farmers need to undertake a self-insurance mechanism to manage production risks. Poor households in developing and low-income countries are more vulnerable to weather risk and rely on production decisions and crop choices to hedge against weather risk (Rosenweig and Parry, 1994; Kurukulasuriya and Mendelsohn, 2007). As risk averse agents, famers may undertake activities such as maintaining crop diversity, crop sequencing or rotation, intercropping, and multicropping to stabilize returns from cultivated lands and to restore soil productivity (Jodha, Singh, and Bantilan, 2012; Benin et al., 2004). Since choice and diversification activities have risk hedging or risk-coping motives rather than profit maximizing, these may be viewed as sub-optimal behavior. For example, farmers manage risk by choosing less profitable but less risky crops instead of high yielding risky crops (Morduch 2002; Kurukulasuriya and Mendelson 2007).

Lamb (2002) presented an evidence of risk aversion behavior in crop choice among poor farmers in India by presenting farmers' deviation from profit maximizing behavior. He argues that a higher wealth level provides farmers the ability to choose a mix of crops with average profits, for example by choosing riskier high yielding varieties (Lamb, 2002). In another study, Seo and Mendelson (2008) analyzed crop choices among seven main crops by South American farmers. They found that farmers adjust the choice of crops as well as the area under those crops to fit with local climatic conditions. Kurukulasuriya and Mendelson (2008) found that farmers often choose crop combinations such as maize-beans, cowpea-beans, cowpea-sorghum and millet-groundnut to ensure more flexibility against harsh climatic conditions in Africa. Moreover, greater diversity in crops can reduce the risk of crop failure (Di Falco and Chavas, 2009).

Dercon (1996, 2002) examined poor household's use of risk management strategies and crop choices in Tanzania. The study found that choosing a less risky crop portfolio results in a low returns, yet it is a common strategy to cope with income variability. For example, growing sweet potato is a risk management practice within a farming system because of its drought resistant and hardy nature resulting in a low yield risk. Recently, Taraz (2014) studied farmers' adaptation to multi-decadal rainfall regimes in India and found that Indian farmers adjusted their crop portfolios and irrigation investments in response to rainfall they experienced in the last decade. Farmers plant less area to drought-tolerant crops following a decade with lots of wet shocks, while area in drought-sensitive crops goes down following the decades with more drier years.

The above mentioned studies have several limitations. First, they are based on subjective assessment of the riskiness associated with crops. Second, studies only deal with major crops while ignoring the nature of multicropping. Third, the study accounting for multicropping (for example, Di Falco, 2012) is focused on Sub-Saharan Africa. However, there are several differences in the nature of crops grown and the structure of farm households between Sub-Saharan Africa and Semi-arid tropical regions in South Asia.

4.3. Data, Variables, and Estimation Procedure

4.3.1. Data

This study uses a micro data survey for the 2008-2012 period collected from rural households in Semi-arid tropical regions in India. Data were collected by International Crop Research Institute for Semi-arid Tropics (ICRISAT) under the Village Dynamics Studies in South Asia (VDSA) program. ICRISAT micro-data collects information on production, price, markets, climate, and socio-economic aspects from representative villages across India and Bangladesh. This study uses households from 18 villages in Semi-arid Tropics (SAT) in five different states, namely Andhra Pradesh (AP), Madhya Pradesh (MP), Maharastra (MH), Gujarat (GJ), and Karnataka (KT) from 2008 to 2012. From each of the villages, 40 households are surveyed and tracked over years. Weather related information is collected from the ICRISAT *meso*-level dataset. Information on annual rainfall and seasonal rainfall for more than 40 years, since 1966, is collected on the district-level and is combined with plot- and household- level micro data.

The farming system in rural Indian households is a mixed crop-livestock system in most of the study villages[31]. Households typically have several plots to cultivate crops as well as some fodder trees. The main crops produced are cereals, legumes, cash crops, oil seeds, and vegetables. Major cereal crops include rice, wheat, maize, and sorghum while pulses include lentils, cowpea, beans, peas etc. Cereals are the main staple food in the study villages and intercropping and multicropping is common in the farm households characterized by the subsistence nature of farming. Table 4.1 presents the description and summary statistics of variables used in this study. Note that all variables are at the household-level (not at the plot-level) because our main regression is on household-level.

Crop-risk variable: One of the objectives of this paper is to generate a measure of crop portfolio riskiness at the farm household-level. To accomplish this, the first-step is to measure the riskiness of each crop and then combine them into a single measure of riskiness at the household-level. We use a single-index model that has been used in the literature (Collins and Barry, 1986; Turvey 1991) to compute the riskiness of each crop in the present study.

The single-index model is based on the portfolio theory. The single-index model enables us to derive coefficients corresponding to the riskiness of each crop. Unlike the Capital Asset Pricing Model (CAPM), the single-index model is not an equilibrium model and can be applied to any portfolio; it is

[31] Village level information such as normal rainfall, soil type, agricultural land, as well as household types are included in table 4.A1 in appendix.

Table 4.1: Household characteristics and summary statistics

Variable	Description	Mean	Std. Dev.
Socio-economic characteristics of the households			
Gender	Gender of the household head (=1 if household head is female)	0.08	0.27
Age	Age of the household head	49.13	12.48
High School	Whether head of the household has at least high school level of education	0.67	0.45
Family Size	Total number of household members	5.19	2.36
Adult male	The number of adult males in the household	2.64	1.31
Adult female	The number of adult females in the household	2.55	1.48
Farming occupation	Occupation of household head (=1 if farming is the main occupation)	0.30	0.44
Service occupation	Occupation of household head (=1 if government or private salaried job or teaching is the main occupation)	0.07	0.26
Draft animals	Number of livestock in the household that can be used for draft purpose	1.92	0.53
Livestock Value	Total value of livestock owned by the household (Rs.)	20,618.65	28,956.67
Physical farm characteristics of the household			
Own land	Share of own land area over total cultivated area	0.76	0.40
Average soil fertility	Proportion of land with good fertility status	2.932	0.57
Fertile soil	(=1 if average fertility status of the total plots is above 2.5 on that scale of 1 to 4).	0.94	0.22
Total value of owned plots	Total Value of owned plots (Rs.)	358730.8	586852.4
Rainfall Variables			
Coefficient of variation, annual	Coefficient of variation of the annual rainfall	0.61	0.18
Coefficient of variation, seasonal	Coefficient of variation of June, July, August rainfall	0.37	0.10
Dependent Variable			
Riskiness index	The average of beta coefficients for each of the crops grown within a household	0.14	0.09

Source: Author's compilation/calculations based on micro-level data under different modules, ICRISAT, 2008 to 2012.

Table 4. 2: Beta coefficient by crop type (standard errors are in parentheses)

Crop type	Beta coefficient	Crop type	Beta coefficient
Rice (Paddy)	0.175 (0.015)	Mustard	0.029 (0.004)
Maize	0.012 (0.002)	Green pea	0.056 (0.011)
Wheat	0.106 (0.006)	Castor	0.066 (0.030)
Cotton	0.243 (0.013)	Lentil	0.041 (0.008)
Sugarcane	0.334 (0.029)	Pearl Millet	0.002 (0.001)
Sorghum	0.021 (0.003)	Cow pea	0.036 (0.005)
Groundnut	0.127 (0.014)	Sesamum	0.088 (0.015)
Pigeon pea	0.054 (0.003)	Cumin/coriander	0.132 (0.035)
Horse gram	0.003 (0.001)	Saffflower	0.055 (0.016)
Chickpea	0.157 (0.012)	Finger Millets	0.003 (0.001)
Soybean	0.291 (0.008)	Chilies	0.556 (0.072)
Black and green grams	0.025 (0.003)	Fruits	0.759 (0.032)
Sunflower	0.080 (0.023)	Others	0.375 (0.022)
Onion	0.044 (0.008)		

Source: Author's computations.

particularly useful to agriculture where markets are incomplete (Veljanoska, 2014). The assumption of the single-index model is that revenue associated with each crop is related only through covariance underlying some basic factor or index, referred as systematic risk. Rooted in the asset pricing theories, every risk has a systematic and a non-systematic component. The systematic component of the risk is non-diversifiable. Basically, this non-diversifiable risk or systematic component measures the proportionate contribution of the individual enterprise's risk (crop, livestock) to the variance of the underlying single-index. The non-systematic component, on the other hand, is the enterprise returns that are uncorrelated with the single-index. Portfolio theory suggests that non-systematic risks are diversified away through the optimal combinations in the portfolio. On the perspective of a single-index model, in our context, we need the stochastic individual crop revenues and the reference portfolio. Reference portfolio can be obtained by summing individual crop revenues. Specifically, a reference portfolio can be expressed as:

$$R_{kh} = \sum_{i=1}^{n} w_{ih} R_{ih} \ , \qquad (1)$$

where w_{ih} represent the weight of crop i for household h and R_{ih} refers to the stochastic crop revenues from individual crop to household h.

Equation 2 below provides the econometric relationship between the reference portfolio, R_{kht}, and the individual crop revenues, R_{iht}, for the i^{th} crop and h^{th} household in time t. Specifically,

$$R_{iht} = \alpha_i + \beta_i R_{kht} + e_{iht} \quad (2)$$

where α_i represents the intercept and β_i represents regression coefficients. Additionally, the beta coefficient (β_i) measures the anticipated response of a particular commodity (crop in our case) to changes in the portfolio returns. By definition of the regression coefficient, $\beta_i = \frac{\sigma_{ik}}{\sigma_k^2}$, σ_{ik} is the covariance between crop and portfolio and σ_k^2 represents the variance of the portfolio. Knowledge of individual beta coefficients provide a sufficient measure of marginal risk (Turvey (1991). Turvey (1991) applied a single-index model to compute the county-level crop risk measures by computing county-betas. Additionally, Bezabih and Di Falco (2012) applied this model to compute crop specific betas. Table 4.2 presents beta coefficients computed with the help of equation 2 for each of the crops grown by rural Indian farm households.

Table 2 shows that crops like rice, wheat, cotton, sugarcane, soybean, chickpea, and groundnut have higher levels of beta, while finger millets, horsegram, a pearl millet have considerably lower levels of beta coefficients.[32] Crops such as fruits, and chilies have considerably higher beta coefficients than pulses and cereal crops. Within legumes and pulses, we notice differences in beta parameters. For example, chickpea, soybean, and pigeon pea have higher betas relative to lentil, cowpeas, black and green grams. Note that the beta coefficients indicate relative variances. For example, the beta coefficient of sorghum, 0.02, compared to soybean, 0.29, suggests that a 1 Rupee (Rs.)[33] increase in the expected revenues for a household's crop portfolio implies a 0.02 Rs. increase in the expected sorghum revenues. However, a similar increase in the expected revenue for a

---

[32]It was difficult to measure beta coefficient for every minor crops grown in the households because of limited observations. Thus, such crops were put into "other" category.
[33] Based on the exchange rate in December 2014, $1 is roughly equivalent to 61.8 Indian rupees.

household's crop portfolio implies a 0.29 Rs. increase in the soybean revenues. This suggests that the revenues of soybean has proportionally more variance than the revenues from sorghum—about 10 times larger. Note that crops with smaller beta coefficients have a more stabilizing effect on the overall household revenues than crops with higher beta coefficients.

The risk index (portfolio beta) is computed as the average of the beta coefficients of crops (riskiness of each crop) that a particular household grows. For example, a household growing cotton, soybean and sunflower, an average beta[34] of 0.2 (derived from the average of 0.243, 0.291, and 0.080 for the three crops) is much higher than the risk of the crop portfolio for a household growing household growing a combination of maize, wheat, lentil, and pearl millet with an average beta of 0.05.

In this study, we considered variability in rainfall as the measure of weather risk. We measured variability in seasonal and annual rainfalls. We collected district-level rainfall information on total annual rainfall (12 months) and total rainfall during June-July-August (seasonal) in each year. From ICRISAT meso-level data set, we collected information for more than 40 years, dating back to 1966. Annual variability is the coefficient of variation (CV) of average annual rainfall over a certain number of years, for each corresponding survey year is then computed. For 2009, for instance, the variability in rainfall is calculated as the CV of annual rainfall for 1966-2008. Similarly, the CV of annual rainfall for the years 1967-2009, 1968-2010, and 1969 to 2011 represents the annual variability in rainfall for the years 2010, 2011, and 2012, respectively. Our seasonal variability measure is also a CV measure, based on total rainfall in June, July, and August for each year, for 42 years. Seasonal variability in rainfall is then computed in a similar manner as annual rainfall variability.

[34] As the beta regression is based on yield, the area is taken into account as the denominator of the dependent variable in equation 2.

The CV for the annual and seasonal rainfall is computed as the ratio of standard deviation to the mean ($CV = \frac{standard\ deviation\ (\sigma)}{mean\ (\mu)}$) of annual and seasonal rainfall. In our data average CV of annual and seasonal rainfall is 0.61 and 0.37, respectively. Higher CV represents the higher fluctuating rainfall. Seasonal summer variability in rainfall is lower than the annual rainfall variability, indicating smaller fluctuation in summer rainfall than in the annual rainfall.

We include other independent variables representing socio-economic characteristics of the farm household and physical characteristics of the plots held by farm households. For example, the average age of the head of the household is about 59 years and most of the households (around 92%) are male-headed (8% were female headed). Around 67% of the household heads have at least a high school level of education. Average family size is about 5 members with male to female ratio as 3: 2.5, on average. Around 30% of the farm household heads have farming as a main occupation, while 7% of the household head report government, or private salaried jobs as a primary occupation. On average, farm households owned 2 draft animals. The value of total livestock holdings per household is around 20,000 Rs. Similarly, the value of land holdings, on average, was 358,000 Rs. On average, farmers perceive that 94% of their land falls into medium to high fertility scale, 2.5, on a scale of 1 to 4 (where 4 represents the most fertile soil).

4.3.2. Estimation Procedure

We are interested in estimating an effect of weather risk on the riskiness of crop portfolio grown by the farm households. This section presents a framework using standard portfolio choice theory. Regarding risk management and hedging, Di Falco and Chavas (2009) have derived a theoretical model based on the expected utility maximization and moment conditions to show that the diversity reduces the cost of risk (implying that the effect of diversity on third momentum (skewness) dominates the effect on the second momentum, variance). Note that the effect on the skewness captures the exposure to downside risk (i.e., crop failure). Reducing the odds of crop failure can be more relevant than reducing yield variance for farmers exhibiting both risk aversion and downside risk aversion (Di Falco and Chavas, 2009). We assume that a risk averse representative farm household chooses an optimal mix of crops to maximize expected returns from the crop mix portfolio; household is subject to land, labor, and other resource constraints (Benin et al., 2004; Bezabih and Di Falco, 2012). Assuming state independent utility function, the portfolio choice (or crop mix) problem can be expressed in following estimable form:

$$P_{ht} = \beta X_{ht} + \delta v_{ht} + \alpha_h + \xi_{ht} \tag{3}$$

where P_{ht} represents riskiness of crop portfolio for household h at time t. X_{ht} represents socio-economic and farm-level characteristics, and v_{ht} captures weather related information at time t. The parameters α, β and δ represent the respective vector of parameter estimates. Error term ξ_{it}, composite error term, can be decomposed into household specific effects α_h and random error term $\xi_{ht} \sim n(0, \sigma_\xi^2)$ such that $\xi_{it} = \alpha_h + \xi_{ht}$.

Under the assumption of α_h not correlated (orthogonal) to the observable covariates, a random effects model would be an appropriate model while fixed effects model is more appropriate when we allow for correlation (or assume a arbitrary correlation) between α_h and observed covariates (Wooldridge, 2010; Baltagi 2008). Under fixed effects, α_h is assumed to be group-specific constant term and needs a transformation before estimation. To overcome the limitation of fixed effects model, because it requires removing the household specific characteristics, Mundlak (1978) suggested replacing the unobserved effects with its linear prediction and a projected error. Under the assumptions of correlation between α_h and X_h, conditional normal distribution with linear expectation and a constant variance, α_h can be estimated as follows:

$$\alpha_h = \varphi + \overline{X_h} + e_h, \quad e_h | X_h \sim N(0, \sigma_\alpha^2) \,, \tag{4}$$

where $\overline{X_h}$ are the averages of time-varying variables in X_{ht} and e_h is the error term with conditional normal distribution with mean zero and variance σ_α^2. Replacing the value of α_h in equation 3, we obtain equation 5. Estimator represented in Equation 5 is called Mundlak-Chamberlain's fixed effects model (Wooldridge 2010). Note that Equation 5 controls for unobserved heterogeneity by adding the means of time varying observed covariates without the data transformation in the fixed effects model.

$$P_{ht} = \beta X_{ht} + \delta v_{ht} + \varphi + \overline{X_h} + \theta_{ht}, \theta_{ht} \sim n(0, \sigma_\theta^2) \quad (5)$$

In our study, we estimate the effect of weather risk on household crop portfolio using random effects estimator and Mundlak-Chamberlain's fixed effects estimator, both efficient and consistent estimator under different sets of assumptions.

4.4. Results and Discussion

Portfolio risk represents the overall risk from a combination of crops grown by rural households. Table 4.3 presents characteristics of rural households' crop portfolio with different levels of risk. Columns 2 to 5 in table 4.3 describes rural households by different quantiles of food crop portfolio, from safest to riskiest. Specifically, the table reveals an average quantile value of the key variables such as weather risk, incomes (farm and off-farm) and land and livestock holdings across each quantiles of crop portfolio. Result suggests that households facing largest variability in annual rainfall (represented as weather risk in the table 4.3, a value of 0.67) held a safest crop portfolio ($<$ 0.08). This is an indication that households sought for a safe combination of crop when they are subjected to a higher weather risk. Similarly, table 4.3 shows an increasing pattern in average quantile-level, in farm income up to three subsequent quantiles of food crop portfolio indicates that higher risk is associated with higher income levels. But it drops after certain level.

Interestingly, from the bottom quantile of crop portfolio (safest portfolio) to top (riskiest) portfolio, average off-farm income increases. This indicates that higher total off-farm income increases the likelihood of opting for relatively riskier portfolio. Similarly, results show that there is an increase in risk bearing capacity in crop portfolio with higher value of livestock holdings. For example, households with highest value of their owned livestock opt for most risky portfolio and vice versa. This supports the findings from previous literature—having higher wealth (or asset) increases

Table 4.3: Characterizing the household-level food crop portfolio

Variables	Food crop portfolio beta quantiles			
	≤ 0.08	> 0.08 & ≤ 0.13	> 0.13 & ≤ 0.17	> 0.17 & ≤ 0.76
Weather risk	0.67	0.62	0.55	0.570
Total farm income (Rs.)	79,250	88,665	12,7223	96,089
Total off-farm income (Rs.)	30,760	36,268	42,567	51,901
Value of total plots (Rs.)	4,61,597	4,76,271	4,53,524	3,98,204
Value of owned plots (Rs.)	3,88,977	3,97,476	3,56,212	3,35,442
Value of total livestock (Rs.)	19,701	20,362	20,874	22,611

Source: Author's compilation using ICRISAT micro-level data, 2008-2012

the risk taking capacity of households in rural Indian villages. However, this asset effect on risk bearing is not clear in the case of land assets (expressed in terms of value of total plots and share of owned plot). Townsend (1994) found that livestock production is typically the least risky enterprise among crop, livestock, handicraft trade, and labor incomes among rural Indian households. This is consistent with Rosenzweig and Wolpin (1993) who found that farmers consider liquidity of assets when it comes to future loss compensation and self- insurance; livestock is considered as a liquid source to provide assured sources of income to farmers. Moreover, in the case of Africa, Fafchamps, Udry, and Czukas (1998) found that around 15 percent of income shortfalls due to income shocks in among African households are compensated by livestock sales. Though the household characteristics across crop portfolio quantiles provides a general response to risk, one needs to be careful that these results are based on average of the households choosing a particular portfolio based on pooled information from 2008 to 2012; these results do not account for time variation. Next, we present panel regression estimates that capture variation across cross-sectional and with time to better understand how farmers respond to weather risk through adjustment in crop portfolio.

Table 4.4 presents the effect of weather risk on crop portfolio; the effects are estimated using different panel data models. In addition to fixed and random effects models, we also present results from pooled ordinary least squares (OLS) and generalized estimating equations (GEE) model in second and third columns of table 4.4, respectively. Pooled OLS is a basic model which does not consider variation across time. Results from pooled OLS serves as a benchmark. The GEE estimation is based on a generalized linear model (GLM) without any specification about the covariance structure. The method GEE is robust to misspecification about variance structure and uses a semi-parametric approach to longitudinal or panel data with continuous and/or categorical/discrete responses. Finally, columns 4 and 5 of table 4.4 presents parameter estimates based on equations 3 and 5 using random effects model and Mundlak-Chamberlin pseudo fixed effects model, respectively. The chi-squares results from a formal Hausman test about model choice suggests that the random effects models perform better than pseudo fixed effects models for our data.

Indian rural households face greater weather variability. Additionally, as many farmers rely on rainfall as a source of irrigation, main source of weather risk in Semi-arid tropical region of India is the variability in rainfall. Table 4.4 shows that households experiencing or realizing greater weather risk are more likely to have less risky crop portfolio. If the variability in rainfall (weather risk) increases by one point, the riskiness of the crop portfolio decreases by 0.12 units. This indicates that farmers choose relatively less risky crop or include less risky crops in their portfolio to reduce the riskiness of the overall crop portfolio. Different crops have different level of sensitiveness to drought and flooding. The crop's yield is diminished if it does not receive its water requirement or have more than necessary. Agronomic researches suggest that one crop is less sensitive to another in water requirements. For example, cotton and sugarcane have relatively high water needs but cotton exhibits low sensitivity to drought, while sugarcane is highly sensitive. Similarly, rice is highly sensitive to drought whereas sorghum is tolerant to drought (Taraz, 2012). Our finding is consistent with Di Falco and Chavas (2009) who found that farmers have incentive to use crop diversity as means of reducing the cost of risk bearing. Including relatively safe crops in their portfolio, farmers prevent their exposure to complete crop failure. Additionally, Townson (1994) reported that diversification of a

Table 4.4: Determinants of crop riskiness per farm household using the risk index measure

	Pooled OLS	Population averaged (GEE)	Random Effects estimation	Mundlak-Chamberlain pseudo fixed effects specification
Weather risk	-0.127**	-0.122**	-0.121**	-0.115**
	(-8.79)	(-5.90)	(-5.88)	(-5.36)
Family size	0.00223**	0.00232*	0.00230*	0.00412*
	(2.11)	(1.71)	(1.68)	(1.84)
Female	-0.0312**	-0.0145**	-0.0158**	-0.0164**
	(3.03)	(2.22)	(2.32)	(2.38)
Married	-0.0156**	-0.0157**	-0.0157**	-0.0137**
	(-2.11)	(-2.47)	(-2.44)	(-2.12)
High school and above	-0.0167**	-0.0096*	-0.0098*	-0.00890
	(-2.76)	(-1.67)	(-1.70)	(-1.46)
Farming occupation	0.00582	0.00145	0.00150	0.0000956
	(0.79)	(0.25)	(0.25)	(0.02)
Service occupation	0.0408**	0.0313**	0.0315**	0.0299**
	(4.59)	(4.47)	(4.42)	(4.19)
Average soil fertility	-0.0175	-0.00476	-0.00532	-0.000106
	(-0.54)	(-0.53)	(-0.58)	(-0.01)
Total livestock value (in log)	0.00311*	0.00237*	0.00239	0.00249
	(1.74)	(1.78)	(1.63)	(1.54)
Value of total plots	0.00256	0.00961**	0.00938**	0.0207**
	(1.01)	(3.25)	(3.13)	(4.78)
Share of owned plot area	0.0104*	0.0137**	0.0136**	0.0173**
	(1.65)	(2.48)	(2.42)	(2.69)
M_familysize				-0.00273
				(-0.97)
M_total plot value (in log)				-0.0214**
				(-3.60)
M_share of owned land				-0.0126
				(-0.96)
Constant	0.217**	0.102**	0.106**	0.234**
	(5.52)	(2.06)	(2.12)	(3.86)
N	1688	1688	1688	1688

Dependent variable: average beta portfolio of the household; higher the value, higher the risk associated with portfolio.
Source: Author's computations

given farmer's landholdings into various spatially separated plots and into various crops reduces farmers' exposure to adverse risks in India. Moreover, our finding supports crop mix or crop diversification as one of the farmers' adaptation strategies to weather risk.

Our study finds that several of the control variables are also significant (table 4.4). Of the socio-economic characteristics, gender, occupation, and marital status of the head of the household, family size, and livestock and land assets are important determinants of household's choice about riskiness of crop portfolio. A negative effect of female coefficient suggests that female-headed households are more likely to opt for combinations of less risky crops. This finding is consistent with the findings from Africa (Bezabih and Di Falco, 2012). Similarly, high school or above level of education of the head of household and married farmers decreases the likelihood of choosing risky crop combinations.

Our results suggest that the households with big family size off-farm occupation are more likely to grow crops with higher combined level of risk. Family members are the most important source of agricultural labor. Bigger family size provides much needed labors (mostly free) allowing households to plant riskier crops and more-labor intensive crops. A positive coefficient of service occupation in our result shows that households with off-farm income are likely to choose riskier crops. Finding here underscores the importance of off-farm labor supply as a key response to stabilize income among Indiana farm households (Andersson, Ramamurtie, and Ramaswami, 2003; Kochar, 1995). Recall that service occupation variable in this study includes income from activities such as regular private or public jobs, teaching, and permanent or temporary wage work off the farm. Income from off-farm jobs is the source of liquid income that perhaps enables farm households to take greater risk in farming. This finding is consistent with Kochar (1995) who reported that off-farm labor supply is one of the important coping mechanisms in response to risks and exogenous shocks in ICRISAT villages.

Our results suggest that the households with better resource endowments, as measured by value of total cultivated plots, value of owned plots, and value of livestock holdings tend to have a riskier portfolio. Results in table 4.4 show a positive effect of total cultivated plots, owned acreage, and livestock assets on the riskiness of crop portfolio. However, significance of the livestock asset is not consistent across estimates. The positive effects of value of total plots and value of owned plots support that risk aversion is decreasing in wealth—a consistent finding from theoretical and empirical studies in low income and developing economies (Rosenzweig and Binswanger, 1993; Townsend, 1994; Andersson, Ramamurtie, and Ramaswami, 2003).

Recall that our dependent variable is crop portfolio. Therefore, our study captures intercropping dependency and possibilities of mixed cropping and intercropping which is a common practice among farming households in India. Practices like mixed farming, intercropping and sequential cropping diversify agriculture to guard against risks and to take advantages of complementarities and linkages between them (Jodha, Singh, and Bantilan, 2012). Rather than focusing on separate regression for a few major crops, overall measure like crop portfolio is a better indicator of combined risk for Indian farming households that is predominantly characterized by subsistence farming.

Finally, we present the results from Mundlak-Chamberlain pseudo fixed effects model in the last column of table 4.4. Most of parameter estimates are similar to other specifications, showing the limited effect of unobserved heterogeneity on our parameter estimates. Overall, regression results confirm that weather risk[35], has a significant impact on the choice of riskiness of crop portfolio among farm households in rural India.

[35] Recall that rainfall variability is measured as coefficient of variation based on long-term observations. We used such measures based on long-term observation rather than rainfall corresponding only to production season or year because as previous studies have documented, farmers base their decisions on observations of long-term trends rather than current rainfall pattern (Bezabih and Di Falco, 2011). In addition to annual rainfall variability, we also estimated model with

4.5. Conclusions

Weather risk is one of the important sources of uncertainty in agricultural production. In Semi-arid tropical villages in India, rainfall variability is the major source of weather risk. In the absence of formal crop insurance mechanism in the village, farmers need to adopt self-insurance mechanisms and need to understand production risk and its management. One of the important informal crop insurance mechanisms for production risks among rural households could be through diversification of a given farmer's landholdings into various crops (Townsend, 1994). Our study considers combination of crop choice as one of the ex-ante risk management mechanism and examines household's risk response towards weather risk. The underlying foundation of our study is that under multicropping settings, we need to allow for intercrop interaction effects. In that, the sensitivity of the combination of crops chosen by farmers is likely to capture more accurate response or adaptation strategies to weather risk; farmers' food crop portfolio would be a better indicator rather than focusing on separate regression for a few major crops.

We computed riskiness of each crop chosen by the households using the single-index method and computed the average risk of the portfolio. Then we examined its link to weather risk. Using a portfolio, our study captures intercrop dependency and crop production under multicropping, a common practice among subsistence farm households in India, which would have been otherwise missed had we focused on few major crops.

We draw at least two major findings from this study. First, narrow dispersion of our crop portfolio measure suggests that farmers utilize ex-ante knowledge about moisture sensitivity of the crops—moisture sensitive crops tend to have high risk (beta coefficients) in most cases. Therefore tend to combine more risky crops and less risky crops in the portfolio. Additionally, Indian farming

seasonal variability in rainfall. Consistent with our main result, the effect of seasonal rainfall variability is also negative on the portfolio risk but effects of other independent variables were not consistent across estimates.

households with subsistence farming where inter or mixed cropping is common, risk of crop portfolio (risk from crop combinations) is important. Second, we found that the level of riskiness of crop portfolio is significantly influenced by weather risk. Farmers tend to opt for relatively less risky crops in the portfolio when they are subject to realization of high weather risk in the area. Additionally, consistent with theory, we found that having more family labors, higher wealth, having liquid assets or an off-farm job increases risk taking capacity in the crop combinations.

Overall, crop portfolio response to weather risk has important policy implications. Crop diversity can be used as an important tool to mitigate adverse effect of weather risk for small holder agriculture in short term. Crop choices is an important approach to mitigate weather related production risk in villages with subsistence farming with low or no infrastructures. However, one should note that adjustments to the weather risks through alternative crop portfolio may not provide maximum profit because high return would have been obtained from high risky crops. In that, there is a cost of adaptation to weather risk through adjustment in crop portfolio. Therefore, food production policies should be linked with climate adaptation policies—for example, weather insurance needs considerable attention along with agricultural investment, infrastructure, and off-farm job or income generation activities in support for farm households. Further research is warranted to assess gains and losses quantitatively. Additionally, further study may include how portfolio is adjusted or rebalanced to get optimal hedge when we allow for risk gain or loss through investment in livestock, productivity enhancing technologies, and off-farm income choices.

4.6. References

Andersson,H., S. Ramamurtie, and B. Ramaswami. "Labor income and risky investments: can part-time farmers compete?." *Journal of economic behavior & organization* 50.4 (2003): 477-493.

Baltagi B. *Econometric analysis of panel data*. Vol. 1. John Wiley & Sons, 2008.

Benin S, Smale M., Pender J., Gebremedhin B., and S. Ehui. "The economic determinants of cereal crop diversity on farms in the Ethiopian highlands." *Agricultural Economics* 31 (2004):197-208.

Bezabih M., Di Falco S., and M. Yesuf. “Farmers’ response to rainfall variability and crop portfolio choice: Evidence from Ethiopia.” Discussion paper, Environment for Development (Efd DP 11-10), December 2011.

Bezabih M., and S. Di Falco. "Rainfall variability and food crop portfolio choice: evidence from Ethiopia." *Food Security* 4.4 (2012): 557-567.

Burke M., and D. Lobell. Food security and adaptation to climate change: what do we know? In: Lobell D, Burke M (eds) *Climate change and food security*. Springer Science + Business, 2010.

Collins R. A., and P. J. Barry. "Risk analysis with single-index portfolio models: An application to farm planning." *American Journal of Agricultural Economics* 68.1 (1986): 152-161.

Dercon, S. “Risk, crop choice, and savings: Evidence from Tanzania.” *Economic Development and Cultural Change*, 44(3), (1996): 485-514.

Dercon, S. "Income risk, coping strategies, and safety nets." *The World Bank Research Observer* 17.2 (2002): 141-166.

Di Falco S., and J.P. Chavas. "On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia." *American Journal of Agricultural Economics* 91.3 (2009): 599-611.

Fafchamps M., Udry C., and K. Czukas. "Drought and saving in West Africa: are livestock a buffer stock?." *Journal of Development economics* 55.2 (1998): 273-305.

Food and Agriculture Organization (FAO) of the United Nations. Web: http://www.fao.org/about/what-we-do/so1/en/ (Accessed: December, 2014).

Haile A. N. *An economic analysis of farmers' risk attitudes and farm households' responses to rainfall risk in Tigray Northern Ethiopia*. Ph. D. Thesis, Wageningen University, 2007.

Jodha N. S., Singh N.P. and M. C. S. Bantilan. Enhancing farmers’ adaptation to climate change in arid and Semi-arid agriculture of India: Evidences from indigenous practices: Developing International Public Goods from Development-oriented Projects.Working Paper Series no. 32. Patancheru 502 324, Andhra Pradesh, India: International Crops Research Institute for the Semi-Arid Tropics, 2012.

Kochar, A. "Explaining household vulnerability to idiosyncratic income shocks." *The American Economic Review* (1995): 159-164.

Kurukulasuriya, P., and R. Mendelsohn. “Crop selection: adapting to climate change in Africa.” World Bank Working Paper 4307, 2007.

Kurukulasuriya, P., and R. Mendelsohn. "A Ricardian analysis of the impact of climate change on African cropland." *African Journal of Agricultural and Resource Economics* 2.1 (2008): 1-23.

Lamb, R. L. “Weather risk, crop mix and wealth in the Semi-arid tropics.” *Department of Agricultural and Resource Economics Report No*, *25*, 2002.

Lobell, D. B., and C. B. Field. "Global scale climate–crop yield relationships and the impacts of recent warming." *Environmental Research Letters* 2.1 (2007): 014002.

Morduch, J. *Consumption smoothing across space: Testing theories of risk-sharing in the ICRISAT study region of South India*. No. 2002/55. WIDER Discussion Papers//World Institute for Development Economics (UNU-WIDER), 2002.

Morton, J. F. "The impact of climate change on smallholder and subsistence agriculture." *Proceedings of the national academy of sciences* 104.50 (2007): 19680-19685.

Mundlak, Y. "On the pooling of time series and cross section data."*Econometrica: Journal of the Econometric Society* (1978): 69-85.

Rosenzweig, C. and M. L. Parry. "Potential impact of climate change on world food supply." *Nature* 367.6459 (1994): 133-138.

Rosenzweig, M. R., and H. P. Binswanger. "Wealth, weather risk and the composition and profitability of agricultural investments." *The Economic Journal* (1993): 56-78.

Rosenzweig, M. R., and K. I. Wolpin. "Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India." *Journal of Political Economy* (1993): 223-244.

Seo, N. S. and R. Mendelsohn. "An analysis of crop choice: Adapting to climate change in South American farms." *Ecological Economics* 67.1 (2008): 109-116.

Stige, L. C., S. J., Kung-Sik C., Lorenzo C., Nathalie P., Glantz M., Herren H.R., and N. C. Stenseth. "The effect of climate variation on agro-pastoral production in Africa." *Proceedings of the National Academy of Sciences of the United States of America* 103, no. 9 (2006): 3049-3053.

Taraz, V. (2013). *Adaptation to climate change: Historical evidence from the Indian monsoon.* Dissertation, Yale University. Retrieved from: http://search.proquest.com/docview/1433964827?accountid=12154

Tao, F., Yokozawa M., Liu J., and Z. Zhang. "Climate-crop yield relationships at provincial scales in China and the impacts of recent climate trends." *Climate Research* 38, no. 1 (2008): 83-94.

Townsend, R. M. "Risk and insurance in village India." *Econometrica: Journal of the Econometric Society* (1994): 539-591.

Turvey, C. G. "Regional and farm-level risk analyses with the single-index model." *Northeastern Journal of Agricultural and Resource Economics* 20.2 (1991).

Veljanoska, S. "Agricultural risk and remittances: the case of Uganda."*2014 International Congress, August 26-29, 2014, Ljubljana, Slovenia*. No. 182788. European Association of Agricultural Economists, 2014.

Wooldridge, Jeffrey M. *Econometric analysis of cross section and panel data*. MIT press, 2010.

Yesuf, M., and R. A. Bluffstone. "Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from Ethiopia."*American Journal of Agricultural Economics* 91.4 (2009): 1022-1037.

CHAPTER 5. CONCLUSIONS

The overriding theme of this dissertation is to analyze consumption and production aspects of the rural agricultural households and to investigate on food, agriculture, and climatic interactions. These issues get considerable attention in the literature. However, there are some limitations or shortcomings in the previous studies either from a data, or from limited implications to generalize, or modeling perspective. Each of the three essays in this dissertation brought a unique representation of the problem, appropriate data, model, and a different viewpoint and addition to the literature.

The most vulnerable population from climate change and food security problem is rural and agricultural households in the developing countries. This has a direct link with poverty because a large majority of poor live in rural areas and depend on agriculture for their livelihoods. On one hand, demand for total food is increasing with increase in population. Failing to meet the demand for food, rural households face malnutrition and chronic hunger. On the other hand, production agriculture is highly affected by weather and climatic factors. In the absence of well-developed irrigation and infrastructures and insurance mechanisms, agricultural households in the rural areas of developing countries need to combat weather risk through different adaptation strategies.

The first essay aims to understand food demand from rural Indian households. The essay employees the Quadratic Almost Ideal Demand System to estimate food demand. Special attention is given to the rural household's two stage budgeting in total food expenditure and then to a demand for a specific food item and also augmenting socio-demographic characteristics. Conditional and unconditional expenditure and price elasticities for seven food groups are estimated. The study found that consumption expenditure share varies across food groups, and more importantly along and across income. The study suggested a significant substituitional and complementary relationships between food groups and a significant impact of demographic attributes on household food consumption behavior. Based on estimates, food demand is projected for next two decades. Demand projection provides an updated picture of projection using recent data and rural consumption patterns.

With changing demographics, there is a change in taste and preferences which drives for a change in the demand for specific food items. A study about food consumption pattern in rural area represents an important element in the development of appropriate policy related to the mitigation of malnutrition among rural poor households; many of whom have an incomes insufficient to secure a balanced diet. Food availability, food access, and food utilizations are considered as three components of food security. Not only a physical presence of total food but also the access to properly balanced food is important to combat malnutrition, chronic hunger, and nutritional insecurity in the rural areas. Additionally, the consumption of total food and primary food groups at a point of time and projected future demand provides an estimate for the direction of agricultural production.

The basic question: 'can we physically produce food to feed growing population?' is inherently linked with food production or supply side of agriculture. Production or supply side of agriculture, particularly in developing countries, is heavily dependent on weather. Using district level panels for 42 years from India and a dynamic panel estimation procedure, the second essay estimated the impact of weather risk on land use intensity. Results suggested that the impact of weather risk on land use intensity in rural India is negative in the short-run, but positive in the long-run. Additionally, results indicate a negative effect of share of production in high-yielding variety and share of irrigated acreage on land use intensity in the long-run. Extending the analysis for different periods, the study indicates that the impact of weather risk on land use intensity has diminished in the post-market reform period—the period marked with implementation of market oriented policies in agriculture, input markets, and infrastructure and irrigation development. The second essay contributes to the literature in several ways. The study uses panel data gathered over a significantly long time period which possesses several significant changes in production agriculture, policies, and weather conditions. Panel analysis provides inferences for both short-run and long-run estimates of weather risk on land use intensity. Methodologically, non-stationary and dynamic heterogeneous panel model was appropriate for the data analyzed and is innovative in the field of agriculture and land use studies.

In Semi-arid tropical villages in India, rainfall variability is the major source of weather risk. In the absence of formal crop insurance mechanism in the village, farmers need to adopt self-insurance mechanisms and need to understand production risk and its management. One of the important informal crop insurance mechanisms for such risks among rural households could be through diversification of a given farmer's landholdings into various crops. The third essay in this dissertation considered combination of crop choice as one of the ex-ante risk management mechanism and examined household's risk response towards weather risk. The sensitivity of the combination of crops chosen by farmers, defined as food crop portfolio in the essay, captured response to weather risk through crop choice. Results suggested that the level of riskiness of crop portfolio is significantly influenced by rainfall variability. Farmers tend to opt for relatively less risky crops in the portfolio when they are subject to realization of high weather risk in the area. However, one should note that response to weather risk by choosing less risky crops in the portfolio is suboptimal outcome in most cases because perhaps higher expected returns would have been achieved by choosing high risky crops. In that there is a cost of adaptation to weather variability through adjustment in crop portfolio. To enable farmers in taking some risk in crops, food production policies should be linked with climate adaptation policies—for example, weather insurance needs considerable attention along with agricultural investment, infrastructure, and off-farm job or income generation activities in support for farm households.

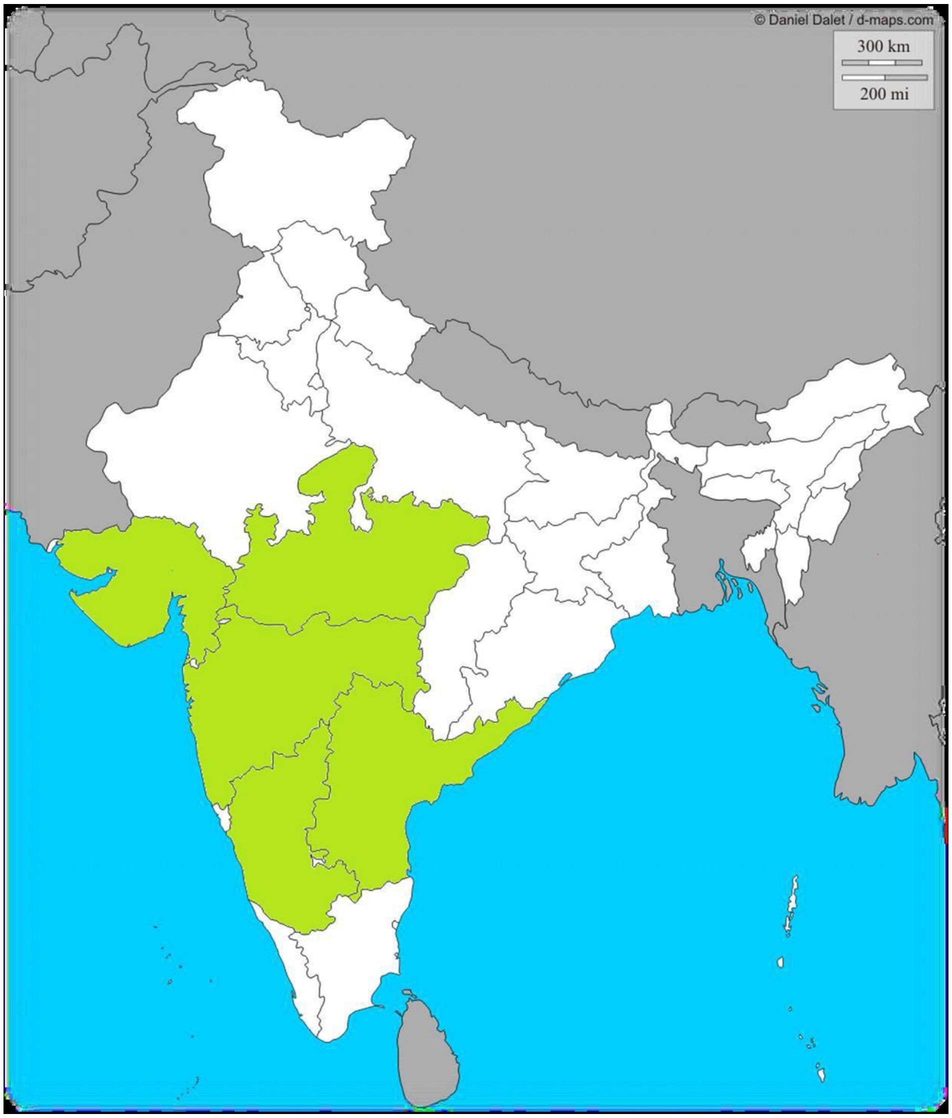
APPENDIX

Table 2.A1: Parameter estimates from QUAIDS model (Chapter 2)

	Cereals	**Fruits & Vegetables**	**Milk & Milk products**	**Oils and Fats**	**Pulses**	**Meats, fish, eggs**	**Other food**
Constant (α_i)	0.2473*	0.1140*	0.2599*	0.0941*	-0.0239*	0.1986	0.1097*
	(0.0192)	(0.0387)	(0.0186)	(0.0163)	(0.0175)	(0.0395)	(0.0301)
Expenditure (β_i)	-0.0209	-0.1329*	0.0208	0.0006	-0.0417	0.1496	0.0246
	(0.0876)	(0.0527)	(0.1115)	(0.0350)	(0.0419)	(0.1669)	(0.0431)
Prices (γ_{ij})	0.0982*	-0.0033	-0.0129*	-0.0237*	-0.0228*	-0.0256*	-0.0096*
	(0.0041)	(0.0002)	(0.0048)	(0.0017)	(0.0022)	(0.0020)	(0.0038)
		0.0151	-0.0199	0.0143	-0.0087*	-0.0184*	0.0215
		(0.0090)	(0.0039)	(0.0025)	(0.0042)	(0.0012)	(0.0075)
			0.0696*	-0.0044*	0.0159*	-0.0155*	-0.0327*
			(0.0090)	(0.0025)	(0.0028)	(0.0030)	(0.0052)
				0.0311*	-0.0084*	-0.0076*	-0.0012
				(0.0017)	(0.0016)	(0.0009)	(0.0025)
					0.0421*	-0.0054*	-0.0125*
					(0.0032)	(0.0010)	(0.0038)
						0.0854*	-0.0127*
						(0.0041)	(0.0020)
							0.0474*
							(0.0085)
Expenditure^2	-0.00001	0.0004	-0.0053*	0.0014*	-0.0018*	-0.0010*	0.0064*
	(0.0008)	(0.0006)	(0.0009)	(0.0003)	(0.0004)	(0.0006)	(0.0006)
Age, in log (*lnage*)	0.0001	0.0015	0.0002	0.0003	-0.0011	-0.0020	0.0009
	(0.0017)	(0.0010)	(0.0021)	(0.0007)	(0.0008)	(0.0034)	(0.0008)
Education, in log	0.0001	0.0010*	-0.0001	0.0001	-0.0006*	-0.0009	0.0004
	(0.0007)	(0.0004)	(0.0009)	(0.0003)	(0.0003)	(0.0014)	(0.0003)
Annual household expenditure, in log	-0.00001	0.0202*	-0.0025	0.0007	0.0037	-0.0211	-0.0010
	(0.0149)	(0.0080)	(0.0190)	(0.0005)	(0.0071)	(0.0283)	(0.0073)
Annual household expend. squared, in log	0.0000	-0.0008*	0.0001	-0.0002	-0.0001	0.0008	0.0001
	(0.0006)	(0.0003)	(0.0008)	(0.0002)	(0.0003)	(0.0012)	(0.0003)
Married	0.0033	-0.0018	0.0037	0.0002	0.0002	-0.0003	0.0015
	(0.0023)	(0.0014)	(0.0029)	(0.0009)	(0.0011)	(0.0043)	(0.0012)
Female	-0.0019	-0.0008	0.0055*	0.0002	0.0000	-0.0023	-0.0004
	(0.0021)	(0.0012)	(0.0028)	(0.0008)	(0.0010)	(0.0040)	(0.0011)
Andhra Predesh (AP)	0.0062*	0.0038	-0.0378	0.0040*	0.0024	-0.0082	0.0294*
	(0.0036)	(0.0026)	(0.0052)	(0.0017)	(0.0020)	(0.0058)	(0.0031)
Gujrat (GJ)	-0.0518*	-0.0310	0.0187	-0.0497*	-0.0101	0.1982*	-0.0742*
	(0.0156)	(0.0095)	(0.0182)	(0.0075)	(0.0074)	(0.0345)	(0.0100)
Madhya Pradesh (MP)	0.0121*	0.0095*	-0.0462*	0.0035*	0.0042*	-0.0045	0.0212*
	(0.0035)	(0.0024)	(0.0052)	(0.0016)	(0.0019)	(0.0060)	(0.0027)
Maharastra (MH)	0.0133*	-0.0006	-0.0322*	0.0014	0.0021	-0.0040	0.0199*
	(0.0030)	(0.0022)	(0.0058)	(0.0015)	(0.0016)	(0.0053)	(0.0034)
Scaling parameters for demographics (ρ)	Coefficient	Standard errors		Coefficient	Standard errors		
ρ_{lnage}	-0.0001	(0.0016)	$\rho_{Married}$	-0.4980*	(0.2164)		
ρ_{lneduc}	-0.0004	(0.0006)	ρ_{AP}	0.2196*	(0.1031)		
$\rho_{lntotexp}$	0.0553*	(0.0268)	ρ_{GJ}	-0.8107*	(0.2259)		
ρ_{lnexp^2}	-0.0023	(0.0011)	ρ_{MP}	0.2328*	(0.1230)		
ρ_{Female}	-0.0027	(0.0022)	ρ_{MH}	0.1704*	(0.0715)		
Log likelihood= 5489.03							

*indicates significant at 10% or higher; Standard errors in parentheses are bootstrapped standard errors.
Source: Author's computations

Figure A1: India map showing Semi-arid tropical states under study (chapter 2)



Note: States covered under this study (*Gujarat, Madhya Pradesh*, *Andhra Pradesh; Maharashtra*, and *Karnataka)* are shown by light green color inside the Indian geographical area; Gray color outside the India map represents neighboring countries of India.

Table 3.A1: Effect of individual independent variables on land use intensity (chapter 3)

	Dependent variable: Land use intensity (in log)					
	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Long run effects						
Weather risk[a]	0.0099**					
	(1.98)					
Ag. labor availability[a]		0.0175				
		(1.36)				
Rural literate share[a]			-0.0171**			
			(-2.39)			
Cultivator share[a]				0.0563**		
				(4.45)		
HYV production[a]					-0.0304**	
					(-8.01)	
Irrigated area share[a]						-0.0763**
						(-8.48)
Short run effects						
D.Weather risk[a]	-0.0055**					
	(-2.83)					
D. Ag. labor availability[a]		0.0037				
		(0.68)				
D. Rural literate share[a]			0.00639			
			(1.64)			
D. Cultivator share[a]				0.00268		
				(0.38)		
D. HYV production[a]					0.00622**	
					(2.85)	
D. Irrig. area share[a]						-0.0151
						(-0.87)
Constant	0.074**	0.062**	0.076**	0.049**	0.097**	0.137**
	(6.79)	(6.83)	(10.16)	(6.36)	(11.16)	(9.54)
Adjustment factor (∅)	0.274**	0.250**	0.254**	0.255**	0.297**	0.314**
	(7.66)	(10.80)	(10.95)	(10.93)	(11.03)	(11.22)

[a] Variables are in log; *t* statistics are in parentheses; single and double asterisks (*, **) indicate significance at the 10% and 5%, level, respectively.
Source: Author’s computations.

Table 4.A1: Village-level information from some selected village

Village	State	Normal Rainfall (MM)	Actual Rainfall	Major Soil Type	Total Agricultural land (Ha)	Total Households	Farming as a main occupation	Average family size
Shirapur	Maharashtra	550	881	Deep Black Soil (55%)	1314.1	546	174 (31.86 %)	4.62
Kalman	Maharashtra	550	637	Shallow Black (47%)	2511	660	261 (39.55 %)	5.06
Kanzara	Maharashtra	700	583	Medium Black (55.6 %)	497.74	319	134 (42.01 %)	4.47
Kinkhed	Maharashtra	700	667	Medium Black (55%)	335	189	79 (41.79 %)	4.64
Aurepalle	Andhra Pradesh	927	1546	Sandy Soil (28%)	1265	984	500 (50.82 %)	4.85
Dokur	Andhra Pradesh	730	877	Red (55%)	1303	545	130 (23.85 %)	5.52

Source: ICRISAT village profiles, http://vdsa.icrisat.ac.in/vdsa-vaag.htm

VITA

Aditya Khanal was born and raised in Nepal. In 2006, he received a BS degree in Agricultural Sciences from Tribhuvan University, Nepal and worked as a socio-economist in a non-governmental organization called LI-BIRD for 2 years. He came to the United States in 2008 to pursue higher studies in agricultural economics. Ha has received a MS in agricultural economics from Louisiana State University, a MA in economics from Virginia Tech and a MS in finance from Louisiana State University. Aditya joined the doctoral program in agricultural economics at Louisiana State University in 2012. During his graduate study at Louisiana State University, he has authored 12 articles published in peer-reviewed journals and has made 13 conference presentations. In August 2015, Aditya will be awarded the doctoral degree.