# Can Weather Risk Alter Food Crop Portfolio Choices? Empirical Evidence from India

Aditya R. Khanal

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Ashok K. Mishra[1]

*Correspondence to:*

Ashok K. Mishra
Marley Foundation Chair in Food Management
Morrison School of Agribusiness
Arizona State University
223L SanTan Hall
7001 East Williams Field Road
Mesa, AZ 85212
Tel. 480-727-1481
Fax: 480-727-1961
ashok.mishra@asu.edu

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***Abstract:*** This study considers the combination of crop choices as one of the ex-ante risk management strategies and examines farm households' crop portfolio choices as a response to weather risk in India. Unlike in other countries, intercropping and mixed cropping are prevalent among Indian farmers. Results show a significantly lower riskiness in the crop portfolio choices among farmers in semi-arid tropics of India than farmers in Africa. Secondly, using a panel estimation approach, our findings suggest a negative and significant impact of weather risk on the riskiness of food crop portfolios. Finally, we find that households with greater land assets and off-farm jobs are more likely to choose the riskier food crop portfolio choices in the presence of weather risk.

***Keywords:*** Weather risk, food crop portfolio, panel data, India, rural farm households, off-farm income, single-index approach, rainfall, soil fertility, intercropping, mixed cropping.

**JEL codes:** C33, D13, G11, Q12, Q15

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## 1. Introduction

Agriculture is sensitive to short-term changes in weather and to seasonal, annual and longer-term variations in climate. Weather risk, or variability in weather, is one of the important factors affecting agricultural production and land allocation (Lobell and Field, 2007; Stige et al. 2006; Tao et al. 2008). As a result, weather-induced changes in agriculture affect the livelihood of farm households[1] because they are likely to affect both farm income received by poor rural farm households and food prices paid by households in general (Burke and Lobell, 2010; Morton 2007). To cope with fluctuating weather, farm households engage in several risk management strategies. These include food crop choice mix (or crop diversification), off-farm work and weather insurance -- available in only a few developing countries. As a self-insurance mechanism to manage climatic variabilities, in the presence of pervasive risk, farm households are likely to employ a number of adaptation strategies (Antwi-Agyei, Stringer, and Dougill, 2014; Lashley and Warner 2015). Previous studies have found that rural farm households in the low-income countries are likely to behave sub-optimally under such risks rather than as profit-maximizing agents (Rosenzweig and Binswanger, 1993; Yesuf and Bluffstone, 2009). Hence, in the anticipation of different degrees of weather and production risks, rural farm households might choose to diversify their crops by growing less profitable but less risky crops (Benin et al., 2004) to hedge risk rather than undertaking investments for higher expected returns.

[1] Most rural households in developing and low-income countries depend, to a significant extent, on agriculture for their livelihood. Additionally, small farm households represent not only a significant proportion of the rural population but also contribute a significant share of the total agricultural output (Mishra, Mottaleb and Mohanty, 2015).

Several studies have discussed the nature of crop riskiness and its relation to weather and market uncertainties (Lamb, 2002; Haile, 2007). However, previous studies have several limitations. These include: (1) most of the studies are based on subjective assessment of the riskiness associated with the crops under study; (2) studies deal only with major crops while ignoring the nature of intercropping and mixed cropping; (3) studies have failed to include soil information (soil productivity) and food crop portfolio choices. Take the case of India, and in particular the rain-fed semi-arid tropics region of India, where water is one of the most limiting resources for crop growth. Rainfall is usually low and highly variable, and crops often are subjected to drought, particularly on light-textured soils with low moisture-holding capacity. The farmer's choice of adaptations and adjustments ultimately is influenced by the risk-generating agro-climatic circumstances. Hence, the patterns of farming practices are differentiated on the basis of characteristics of weather risk. To this end, Indian agriculture thrives on intercropping and mixed cropping (Willey, 1990).

To the best of our knowledge, none of the previous studies has investigated the impact of weather risk on farmers' food crop portfolio choices (measured by risk-based crop portfolio index) in South Asia. There are several differences in the nature of crops grown and in the structure of farms and farm households between sub-Saharan Africa (a country like Ethiopia)[2] and semi-arid tropical regions in South Asia (e.g., India), which are the focus of this study. For instance, cash crops and crops such as coffee, pulses, oil seeds, teff and corn are the major components of Ethiopian agriculture. However, in South Asia, and in the sub-tropical region of India in particular, cereal crops such as rice and wheat are staple crops, and the intercropping of legumes and mixed cropping with corn, potato, sugar cane and oil seeds on the same plot are

[2] Bazabih and Di Falco (2012) study uses Ethiopia data. However, their study differs in several ways from the present study. We will discuss those differences in the literature review section.

common occurrences. It should be noted that intercropping and mixed cropping are common features of subsistence farming in India. Finally, our empirical analysis includes information on the farm soil type, or average soil fertility of the farm. Recall that soil type plays an important role in production agriculture because certain soil types might be suited only for a particular crop.

The objective of this study is twofold. The first is to investigate how crop choices make up food crop portfolios in rural Indian farm households, based on riskiness. The second is to assess the impact of weather risk on crop portfolio choices. This study uses household-level panel data for five years (2008 to 2012) collected by the International Crop Research Institute for Semi-arid Tropics (ICRISAT) from 18 different villages in the semi-arid tropical region of India. Two aspects are important in the household-level crop choice decision. The first is the riskiness of each crop, and the second is the household's management of crop riskiness by choosing appropriate crops in its food crop portfolio. Farmers' responses to weather risk through adjustments in their food crop portfolios might help in understanding farmers' behavior in mitigating the non-systematic component of risk through crop diversification. Additionally, diversification through crop portfolios provides insights for both private and public sectors, including policymakers, in designing public policies such as crop insurance programs and in quantifying risk premiums.

## Literature Review

### *Crop Management—Weather a Driving Factor*

The agriculture sector represents 23% of India's Gross Domestic Product (GDP), plays a crucial role in the country's development and continues to occupy an important place in the national economy. Additionally, about 59% of the population still lives in rural areas and heavily depends on agriculture for employment and livelihood (Mishra and Tripathi, 2014). Nonetheless, 60% of the total cropped area in India is still rain-fed and depends relatively on the uncertainties of monsoon. Agriculture is sensitive to short-term changes in weather and to seasonal, annual and longer-term variations in climate.[3] Climatic variability in the sense of inter-season or intra-season fluctuations for agriculturally relevant weather conditions is an important source of instability in farming (Dash and Hunt, 2007). However, in subsistence-oriented societies, like India, most of the formal means of combating instability and risk are not readily available. (This might be due to credit constraints, educational attainment of farmers, etc.) Rural farm households still rely heavily on traditional farming systems.[4] In such a system, farmers make their own decisions with regard to risk management strategies. Farmers first try to ameliorate the effects of drought or rainfall variability through crop management. Agricultural extension in India, with the help of universities and International organizations like the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) over the past 50 years, has educated famers on how to minimize risk and maximize available sun and soil moisture by adapting alternatives to shifting cultivation and monoculture, such as intercropping, double cropping and mixed cropping (Khan et al., 2009).

Intercropping also is practiced to use the space left between two rows of the main crop (e.g., sorghum/pigeon pea; millet/groundnuts). More emphasis in given to the main crop, there is no competition between the crops, and the intercrop is harvested much earlier than the main crop, although sowing times could be the same or different. Further, intercropping gave higher

[3] Dash and Hunt (2007) concluded that changes in climate for agriculture and effects on human health are likely to be serious and vary significantly across the regions in India.

[4] Traditional agriculture means low but stable yields, low inputs, large families, low incomes, and lower living standards.

and more dependable gross returns per hectare than did sole crops (Mathur, 1963; Norman et al., 1979). In mixed cropping, two or more crops can be grown together, but at least one crop is under favorable conditions (weather and fertility); both crops are equally cared for; and there is competition between all crops grown. The crops are sown and harvested at almost the same time. Both cropping systems have resulted in increased farm production and profitability per unit of land area in food crops in India. Additionally, intercropping and mixed cropping can increase diversity in the agricultural ecosystem and allow for ecological balance, increased utilization of resources and increasing yield of crops (Gliessman, 1997; Hatfield and Karlen, 1993). Intercropping and mixed cropping also ensure a greater and more even distribution of employment of family labor (Jodha, 1980).

Two intercropping strategies that focus on water capture and utilization by crops (Willey, 1990) are described in the literature. In the first strategy, a primary crop component, intended to yield near its full potential, is planted at optimum plant density. A secondary component is planted at a density often lower than its optimum and is harvested much earlier or later than the primary species. This first strategy is typical in monsoonal or semi-arid environments, like India, where the late-maturing crop will deplete most of the available soil water as it grows into the early dry season. Note that the goal for both intercropping and mixed cropping is to maximize yield on a given piece of land by making use of resources, better controlling weeds, improving soil structure and organic matter, and improving fertility (Natarajan and Willey, 1980). Nonetheless, intercropping and mixed-cropping strategies can be used to reduce the impact of rainfall variability and provide households with food crop portfolio choices. Thus, in the intercropping and mixed-cropping system, like India, farmers choose a combination of crops that are sensitive to moisture and affect the riskiness of crop portfolio choices of rural farm households in India.

*Weather Risk and Crop Production Choices*

The effect of weather and climatic variations in agricultural production gets considerable attention in agronomic, geographic, environmental and development economics literature. In the absence of well-functioning insurance and credit markets, farmers need to undertake self-insurance mechanisms 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). Note that like any other risk-averse agent, farmers might undertake activities such as crop diversity, crop sequencing or rotation to stabilize returns from cultivated lands and to restore soil productivity (Bradshaw, Dolan, and Smit 2004; Jodha, Singh, and Bantilan, 2012). Since choice and diversification activities have risk-hedging or risk-coping motives rather than profit-maximizing motives, these might be viewed as suboptimal behavior. For example, farmers might choose less profitable and less risky crops instead of high-yielding risky crops (Morduch 2002; Kurukulasuriya and Mendelson 2007).

Lamb (2002) presented evidence of risk-averse behavior in crop choices among poor farmers in India by presenting farmers' deviation from profit-maximizing behavior. He argues that higher wealth levels provide farmers with 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 adjusted their choice of crops as well as the area under those crops to fit with local climatic conditions. It should be pointed out, though, that the authors did not focus their study on weather risk and its consequence on crop choices. 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 through intercropping and mixed cropping can reduce the risk of crop failure (Jodha, 1980).

Dercon (2002) examined poor households' use of risk management strategies and crop choices in Tanzania. The author found that choosing a less risky crop portfolio results in low returns, yet it is was 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 locust-resistant nature, resulting in a low yield risk. Finally, Bezabih and Di Falco (2012) investigated the impact of rainfall in Ethiopia. The rural farm households surveyed were located in two zones (South Wollo and East Amhara) of the Amhara National Regional State, part of the north and central highlands of Ethiopia. The survey was done of the same households for 2000, 2002, 2005 and 2007 crop seasons, and rainfall data was collected from meteorological stations for 1976-2006. The authors find that the combined riskiness of crops grown at a household level responded negatively to long-run annual rainfall. Note that there are several differences between Bezahib and Di Falco's (2012) study in Ethiopia and our study in India. First, due to higher levels of intercropping and mixed cropping in India, crop riskiness and portfolio choices could be significantly different. Secondly, Bezahib and Di Falco (2012) investigated the impact of annual mean rainfall and seasonal rainfall[5] on crop portfolio riskiness. However, in our study we explicitly estimate and use variability in rainfall (weather risk), both annual and seasonal rainfall, as a factor affecting riskiness in crop portfolios. Finally, compared

[5] The authors use "climate change" in their paper to define variables like *mean annual* and *mean seasonal* rainfall. Note that the authors do not use variability (or riskiness) in these two measures.

to Ethiopia, where land ownership[6] is not defined (farmers don't own land, *see* Deininger et al., 2011), Indian farmers tend to own about 76% of their land, though the farms are small (less than 0.5 hectares). Literature reveals that land ownership (or tenure) has a significant impact on technology adoption and land improvement (Abdulai, Owusu, and Goetz, 2011). Further, Jacoby and Mansuri (2008) find in their study on Pakistan that farmers invest less in their leased plots than they do in their owned plots.

Recently, Taraz (2014) studied farmers' adaptation to multi-decade 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 planted less area in drought-tolerant crops following a decade with many wet shocks, but they decreased the area planted in drought-sensitive crops following the decades with more dry years. One can point out two weaknesses of Taraz's (2014) study: The author fails to incorporate variability in weather (or weather risk) in his study, and he fails to include crop portfolio choices in his analysis.

The above studies have several limitations. First, they are based on subjective assessment of the riskiness associated with crops. Second, the studies deal only with major crops and ignore the nature of mixed cropping and intercropping. Third, the study accounting for mixed cropping (for example, Bezabih and Di Falco, 2012) is focused on sub-Saharan Africa, where there are no land ownership rights. There also 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. For example, Ethiopian agriculture faces significant constraints with regard to limited crop choices, low resource utilization, low-tech farming techniques,

[6] Ethiopia went through a radical land tenure reform process in 1975, in which all land was declared to be state land, and user rights to land were distributed in an equitable manner within communities. Land sales, rentals and hired labor were prohibited. In 1991, a new regime introduced more market-friendly policies, but land sales remained illegal, and restrictions on the duration and extent of land renting were introduced.

inappropriate land tenure policy, degradation of land and other natural resources, and political unrest. These constraints, coupled with the rapid population growth, have significantly contributed to the problem of food insecurity since the 1960s (Yonas, 2007). On the other hand, India has made significant progress in agriculture, with the help of the Green Revolution. Farmers cultivate several crops, vegetables, oilseeds and other legumes, and intercropping and mixed cropping are common features of subsistence farming in India. Finally, the land tenure system is well defined, and farmers own the majority of the land they operate.

**Estimation Procedure**

We are interested in estimating the effect of weather risk on the riskiness of food crop portfolios grown by rural Indian households. We assume that a risk-averse representative farm household chooses an optimal mix of crops to maximize expected returns from the crop mix portfolio, and that the 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 the following estimable form:

$$FCP_{ht} = \beta X_{ht} + \delta v_{ht} + \alpha_h + \xi_{ht} \qquad (1)$$

where $FCP_{ht}$ represents riskiness of food 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 $\alpha$, $\beta$ and $\delta$ represent the respective vector of parameter estimates. Error term $\xi_{it}$, composite error term, can be decomposed into household specific effects $\alpha_h$ and random error term $\xi_{ht} \sim n(0, \sigma_\xi^2)$ such that $\xi_{it} = \alpha_h + \xi_{ht}$.

Use of the panel dataset enables to estimate the model through different methods that control for unobserved heterogeneity. Commonly used methods are fixed effects (FE) and random effects (RE) models. Under the assumption of $\alpha_h$ not correlated (orthogonal) to the

observable covariates, a random-effects model would be an appropriate model, while a fixed-effects model is more appropriate when we allow for correlation (or assume an arbitrary correlation) between $\alpha_h$ and observed covariates (Wooldridge, 2010; Baltagi 2008).
In many instances, the assumption of RE is likely too strong. The FE method relaxes this assumption, but does not allow estimation of coefficients on time invariant parameters. Introduced by Mundlak (1978) and Chamberlain (1980), correlated random effects (CRE) models allow for correlation between the unobserved variables and explanatory variables and also enable us to estimate the effects of time invariant variables. Wooldridge (2009) extended Mundlak and Chamberlain model and showed that CRE can also be used in unbalanced panels models.

Under the assumption of $\alpha_h$ not correlated (orthogonal) to the observable covariates, a Under the assumptions of correlation between $\alpha_h$ and $X_h$, conditional normal distribution with linear expectation and a constant variance, $\alpha_h$ can be estimated as follows:

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

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 $\sigma_\alpha^2$. Replacing the value of $\alpha_h$ in equation 1, we obtain equation 3. Note that Equation 3 controls for unobserved heterogeneity by adding the means of time varying observed covariates without the data transformation in the fixed-effects model.

$$FCP_{ht} = \beta X_{ht} + \delta v_{ht} + \varphi + \overline{X_h} + \theta_{ht}, \theta_{ht} \sim n(0, \sigma_\theta^2) \tag{3}$$

In our study, we estimate the effect of weather risk on household food crop portfolio riskiness using pooled ordinary least squares (OLS), random-effects estimator (RE) and correlated random effects (CRE) estimators. Note that both RE and CRE estimators are efficient and consistent under different sets of assumptions. However, before we estimate the above equation we need to construct the crop-risk variable $FCP_{ht}$.

*Crop-risk variable*

We use the single-index model to compute the riskiness of each crop in this study (*see i.e.*, Collins and Barry, 1986; Turvey 1991). The single-index model is based on portfolio theory and 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 particularly useful in agriculture where markets are incomplete (Veljanoska, 2014). The assumption of the single-index model is that the revenue associated with each crop is related only through the covariance underlying some basic factor or index, referred as *systematic risk*. Rooted in asset-pricing theories, every risk has a *systematic* and a *non-systematic* component. The systematic component of the risk is non-diversifiable and 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 through optimal combinations in the portfolio. From the perspective of the single-index model, in our context, we need the stochastic individual crop revenues and the reference portfolio. A reference portfolio can be obtained by summing individual crop revenues. Specifically, a reference portfolio can be expressed as:

$$R_{kh} = \sum_{i=1}^{n} w_{ih} R_{ih} \quad (4)$$

where $w_{ih}$ represents the revenue based weight of crop $i$ for household $h$ and $R_{ih}$ refers to the stochastic crop revenues from individual crops to household $h$. Equation 5 below provides the econometric relationship between the reference portfolio, $R_{kht}$, and the individual crop revenues, $R_{iht}$, for $i^{th}$ crop and $h^{th}$ household in time $t$. Specifically,

$$R_{iht} = \alpha_i + \beta_i R_{kht} + e_{iht} \tag{5}$$

where $\alpha_i$ represents the intercept and $\beta_i$ represents a vector of regression coefficients. Additionally, the beta coefficient ($\beta_i$) measures the anticipated response of a particular commodity (crop in our case) to changes in the portfolio returns. By definition of the regression coefficient, $\beta_i = \frac{\sigma_{ik}}{\sigma_k^2}$, $\sigma_{ik}$ it is the covariance between crop and portfolio and $\sigma_k^2$ represents the variance of the portfolio. Knowledge of individual beta coefficients provides a sufficient measure of marginal risk (Turvey, 1991).

**Data and Construction of Variables**

This study uses micro-level data surveys for 2008-2012 collected from rural farm households in semi-arid tropical regions of India. Surveys are collected and cataloged by the International Crop Research Institute for Semi-arid Tropic (ICRISAT) under the Village Dynamics Studies in South Asia (VDSA) program. ICRISAT micro-level data collects information on production, price, markets, climate and socio-economic aspects from representative villages across India. This study uses farm households from 18 villages in five different states, namely Andhra Pradesh (AP), Madhya Pradesh (MP), Maharashtra (MH), Gujarat (GJ) and Karnataka (KT). In each village, 40 households are randomly chosen, surveyed and tracked over the years.

Weather-related information is collected from ICRISAT *meso*-level data sets. Information on annual rainfall and seasonal rainfall for more than 50 years, since 1966, is collected at the district level and is combined with plot- and household- level micro data. 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 main staple food in the villages, and intercropping and mixed cropping is common in the farm households characterized by a subsistence nature. Table 1 presents the description and summary statistics of variables used in this study.

Table 2 shows that crops like rice, wheat, cotton, sugar cane, soybean, chickpea and groundnut have higher levels of beta coefficients, while finger millets, horse gram and pearl millets have considerably low levels of beta coefficients.[7] 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 beta coefficients relative to lentil, cowpeas and black and green grams. Note that 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.)[8] increase in the expected revenues for a household's food crop portfolio implies a 0.02 Rs. increase in the expected sorghum revenues. Similarly, 1Rs. increase in the expected revenue for a household's food crop portfolio implies a 0.29 Rs. increase in soybean revenues. This suggests that revenues from soybean have a proportionally higher variance than the revenues from sorghum—about 10 times greater. Finally, it should be noted that crops with smaller beta coefficients have a more stabilizing effect on the overall farm household revenues than crops with higher beta coefficients.

*Calculation of Risk Index and Other Variables*

*The risk index* (portfolio beta) is computed as the average of the beta coefficients of food crops (riskiness of each crop) for a given household. For example, for a household growing cotton,

[7] It was difficult to measure beta coefficient for every minor crop grown in the household because of limited observations. Thus, such crops were put into "other" category.
[8] Based on the exchange rate in March 2016, $1 is roughly equivalent to 66 Indian rupees.

soybean and sunflower, an average beta 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 food crop portfolio for a household growing a combination of maize, wheat, lentil and pearl millet with an average beta of 0.05. Finally, the average of the beta coefficients of food crops for a rural farm household in our study is about 0.14, much lower than those obtained by Bezabih and Di Falco (2012) in their study of Ethiopian farmers (0.46). A plausible reason could be, in addition to other factors, the higher incidence of intercropping and mixed cropping in India.

*Weather risk variable*

Unlike Bezabih and Di Falco (2012), who used long-term average rainfall and long-term average spring rainfall from 1976-2006 as a proxy for rainfall variability, we use mean and standard deviation of rainfall in selected districts as a measure of rainfall variability. In particular, we have used variability in rainfall as a measure of weather risk. We collected district-level information on total annual rainfall for each year. From ICRISAT *meso*-level data sets, we collected information for 42 years, dating back to 1966. Annual variability, the coefficient of variation (CV) of average annual rainfall over a specified number of years, for each corresponding survey year is then computed. The CV is computed as the ratio of standard deviation to the mean ($CV = \frac{standard\ deviation\ (\sigma)}{mean\ (\mu)}$) of annual rainfall. Therefore, CV in rainfall for 2009 is calculated as the CV of annual rainfall for 1966-2008. Similarly, the CV of annual rainfall for the periods 1967-2009, 1968-2010 and 1969-2011 represent the annual variability in rainfall for the years 2010, 2011 and 2012, respectively. The CV computed with 42 years of annual rainfall is denoted as *WR1* in this paper. To check the robustness of our findings, we also compute CV for different time windows. Specifically, *WR2* denotes CV computed with 20 year rainfall data (e.g., 1988-2008 for CV in rainfall for 2009; 1989-2009 for CV in rainfall for 2010;

1990-2010 for CV in rainfall for 2011; 1991-2011 for CV in rainfall for 2012, respectively). Similarly, *WR3* denotes CV computed on 10 year rainfall data (e.g., 1998-2008 for CV in rainfall for 2009; 1999-2009 for CV in rainfall for 2010; 2000-2010 for CV in rainfall for 2011; 2001-2011 for CV in rainfall for 2012, respectively). In our data, average CV of annual rainfall is about 0.61 (*WR1*, based on 42 years), 0.27 (*WR2*, based on 20 years), and 0.26 (*WR3*, based on 10 years). Note that a higher CV indicates a higher degree of variability in rainfall.

*Other Independent Variables*

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, and most of the households (about 92%) are male-headed. About 67% of the household heads have at least high school education. Around 80% of the households have farming as their main occupation while 7% of the household has public/private service occupation or salaried jobs. Average family size is about 5 members. On average, farm households owned 2 draft animals. Value of total livestock holdings per household was about 20,000 Rs. Similarly, the average land holdings was about 3.5 hectares. On average, 94% of the farmers perceived that their land was of medium to high fertility—fertility scale of 2.5 (on a scale of 1 to 4, where 4 represents the most fertile soil).

## Results and Discussion

Table 3 presents the characteristics of rural farm households' food crop portfolios with different levels of risk. Recall that our dependent variable is the food crop portfolio. Therefore, our study captures intercropping dependency and the possibilities of mixed cropping and intercropping, which is a common practice among farming households in India. Practices like mixed cropping, intercropping and sequential cropping diversify farming to protect against risks and to take advantages of complementarities and linkages between the crops (Jodha, Singh, and Bantilan, 2012). Columns 2 to 5, in Table 3, describe rural farm households by quantiles of riskiness in food crop portfolios, from the safest to the riskiest. Specifically, the table reveals the average quantile values of key variables such as weather risk, incomes (farm and off-farm) and land and livestock holdings across each quantile of riskiness in food crop portfolios. The results suggest that households facing the largest weather risk (weather risk of 0.67, Table 3) held the safest food crop portfolios (beta of < 0.08). This is an indication that farm households in this group sought a safe combination of food crops when they were subjected to higher weather risk. Additionally, Table 3 shows an increasing pattern in average quantile-level for farm income. This indicates that higher weather risk is associated with higher farm income levels.

Our results show an interesting finding when it comes to off-farm income. For example, the average off-farm income increases from the bottom quantile (safest) to the top quantile (riskiest) food crop portfolios. This indicates that higher levels of total off-farm income increase the likelihood of opting for relatively riskier food crop portfolio choices. Similarly, results show an increase in the risk-bearing capacity in food crop portfolio choices with higher values of livestock holdings—a wealth effect. For instance, households with the highest value of owned livestock opt for more risky portfolios, and vice versa. Higher wealth (or assets) increases the risk-taking capacity of rural households in India. Townsend (1994) found that livestock production is typically the least risky enterprise in farming, in relation to handicraft trade and labor incomes among rural Indian households. Our findings are 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 a liquid source for farm families. Moreover, in the case of Africa, Fafchamps, Udry and Czukas (1998) found that about 15% of income shortfalls, due to income shocks, among African households were compensated for by livestock sales.

Although the household characteristics across riskiness in food crop portfolio quantiles provide a general response to risk, one needs to be careful that these results are based on averages of the households choosing a particular portfolio based on pooled information from 2008 to 2012; these results do not account for time variation. Therefore, one needs to estimate a panel regression model that captures variation across space and time.

Table 4, 5, and 6 present the parameter estimates of the effects of weather risk ***WR1***, ***WR2***, and ***WR3***, respectively on food crop portfolio choice. Recall that *WR1, WR2*, and *WR3* are weather risk measures computed based on the weather data for 42-years, 20 years, and 10 years, respectively. In addition to random-effects models and correlated random effects models, we also present results from the pooled ordinary least squares (OLS) model ($2^{nd}$ column in each table). Pooled OLS is a basic model that does not consider variation across time and these results serve as a benchmark. Finally, columns 3 and 4 in tables 4, 5, and 6 report parameter estimates based on equations 2 and 3 using the random-effects model and correlated random effects model, respectively. We also estimated fixed effects model but the chi-squares result from a formal Hausman test on the model choice suggested that the random-effects models performs better in our study. Therefore, we have presented results of random effects model.

Our results across three different models and three different weather risk measures consistently show that rural farm households experiencing greater weather risk are more likely to choose less risky food crop portfolio. Table 4 shows that if weather risk (***WR1***) increases by one point (unit), for example (column 3, Table 4), the riskiness of food crop portfolios decreases by 0.14 units. This indicates that farmers choose relatively less risky food crops or include less risky food crops in their portfolios in order to reduce the riskiness of their overall food crop portfolio. Recall that different crops have different level of sensitivity to drought and flooding. Agronomic research suggests that one crop is less sensitive to another in terms of water requirements. For example, cotton and sugarcane have relatively high water needs, but cotton exhibits a low sensitivity to drought, while sugarcane is highly sensitive. Similarly, rice is highly sensitive to drought, whereas sorghum is tolerant to drought (Jodha, 1980). By including relatively safe crops in their portfolio, farmers prevent their exposure to complete crop failure. Our finding support crop diversification as one of farmers' adaptation strategies to weather risk. Finally, recall that Bezabih and Di Falco (2012), who used long-term average rainfall as a measure of "rainfall variability," found that long-term average rainfall and long-term average spring rainfall had a significant effect on the riskiness of crop portfolio, but the magnitude of these two coefficient was negligible or very small (0.000).[9]

Next, note that some control variables are also significant in explaining riskiness in food crop portfolio choices. For example, occupation of the head of the household, and land assets are important determinants of a rural farm household's riskiness in food crops portfolio choice. A positive coefficient of service occupation indicates that rural households with off-farm income are more likely to choose riskier food crops portfolio. Findings here underscore the importance of off-farm labor supply in stabilizing and increasing total rural farm household income. Recall that the 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. Additionally, income from off-farm jobs help relax the liquidity constraint of rural farm households (Stampini and Benjamin, 2009). Finally, coefficients on owned land area (proxy for

[9] Due to very low magnitude, the authors (Bezabih and Di Falco, 2012) fail to quantify the impact of long-term average rainfall and long-term average spring rainfall.

farm size) is positive and significant. Results suggests that increase in owned acreage increases the likelihood of choosing risky crops portfolio. Large farms are likely to have higher profits and are usually linked with higher risks (Harwood et al., 1999).

Let us turn our attention to the second measure of weather risk, ***WR2.*** Recall that this measure, ***WR2***, uses 20 year prior rainfall data to calculate weather risk. Such analysis is needed to test the robustness of the above findings and table 5 reports parameter estimates. Recall the only difference in this table is the measure of risk, ***WR2***. Interestingly, the coefficient on ***WR2*** is the highest compared to estimates on ***WR1*** and ***WR3***. A plausible explanation for higher estimates is that India faced significant drought in 1987-1990 and 1993-1994 (De, Dube, and Rao, 2005; Gupta, Tyagi, and Sehgal, 2011). As a result we observe higher variance in rainfall and higher CV in the measurement of ***WR2***. Table 5 shows that if weather risk (***WR2***) increases by one point (unit), for example (column 3, Table 5), the riskiness of food crop portfolios decreases by 0.40 units, about 4 times larger impact than ***WR1***. Finally, we use ***WR3*** measure of weather risk that uses 10 years of prior data to compute CV in rainfall. Specifically, ***WR3*** risk is calculated by taking 10 year CV from 1998-2008; 1999-2008; 2000-2010; 2001-2011 in rainfall for weather risk in 2010, 2011 and 2012, respectively. Coefficient on ***WR3*** is close to those obtained in table 4 that uses WR1 as a measure of weather risk. For instance, parameter estimates in Table 6 shows that if weather risk (***WR3***) increases by one point (unit) the riskiness of food crop portfolios decreases by 0.17 units.

Finally, our results suggest that households with better resource endowments, as measured by the owned land area, tend to have riskier food crop portfolios. The positive effect of land assets on riskiness of crop portfolio supports the finding that risk aversion is decreasing with wealth—a consistent finding from theoretical and empirical studies (Rosenzweig and

Binswanger, 1993; Townsend, 1994). Our result also suggest that the households with off-farm public or private salaried jobs (service occupation) are more likely to hold riskier food crop portfolio. This is plausible because off-farm job may enhance ex-ante risk bearing ability of farm households (Harwood, et al., 1999). Additionally, off-farm income allows a farm household to smooth its consumption in case of adverse rainfall and agricultural outcome; perhaps allows them to undertake risky crops portfolio. Finally, off-farm income may serve as insurance against the primary catastrophic risk they face, farmers are able to find resources to increase expenditure on their farms—take additional risk on the farm.

**Conclusions and Implications**

In semi-arid tropical villages in India, variability in rainfall is the major source of weather risk. In the absence of formal crop insurance mechanisms in the villages, farmers adopt self-insurance mechanisms. Our study considers combination of crop choices as one of the *ex-ante* risk management mechanisms and examines households' food crop portfolio choices as a response to weather risk. Note that the "weather risk" variable (variability in rainfall) is a better measure of risk than in the previous studies. Using crop portfolios, our study captures intercropping and crop production under mixed cropping, a common practice among subsistence farm households in India, which would have been missed had we focused on only a few major crops. We computed riskiness of each crop chosen by rural Indian farm households using the single-index method and computed the average risk of their food crop portfolios.

Findings from our study show: (1) narrow dispersion of food crop portfolio measure, suggesting 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, rural Indian farm households tend to combine more risky crops and less risky crops in their portfolios; (2) the level of riskiness in food crop portfolio choice is significantly influenced by weather risk, regardless which measure of weather risk one uses; (3) consistent with the theory, we find that higher wealth as indicated by greater land holdings, and liquid assets or off-farm income increases farm households' likelihood of choice in making risky food crop portfolio choices.

Overall, food crop portfolio choice as a response to weather risk has important policy implications. In the short term, crop diversity can be used as an important tool to mitigate adverse effects of weather risk for small-holder agriculture. However, it should be noted that adjustments to weather risks through alternative food crop portfolio choices might not provide maximum profits. This is because there is a cost of adaptation to weather risk through adjustment in food crop portfolio choices. 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 jobs in supporting the rural economy and rural farm households.

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Table 1: Variable definition and summary statistics

| Variable | Description | Mean | Std. Dev. |
|---|---|---|---|
| ***Socio-economic attributes of households*** | | | |
| *Female* | =1 if head of household is female; 0 otherwise | 0.08 | 0.27 |
| *Married* | =1 if head of the household is married; 0 otherwise | 0.91 | 0.49 |
| *High school* | =1 if head of the household has at least high school level of education; 0 otherwise | 0.67 | 0.45 |
| *Family size* | Total number of household members | 5.19 | 2.36 |
| *Farming occupation* | =1 if main occupation is farming; 0 otherwise | 0.80 | 0.44 |
| *Service occupation* | =1 if head of the household has a government or private salaried job; 0 otherwise | 0.07 | 0.26 |
| *Draft animals* | Number of draft animals in the household | 1.92 | 0.53 |
| ***Physical farm attributes*** | | | |
| *Total owned land* | Total owned land area (in hectares) | 3.65 | 5.95 |
| *Soil fertility status* | (=1 if average fertility status of the total plots is above 2.5 on the scale of 1 to 4); 0 otherwise | 0.89 | 0.31 |
| *Irrigated area* | Share of irrigated area over total cultivated area in the household | 0.46 | 0.41 |
| ***Weather risk variables*** | | | |
| *WR1* | Coefficient of variation in rainfall based on forty-two years of annual rainfall data in the area | 0.61 | 0.18 |
| *WR2* | Coefficient of variation in rainfall based on twenty years of annual rainfall data in the area | 0.27 | 0.06 |
| *WR3* | Coefficient of variation in rainfall based on ten years of annual rainfall data in the area | 0.26 | 0.07 |
| ***Dependent variable*** | | | |
| *Riskiness index* | The average beta portfolio based on crops grown within a household | 0.14 | 0.09 |

Source: Author’s compilation based on micro-level data under different modules, ICRISAT, 2009 to 2012.

Table 2: Beta coefficient by crop type

| 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. Figure in parentheses are standard errors.

**Table 3: Characterizing the household-level food crop portfolio**

| **Variables** | **Food crop portfolio beta** *Selected quantiles* | | | |
|---|---|---|---|---|
| | <= 0.08 | > 0.08 & <= 0.13 | > 0.13 & <= 0.17 | > 0.17 & <= 0.76 |
| Weather risk (*WR1*) | 0.67 | 0.62 | 0.55 | 0.51 |
| *All variables reported in Rupees*[1] | | | | |
| Total farm income | 79,250 | 88,665 | 12,7223 | 96,089 |
| Total off-farm income | 30,760 | 36,268 | 42,567 | 51,901 |
| Value total plots | 461,597 | 476,271 | 453,524 | 398,204 |
| Value owned plots | 388,977 | 397,476 | 356,212 | 335,442 |
| Value of livestock | 19,701 | 20,362 | 20,874 | 22,611 |

Source: Author's compilation using ICRISAT micro-level data, 2008-2012.
[1] Exchange rate, 1 US dollar = 66 Indian Rupees.

Table 4: Weather risk and food crop portfolio choice: Using ***WR1*** measure of weather risk

*Dependent variable: household level food crop portfolio*[a]

| | Pooled OLS | Random Effects (RE) | Correlated Random Effects (CRE) |
|---|---|---|---|
| Weather risk (***WR1*** [b]) | -0.128** | -0.137** | -0.121** |
| | (-4.70) | (-5.83) | (-4.89) |
| Female household head | 0.0395* | 0.0225* | 0.0216* |
| | (1.69) | (1.48) | (1.42) |
| Family size (in log) | 0.00710 | 0.0118 | 0.0164 |
| | (0.62) | (1.43) | (1.20) |
| Married household head | 0.001 | -0.004 | -0.004 |
| | (0.11) | (-0.59) | (-0.62) |
| High school and above education | -0.008 | -0.008 | -0.007 |
| | (-0.83) | (-1.22) | (-1.14) |
| Farming occupation | 0.005 | 0.002 | 0.002 |
| | (0.63) | (0.38) | (0.36) |
| Service occupation | 0.0286* | 0.0248** | 0.0250** |
| | (1.79) | (2.39) | (2.44) |
| Soil fertility status | -0.0234* | -0.00763 | -0.00778 |
| | (-1.87) | (-0.89) | (-0.90) |
| Total Value of livestock (in log) | -0.003 | -0.002 | -0.002 |
| | (-0.97) | (-0.85) | (-0.55) |
| Total owned land area (in log) | 0.0137** | 0.0116** | 0.0117** |
| | (3.15) | (3.33) | (3.35) |
| Share of irrigated area | -0.00784 | -0.00843 | -0.0139 |
| | (-0.80) | (-1.15) | (-1.42) |
| Year 2010 | 0.0217** | 0.0150** | 0.0147** |
| | (3.36) | (2.80) | (2.74) |
| Year 2011 | 0.0223** | 0.0167** | 0.0166** |
| | (3.22) | (2.91) | (2.90) |
| Year 2012 | 0.0315** | 0.0262** | 0.0263** |
| | (4.45) | (4.59) | (4.63) |
| Mean of family size | | | -0.00112 |
| | | | (-0.27) |
| Mean of draft animal holdings | | | -0.009** |
| | | | (-2.46) |
| Mean of irrigated area share | | | 0.00941 |
| | | | (0.70) |
| Constant | 0.218** | 0.206** | 0.202** |
| | (5.35) | (5.54) | (5.28) |
| *N* | 1,424 | 1,424 | 1,424 |

Figures in parenthesis represent t-values; [a] Higher the value crop risk portfolio (beta), higher is the risk associated with portfolio; each model is controlled for year dummies for years 2010, 2011, 2012. [b] Weather risk is calculated by taking CV from 1967-2009, 1968-2010 and 1969-2011 in rainfall for 2010, 2011 and 2012, respectively.
*, ** indicates significance at the 10, and 5 percent, respectively

Table 5: Weather risk and food crop portfolio choice: Using ***WR2*** measure of weather risk

*Dependent variable: household level food crop portfolio*[a]

| | Pooled OLS | Random Effects (RE) | Correlated Random Effects (CRE) |
|---|---|---|---|
| Weather risk (***WR2***[b]) | -0.446** | -0.399** | -0.366** |
| | (-8.10) | (-8.08) | (-7.33) |
| Female household head | 0.0205 | 0.0150 | 0.0149* |
| | (0.95) | (1.03) | (1.02) |
| Family size (in log) | 0.0066 | 0.00928 | 0.0165 |
| | (0.60) | (1.13) | (1.19) |
| Married household head | -0.013 | -0.008 | -0.008 |
| | (-1.39) | (-1.32) | (-1.27) |
| High school and above education | -0.002 | -0.004 | -0.004 |
| | (-0.18) | (-0.65) | (-0.64) |
| Farming occupation | -0.005 | -0.002 | -0.002 |
| | (-0.56) | (-0.36) | (-0.31) |
| Service occupation | 0.0256* | 0.0240** | 0.0244** |
| | (1.65) | (2.32) | (2.37) |
| Soil fertility status | -0.020* | -0.009 | -0.008 |
| | (-1.70) | (-1.02) | (-0.99) |
| Total Value of livestock (in log) | 0.001 | 0.001 | 0.002 |
| | (0.27) | (0.62) | (0.81) |
| Total owned land area (in log) | 0.006 | 0.006** | 0.006** |
| | (1.48) | (1.99) | (1.98) |
| Share of irrigated area | -0.0110 | -0.00814 | -0.0135 |
| | (-1.08) | (-1.09) | (-1.43) |
| Year 2010 | 0.0100* | 0.0124** | 0.0124** |
| | (1.67) | (2.30) | (2.31) |
| Year 2011 | 0.00861 | 0.0119** | 0.0124** |
| | (1.22) | (2.05) | (2.14) |
| Year 2012 | 0.0170** | 0.0207** | 0.0214** |
| | (2.53) | (3.62) | (3.77) |
| Mean of family size | | | -0.0016 |
| | | | (-0.41) |
| Mean of draft animal holdings | | | -0.0103** |
| | | | (-2.95) |
| Mean of irrigated area share | | | 0.00892 |
| | | | (0.67) |
| Constant | 0.247** | 0.205** | 0.205** |
| | (5.83) | (5.65) | (5.53) |
| *N* | 1,424 | 1,424 | 1,424 |

Figures in parenthesis represent t-values; [a] Higher the value crop risk portfolio (beta), higher is the risk associated with portfolio; each model is controlled for year dummies for years 2010, 2011, 2012. [b] Weather risk is calculated by taking 20 year CV from 1988-2008; 1989-2009; 1990-2010; 1991-2011 in rainfall for 2010, 2011 and 2012, respectively.
*, ** indicates significance at the 10, and 5 percent, respectively

Table 6: Weather risk and food crop portfolio choice: Using ***WR3*** measure of weather risk

*Dependent variable: household level food crop portfolio*[a]

| | Pooled OLS | Random Effects (RE) | Correlated Random Effects (CRE) |
|---|---|---|---|
| Weather risk (***WR3***[b]) | -0.261** | -0.172** | -0.156** |
| | (-6.36) | (-4.47) | (-4.05) |
| Female household head | 0.0240 | 0.0195 | 0.0192 |
| | (1.05) | (1.30) | (1.27) |
| Family size (in log) | 0.002 | 0.007 | 0.0196 |
| | (0.18) | (0.82) | (1.43) |
| Married household head | -0.0106 | -0.00316 | -0.00332 |
| | (-1.02) | (-0.47) | (-0.48) |
| High school and above education | -0.00184 | -0.00518 | -0.00494 |
| | (-0.18) | (-0.81) | (-0.77) |
| Farming occupation | 0.001 | -0.000 | 0.000 |
| | (0.17) | (-0.01) | (0.00) |
| Service occupation | 0.0266* | 0.0253** | 0.0258** |
| | (1.69) | (2.43) | (2.49) |
| Soil fertility status | -0.0204* | -0.009 | -0.008 |
| | (-1.65) | (-1.01) | (-0.99) |
| Total value of livestock (in log) | -0.001 | 0.000 | 0.001 |
| | (-0.27) | (0.03) | (0.34) |
| Total owned land area (in log) | 0.0121** | 0.0104** | 0.0106** |
| | (2.81) | (2.94) | (3.01) |
| Share of irrigated area | -0.008 | -0.007 | -0.0154* |
| | (-0.85) | (-0.91) | (-1.68) |
| Year 2010 | 0.00975 | 0.0133** | 0.0133** |
| | (1.52) | (2.41) | (2.42) |
| Year 2011 | 0.00701 | 0.0127** | 0.0133** |
| | (0.94) | (2.16) | (2.28) |
| Year 2012 | 0.0163** | 0.0223** | 0.0232** |
| | (2.30) | (3.88) | (4.06) |
| Mean of family size | | | -0.003 |
| | | | (-0.76) |
| Mean of draft animal holdings | | | -0.0134** |
| | | | (-3.82) |
| Mean of irrigated area share | | | 0.0145 |
| | | | (1.11) |
| Constant | 0.209** | 0.154** | 0.159** |
| | (5.04) | (4.37) | (4.47) |
| *N* | 1,424 | 1,424 | 1,424 |

Figures in parenthesis represent t-values.[a] Higher the value crop risk portfolio (beta), higher is the risk associated with portfolio; each model is controlled for year dummies for years 2010, 2011, 2012. [b] Weather risk is calculated by taking 10 year CV from 1998-2008; 1999-2008; 2000-2010; 2001-2011 in rainfall for 2010, 2011 and 2012, respectively.

*, ** indicates significance at the 10, and 5 percent, respectively