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Farmers' Response to Rainfall Variability and Crop Portfolio Choice

Evidence from Ethiopia

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Farmers' Response to Rainfall Variability and Crop Portfolio Choice: Evidence from Ethiopia

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Abstract

This paper studies the patterns of farmers' crop choices for a multiple-crop portfolio, where production risk considerations and rainfall uncertainty are likely to be critical factors. Our analysis employs plot-level panel data from Ethiopia, combined with seasonal and yearly rainfall variability (from 30 years of meteorological data corresponding to the survey villages). Using the single index approach, our results indicate that the combined riskiness of crop portfolios at a household level responds negatively to annual rainfall variability, while seasonal rainfall variability has less consistent impact. Farmers are more likely to select less risky crops with less return, even when intercrop interactions are taken into account. Moreover, development policies designed to enhance accumulation and risk taking should take into account the importance of such exogenous factors as weather in ex-ante risk taking.

Key Words: crop choice, risk index, Ethiopia, annual and seasonal rainfall variability

JEL Classification: Q12, Q54, C23

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Introduction

Pervasive economic and social risks are facets of life for rural households in low-income developing countries (e.g., Mogues 2006; Yesuf and Bluffstone 2009). Partly due to the scope and diversity of such risks, formal insurance markets are scarce in such settings, and farmers employ relatively sophisticated methods to offset the risks they face (Clark and Dercon 2009; Udry 1994). The existence of such risks can alter behavior in ways that at first glance seem sub-optimal, particularly if they make farmers less willing to undertake activities and investments with high expected outcomes (e.g., Rosenzweig and Binswanger 1993; Yesuf and Bluffstone 2009).

As part of self-insurance measures, households alter the composition of productive and non-productive assets in response to their anticipation of different degrees of weather and other production risks (Allen, Gichuki, and Rosenzweig 1991; Isik 2002). Diversification into less profitable, but less risky crops—an example of conservative crop production strategies—is one such ex-ante risk coping mechanism (Benin et al. 2004; Morduch 2002), especially to hedge against weather risk (Kurukulasuriya and Mendelsohn 2006).

Given the pervasiveness of weather uncertainty and the almost exclusive dependence of smallholders on rainfall for productivity, a number of studies have looked into the nature and degree of crop riskiness in relation to the presence of production and market risks (e.g., Fafchamps 1992; Haile 2007; Dercon 1996). It should be noted, however, that these earlier studies either rely on subjective measures of the riskiness of the crops or focus on selected or the major crops. An objective way of measuring the riskiness of individual crops and aggregating them (in a multiple-crop setting) allows a more accurate measurement of the contribution of

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individual crops to the riskiness of a crop portfolio, incorporating the mutual interdependence across crops at a farm-household level.

Accordingly, the aim of this paper is to investigate the riskiness of a combination of crops at a farm-household level in relation to rainfall variability, using a method of measuring and aggregating crop riskiness applied to farm management studies. In particular, we follow Turvey (1991) in measuring individual crop risk and portfolio risk, using the single index model.

We use plot-level data from the Sustainable Land Management Survey, consisting of four rounds of data collected in 2000, 2002, 2005, and 2007, in the Amhara National Regional State of Ethiopia. Because the data contains production information by plot, it enables us to estimate both plot (crop level) riskiness, as well as crop portfolio (farm-household level) riskiness by aggregating the individual crop riskiness measures.

Important implications for development strategy can emerge from understanding the responsiveness of crop portfolio choices to seasonal and annual rainfall variability. Given the subsistence nature of agriculture in Ethiopia and general rudimentary agricultural technology, suppose that there is evidence of stability of crop composition over time, with choices mainly dependent on physical farm and socioeconomic characteristics, but relatively unresponsive to weather uncertainty. This implies that improved productivity and increased welfare for the rural poor can be achieved through structural changes that enhance agricultural productivity, off-farm employment, and investment in productive assets. On the other hand, if crop choice is responsive to weather uncertainty, then a case can be made that climate change-related interventions ought to place more emphasis on providing weather insurance for farmers.

The rest of the paper is organized as follows. We review the literature on crop choice and weather uncertainty in section 1. Section 2 details the data used in the empirical analysis, the variables, and the estimation methodology, plus some considerations in the estimation procedure. Section 3 presents our empirical findings and discussion, and section 4 concludes.

1. Crop Choice in Agricultural Risk Management and Weather Shocks

There is a growing consensus among scientists and policymakers that climate change-induced weather variability has tremendous impact on the performance of agriculture. This is particularly true in low-income countries, where agricultural production is highly sensitive to weather and adaptive capacities are low (Rosenzweig and Parry 1994; Reilly et al. 1996; Reilly and Schimmelpfennig 1999; Kates 2000; Kurukulasuriya et al. 2006; Seo and Mendelsohn 2008; Deressa et al. 2009). For smallholders in low-income countries, where droughts and floods are frequent, where precautionary savings is almost impossible, and where public safety nets and financial markets are not adequate or available to help manage risk (Barrett et al. 2007; Dercon 2002; Morduch 2002), households mostly rely on production decisions and crop choices to hedge against weather risk (Kurukulasuriya and Mendelsohn 2006; Rosenweig and Parry 1994).

In a pioneering study of crop choices under multivariate risk, Fafchamps (1992) showed that crop diversification, which is a characteristic feature of small farmers in developing countries, is a response to high variance in food prices and other risks that they are poorly insured against. Similarly, using data from the Punjab area of Pakistan, Kurosaki and Fafchamps (2002) demonstrated that farmers' crop choices are dependent on price and yield risk. Crop diversity, crop sequencing or rotation (Amede et al. 2001; Benin et al. 2004), and intercropping (Corbeels et al. 2000) are traditional ways of restoring soil productivity (renewing soil nutrients) and obtaining the maximum return from cultivated land under uncertain conditions. Planting varieties that mature earlier in the season (short-season crops) and protecting crops against the moisture shortage and yield loss are also common agricultural practices of farmers.

Di Falco and Chavas (2009) showed that greater diversity can reduce the risk of crop failure. Seo and Mendelsohn (2008) and Kurukulasuriya and Mendelsohn (2006) also looked at the climate sensitiveness of crop choices, using cross-country data in Latin America and Africa.[1]

Understanding household-level crop choices can generate important information about how farm households change the riskiness of their crop composition in reaction to weather-related risk. Haile (2007) showed that Ethiopian farmers choose crops most suited to a specific rainfall condition as a strategy for coping with unpredictable rainfall. In particular, in times of low rainfall, farmers predominantly choose moisture- and stress-tolerant crops, such as teff and grass peas, and not moisture-sensitive crops, such as wheat and lentils.

Although this analysis examines household-level choices for crops as a response to weather risk, the categorization of crops as risky and non-risky is arbitrary. Dercon's (1996)

[1] In low-income, risk-prone settings, crop biodiversity can be a critical resource to ensure efficient use of complementary resources and shield against natural risk. From an ecological perspective, increased species diversity contributes to an ecosystem's performance through overall productivity, stability, and facilitative interaction (Hooper et al. 2005; and Baumgartner 2007). Diversity helps productivity by increasing the likelihood of key productive species present, enhanced complementarity between functionally different species, and efficient use of available resources (Aarssen1997; Loreau 2000). In addition, it improves facilitative interaction between species, whereby certain species alleviate harsh environmental conditions or provide a critical resource for others (Mulder et al. 2001). Furthermore, with diversity, more species with different sensitivities to fluctuations may be present, providing overall ecosystem stability (Borrvall et al. 2000).

analysis of allocation of inputs onto high- and low-risk activities made the argument that about 90 percent of the difference in land allocation (for risky and less-risky crops) between the poorest and the wealthiest groups of households was the result of asset differences. This result is also similar to Rosenzweig and Binswanger's (1993) study of the choice of investment portfolio in rural India.

Given Ethiopia's almost exclusive dependence on rainfall for agricultural production and its well-known experience with failing and erratic rainfall, examining farmers' responsiveness to weather uncertainty is crucial for the design of effective agricultural and development policies.

The analysis in this paper uses a rich and comprehensive farm-panel dataset from more than 2,800 Ethiopian households that were followed in two different rounds of interviews and surveys. Ethiopia is an interesting case study for our purpose as one of the least developed countries in the world, with a gross domestic product (GDP) slightly over US$ 10 billion and a population of over 70 million. Agriculture is the primary livelihood for the overwhelming majority of Ethiopia's population and accounts for about 44 percent of total GDP, with crop production accounting for 28 percent in 2005–2006 (MoFED 2006). It is the main source of export earnings and raw materials for Ethiopia's local agro-industry.

Despite its heavy dependence on rainfall, only around 1 percent of the total cultivated land is irrigated. Given the predominance of small-scale and subsistence farming in Ethiopia, the amount and geographic and temporal distribution of rainfall—in addition to the climate temperature—is one of the most important determinants of crop production. Throughout the 20th century, Ethiopia has been devastated by droughts and erratic rainfall variability, the major causes of its food shortages and famines.

2. The Data, Variables, and Estimation Procedure

In this section, we start by briefly describing the data and discuss the operationalization of the variables used in the analysis. We then outline our estimation strategy and econometric considerations.

2.1 The Data

Our data was collected through a rural household survey of the same households in the 2000, 2002, 2005, and 2007 crop seasons.[2] The survey households are in two zones (South Wollo and East Amhara) of the Amhara National Regional State, a region that encompasses part of the northern and central highlands of Ethiopia. The monthly rainfall data from 1976 to 2006, supplied by the Ethiopian Meteorology Authority, was collected in stations close to the study villages, or *kebeles*.

Local farming is a mixed crop-livestock system, where a farm household has several field plots to cultivate crops plus some livestock that grazes mainly in communal fields.[3] The crops produced are cereals, pulse and legume crops, oil seeds, and others. The major cereal crops include teff, wheat, barley, sorghum, and maize. Pulses cover several kinds of beans and peas, as well as lentils and vetch. Perennials include coffee, fruit trees (orange, mango, papaya, banana, avocado, guava, and pineapple), and spices.

Cereals are the predominant crops grown in the study area, followed by pulse crops and legumes. Oil crops are a small, but significant, share of the crops grown, as are vegetable crops, spices, and perennials. In addition to these major crops, households grow several other types of crops, albeit in much smaller quantities.

Table 1 presents the variables and their descriptive statistics. Please note that since the regressions are based on household-level, *not* plot-level, observations, all the variables reflect this.

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[2] This multi-year survey was conducted by the Ethiopian Development Research Institute and Addis Ababa University, in collaboration with the University of Gothenburg, and with financial support from the Swedish International Development Agency (Sida).

[3] Livestock, while theoretically part of a farm or household production portfolio, are not included in our analysis. The major reason we excluded livestock is the difference in the decision time frames for choosing crop types and managing livestock. Crop production is a seasonal choice, while livestock are a much longer-term investment. However, we do use livestock as a control representing the wealth levels of the households in the dataset. Livestock, particularly oxen, are seen by many as a means of saving and an important component of agricultural input.

Table 1. Description of Variables Used in the Regressions

Variable	Description	Mean	Std. dev.
Socio economic characteristics of the household			
Sex	Sex of the household head	0.182	0.386
Age	Age of household head	50.461	16.224
(Ability to) write	Household head's formal education (1 = read and write; 0 = otherwise)	0.362	0.481
Adult male	The number of male working-age family members of the household	1.902	1.194
Adult female	The number of female working-age family members of the household	1.815	1.021
Oxen	The number of oxen	1.982	1.371
Livestock	The number of livestock (in tropical livestock units)	5.387	4.419
Physical farm characteristics of the household			
Land area	Total farm size of the household in hectares	1.414	1.310
Avg_fertile	Proportion of highly fertile plots in the total plots managed by the household	0.413	0.373
Avg_red	Proportion of red-soil plots in the total plots managed by the household	0.511	0.373
Avg_flat slope	Proportion of flat-sloped plots in the total plots managed by the household	0.676	0.337
Time variant variables (averaged over the survey years)			
Mean_female	Number of female adults averaged over the survey years	5.769	8.719
Mean_male	Number of male adults averaged over the survey years	8.341	29.180
Mean_ox	The number of oxen averaged over the survey years	1.952	1.082
Mean_livestock	The number of livestock averaged over the survey years	1.841	0.867
Rainfall variables			
Coefficient of variation	The coefficient of variation of the annual rainfall	0.540	0.336
Summer coefficient of variation	The coefficient of variation of the summer season (*kiremt*) rainfall	0.274	0.083
Spring coefficient of variation	The coefficient of variation of the spring season (*belg*) rainfall	0.495	0.154
Dependent variables			

Riskiness index	The average of beta coefficients for each of the crops grown within a household.	0.458	0.315
Risk ranking	The sum of risk ranks attached to each of the crops grown within a household	0.864	0.542

2.2 Crop-Risk Variable

One of the objectives of this paper is to generate a measure of crop portfolio riskiness at a household level by using the riskiness measures of individual crops and combining them into a measure of riskiness at a household level. To this end, we use the single index measure developed by Turvey et al. (1991).

The single index approach enables us to derive coefficients for the riskiness of each crop, based on information about their corresponding revenues. This approach, as applied to crop portfolios, works under the assumption that revenues associated with various farm enterprises are related only through their covariance with some basic underlying factor. Two measures form the basis of the single index method: the stochastic individual crop revenues; and the reference portfolio, which is the sum of individual crop revenues. Equation (1) gives the econometric relationship between the reference portfolio S_{Kh} and the individual crop revenues S_{ih} for the i^{th} crop and h^{th} household:

$$S_{ih} = \alpha_i + \beta_i S_{Kh} + e_{ih} \; , \tag{1}$$

where α_i is the intercept, β_i is the regression coefficient, and e_{it} is the error term.[4]

Table 2 presents the beta coefficients corresponding to the crops grown by the sample households. Crops, such as white teff, wheat, maize, millet, sinar, beans, and vetch, have a higher level of beta coefficients, while mixed teff, chickpeas, gibto, potatoes, and a collection of all other minor crops have a considerably lower level of beta coefficients.[5] There are also considerable differences in crop beta coefficients between crop categories. Such crops as

[4] For details on the derivation of the single index measure, the differences in the nature of the data used in Turvey et al. (1991), and our analysis, see appendix 1.

[5] Due to the limited number of observations and difficulties in obtaining sensible estimates for the crop riskiness measures, all the minor crop categories were grouped into the ―other crops" category. Hence, any household growing one or more of these minor crop categories will have the beta risk coefficients calculated on groupings with other categories.

potatoes, vetch, and gibto have high beta coefficients (above 0.181), while lentils, oats, and millet have low beta coefficients (below 0. 1)

Table 2. Beta Coefficients by Crop Type

Crop type	Beta coefficient	Crop type	Beta coefficient
White teff	0.154	Lentils	0.078
Mixed teff	0.141	Vetch (guaya)	0.311
Black/red teff	0.040	Chickpea (shimbra)	0.060
Wheat	0.062	Gibto	0.349
Barley (gebs)	0.046	Potatoes	0.181
Maize (bekolo)	0.073	Pepper	0.512
Sorghum	0.183	Fenugreek (abish)	0.041
Millet (zengada)	0.014	Coffee	0.426
Oats (aja)	0.019	Chat	0.181
Sinar (gerima)	0.126	Grass	0.241
Beans	0.071	Eucalyptus	0.220
Cow peas (ater)	0.070	Other crops	0.233

We interpret the beta coefficients as follows. For example, the beta coefficient of barley (0.046), compared to white teff (0.154), suggests that an ETB[6] 1.00 increase in expected revenues for a representative household's portfolio implies an ETB 0.046 increase in expected barley revenues, whereas a similar increase in teff implies an increase of ETB 0.154. This implies that the revenues of white teff have, proportionately, about twice as much variance as the revenues for barley. This implies that crops with a smaller beta coefficient have a more stabilizing effect on the overall farm household revenue than crops with a higher beta coefficient.

The coefficients are consistent with expectations about the riskiness of the crops. In addition, the riskiest crops identified by agronomic studies are the same ones in our study with higher beta coefficients. Our results are also in line with Haile's (2007) findings that rainfall variability has a significant negative effect on the probability of growing wheat and lentils.

The risk index (portfolio beta) is computed as the average of the beta coefficients for each of the crops grown by a household. For instance, if a household grows teff, maize, and beans, an average beta coefficient will be 0.269, which is the average of 0.154, 0.016, and 0.451

[6] ETB = Ethiopian birr; ETB 1 = approximately US$ 0.0625.

for the three crops, respectively. The risk of this portfolio is substantially higher than a portfolio beta (risk index) of 0.1, for example, for a household growing a combination of red teff, barley, maize, and potatoes.

For comparison purposes, we added an additional risk measurement using simple ranking, which we call risk ranking. To compute this measure, all the crops are categorized into three risk groups and numbers are assigned to each of the crops grown by the household: a higher number reflects a higher riskiness, and vice versa. Risk ranking is calculated by summing up these numbers. While this measure may not capture riskiness in a systematic manner and is not necessarily well founded in theory, it is simpler and more transparent, and can be used where such relatively extensive data might not exist, as is the case in most developing countries where multiple-crop farms are common.

2.3 Rainfall Variables (Seasonal and Annual Variability)

We obtained rainfall data from eight meteorological stations close to the 12 study villages. In consultation with the Meteorology Authority, the rainfall values assigned to the villages are based on proximity. Hence, our rainfall data is at the village level; in some instances, households in two villages may share the same rainfall values.

We measured rainfall uncertainty using seasonal and annual variability. Annual variability is the coefficient of the variation of average annual rainfall over a certain number of years, each corresponding to the survey year. For 2007, for instance, the rainfall variability is calculated as the coefficient of variation of annual rainfall for 1982–2006. Similarly, the coefficients of variation of annual rainfall for the years 1980–2004, 1978–2002, and 1976–2000 represent the annual rainfall variability for the years 2005, 2002, and 2000, respectively.

For the seasonal variability measures, we use *belg* (spring) and *kiremt* (summer), the minor and major rainy seasons, respectively.[7] Accordingly, the coefficient variation of the average kiremt rainfall variability measure includes the mean rainfall values for the 26 years in the summer season. Similarly, the belg rainfall variability is measured as the coefficient of variation of the mean rainfall values for the spring months. Just like the yearly rainfall variability, belg and kiremt seasonal rainfall variability is computed as coefficient of variation of

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[7] *Meher* season (approximately June–September) crops, harvested September–December, make up the bulk of food production (90%–95%). *Belg* is the short rainy season, which extends February–May, and production during this time typically accounts for only 5%–10% of total annual production (CSA 2001).

the seasonal means for the years 1976–2000, 1978–2002, 1980–2004, and 1982–2006 for the years 2000, 2002, 2005, and 2007, respectively.

The coefficient of variation for the annual rainfall, computed as the ratio of the mean to the variance of annual rainfall, is 0.972. This is also accompanied by a much lower spring and summer coefficient of variation, 0.27 and 0.49, respectively. The high annual coefficient variation represents the notoriously fluctuating rainfall across the years. However, the very low coefficient of variation of summer rainfall shows the relative stability of rains in the main rainy season.

2.4 Other Independent Variables

Female-headed households make up around 19 percent of the respondents. On average, 39 percent of the respondents are able to write. The average age of the respondents is 47 years, and households average 2 adult male and 1.9 adult female members. This is not surprising, considering the limited off-farm opportunities and limited mobility out of agriculture in the study area and in rural Ethiopia in general. The average livestock holding is 5.182 tropical livestock units and average number of oxen owned per household is around 1.87. The average land holding per household in the area is less than 1.18 hectares. The proportion of fertile plots is 0.41, and 0.67 of the plots are flat-sloped, compared with red-soil plots at 0.51.

3.5. Estimation Procedure

This section sets up a framework for analyzing the link between the riskiness in the crop composition grown by a farm household and rainfall variability. We frame our analysis within the standard theory of portfolio choice, where the problem facing a representative risk-averse farm household is choosing an optimal mix of crops (crop diversity) for its production portfolio in order to maximize expected utility from final wealth at the end of the production period, given the production function and the land, labor, and other resource constraints (Benin et al. 2004).

Assuming that the utility function is state independent, solving such a portfolio choice problem gives an optimal portfolio choice function, the estimable form of which is given by equation 2:[8]

[8] For details on the derivation of the estimable equation, see Di Falco and Chavas. (2008).

$$r_{ht} = \beta x_{ht} + \gamma v_{ht} + \alpha_h + \xi_{ht} \quad , \qquad (2)$$

where *ht* is farm household *h* in period *t*. Farm household-level riskiness of crop portfolio at time *t* is denoted by R_{ht},[9] X_{ht} represents the socioeconomic and farm-level characteristics, and V_{ht} stands for weather-related variables at time *t.* α , β , and γ represent the respective vector of parameter estimates, and ξ_{it} represents the error term. The composite error term $\xi_{it} = \alpha_i + u_{it}$ is composed of a normally distributed random error term u_{ij} ~ n(0, σ_u^2) and an unobserved household specific effect, α_h.

Under the assumption that α_h is orthogonal to the observable covariates, a random effects estimator can be employed as an effective estimator of equation (2) (Baltagi 2001; Wooldrige 2002). However, allowing arbitrary correlation between α_h and the regressors/observed covariates requires a fixed effect, as it takes α_h to be a group-specific constant term and uses a transformation to remove this effect prior to estimation (Wooldrige 2002).

To remedy the major drawback of removing the household specific effects of the fixed effects estimator, Mundlak (1978) and Chamberlain (1982; 1984)[10] suggest replacing the unobserved effect, with its linear projection onto the explanatory variables, in all time periods plus the projection error. Allowing for correlation between α_h and x_h, and assuming a conditional normal distribution with linear expectation and constant variance, implies that α_h can be approximated by the linear function in equation (3):

$$\alpha_h = \psi + \bar{x}_h + e_h \qquad e_h \mid \bar{x}_h \sim N(0, \sigma_\alpha^2) \quad , \qquad (3)$$

where $\bar{x}_h$ is the average of the time varying variables in x_{ht}, and σ_e^2 is the variance of e_h in equation (3). Substituting the expression in equation (3) for α_h in equation (2) gives:

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[9] Note that R_{it} takes two distinct measures in our analysis: the beta coefficient and the risk ranking measure.

[10] Also note that the strict exogeneity assumption on the observed covariates conditional on α_h is maintained, although the arbitrary correlation between the two is allowed in this case. This implies that the observed covariates only contain time-varying explanatory variables.

$$r_{ht} = \beta x_{ht} + \gamma v_{ht} + \psi + \bar{x}_h + \theta_{ht}, \qquad \theta_{ht} \sim N(0, \sigma_\theta^2) \quad (4)$$

This approach of adding the means of time-varying observed covariates as controls for the unobserved heterogeneity without the data transformation in the fixed effects estimator is commonly known as pseudo fixed effects or the Mundlak-Chamberlain random effects model (Wooldridge 2002).

3. Results and Discussion

In this section, we report the results based on the regressions in equation (2), representing the random effects specification; and in equation (4), representing the Mundlak-Chamberlain random effects specifications, are discussed. The results of these two specifications are presented in the first and second panels in table 3, respectively. Each of the panels presents the results from three regressions; the first column includes annual rainfall availability, as measured by the coefficient of variation of annual rainfall for 26 years, in addition to other control variables. The second regression contains the same set of variables as column (1), in addition to variability for the major rainy season, kiremt. The third regression contains the same set of variables as column (1), in addition to variability for the minor rainy season**,** belg. The chi square results show that the random effects models perform better than the pseudo fixed effects models.

Table 3. Regression Results: Determinants of Crop Riskiness per Farm Household Using Risk Index Measure

	Random effects specification			Mundlak-Chamberlain random effects specification		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Age	0.0002 (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.0002 (0.000)	0.0001 (0.000)	0.0001 (0.000)
Sex	-0.033*** (0.012)	-0.032*** (0.012)	-0.032*** (0.012)	-0.029** (0.012)	-0.028** (0.012)	-0.028** (0.012)
Adult male	0.022*** (0.004)	0.023*** (0.004)	0.024*** (0.004)	0.009 (0.007)	0.012 (0.007)	0.016** (0.007)
Adult female	0.024*** (0.004)	0.024*** (0.004)	0.025*** (0.004)	0.032*** (0.007)	0.034*** (0.007)	0.036*** (0.007)
(Ability to) write	0.028*** (0.009)	0.028*** (0.009)	0.029*** (0.009)	0.027*** (0.009)	0.027*** (0.009)	0.028*** (0.009)

Number of livestock	0.004***	0.004***	0.005***	0	0	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of oxen	0.003	0.004	-0.001	0.002	0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Total land area by household	0.031***	0.032***	0.034***	0.030***	0.031***	0.032***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Avg_red soil	-0.013	-0.012	-0.01	-0.014	-0.013	-0.011
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Avg_white soil	-0.019	-0.015	-0.012	-0.018	-0.014	-0.011
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Avg_flat slope	-0.018	-0.017	-0.019	-0.019	-0.018	-0.02
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Avg_fertile soil	-0.01	-0.012	-0.007	-0.009	-0.011	-0.006
	(0.011)	(0.011)	(0.11)	(0.011)	(0.011)	(0.011)
Mean_female				-0.015*	-0.018**	-0.020**
				(0.009)	(0.009)	(0.009)
Mean_male				0.015*	0.012	0.008
				(0.008)	(0.008)	(0.008)
Mean_ox				-0.010***	-0.010***	-0.009***
				(0.002)	(0.002)	(0.002)
Mean_livestock				0.010***	0.010***	0.009***
				(0.002)	(0.002)	(0.002)
Uncertainty	-0.775***	-0.778***	-0.980***	-0.781***	-0.776***	-0.964***
	(0.036)	(0.036)	(0.045)	(0.038)	(0.038)	(0.047)
Su_uncertainty		-0.391***	-0.377***		-0.373***	-0.375***
		(0.131)	(0.130)		(0.133)	(0.132)
Sp_uncertainty			-0.361***			-0.348***
			(0.050)			(0.050)
Constant	0.821***	0.902***	1.221***	0.823***	0.899***	1.208***
	(0.032)	(0.042)	(0.061)	(0.032)	(0.042)	(0.061)
N	5339	5339	5339	5339	5339	5339
Chi2	1546.12	1555.43	1616.46	1500	1501	1501
Prob>Chi2	0	0	0	0	0	0
Sigma_u	0.08183295	0.08106256	0.08277666	0.08213528	1501	0.083168
Sigma_e	0.25969729	0.25963803	0.25799878	0.25969729	0.08146	0.257999
Rho	0.09032497	0.08881951	0.09333164	0.09093282	0.259638	0.094132

Notes: Column (1) is the annual rainfall availability, (as measured by the coefficient of variation of annual rainfall for 26 years, in addition to other control variables.
Column (2) has the same set of variables as column (1), plus variability for the major rainy season (kiremt).

Column (3) contains the same set of variables as column 1, in addition to variability for the minor rainy season (belg).
Significance levels: * = 10%; ** = 5%; and *** = 1%.
Village-level dummies are used as controls for differences in village-level characteristics.

As can be seen from the results in table 3, households experiencing high annual rainfall variability are more likely to have a lower value of riskiness corresponding to their crop portfolio. In particular, the coefficient for annual rainfall variability indicates that if the coefficient of variation increases by 1 unit, the riskiness of the overall portfolio decreases by 0.981 units (see table 1, column 3). Similarly, negative and significant coefficient of the coefficient of variation of summer rainfall indicates that lower levels of summer rainfall variability lead to higher levels of risk composition, and vice versa. The variability in the spring rainfall also appears to be equally important as the summer rainfall in affecting the riskiness of the crop portfolio.

This importance of belg seasonal rainfall variability on riskiness may be due to the role belg rains (spring) play for the meher crop production (approximately June–September). Belg rains are crucially important for seed-bed preparation for short and long-cycle meher crops, and planting of long-cycle cereal crops, such as maize, sorghum, and millet (Eggenberger and Hunde 2001; USAID 2003), even though belg crops contribute less than 10 percent of the total grain production (CSA 2001). This implies that, although favorable belg rains are important for belg production, the choice of planting meher season crops during the belg season is actually made in anticipation of the meher season rainfall.

Several of the control variables are significant. Of the socioeconomic characteristics, only gender of household head has a negative effect on the riskiness of crop portfolio, implying that female-headed households are more likely to opt for combinations of less-risky crops, all else being constant. Both age and education increase the variation in risk composition of crop choices across farm households, suggesting that older and more educated households grow crops with higher combined levels of riskiness. Households with large numbers of adult males and females seem to select riskier crop compositions than others. This could be due to the fact that family members are the most important source of agricultural labor, and households highly endowed with potential laborers can afford to venture into riskier and (at times) more labor-intensive crops.

Households with better resource endowments, as measured by number of livestock, tend to have a riskier portfolio. However, the impact of oxen is less consistent, being either insignificant or negative across estimations. This may be due to the non-uniform requirements of different crops (and their combinations) for draft power. Most of the physical farm characteristics are comparatively insignificant predictors of risky or non-risky crop choices. Households are less likely to select a less-risky crop portfolio, if the household's proportion of red- and white-soil plots is high, possibly due to the high and low water-retention capacities of such plots. (Plots with black soil are believed to have balanced water-retention capacities.) Households with high proportions of fertile and flat-sloped plots also tend overall to have a higher level of riskiness in their crop mix.

In table 4, we present the results from the random effects and Mundlak-Chamberlain random effects estimations, using risk ranking (instead of the risk index used in table 3) as the dependent variable. Most of our results are consistent across the different specifications, showing the limited effect of unobserved heterogeneities and measurement of the dependent variable on our parameter estimates. The regression results confirm that both annual and seasonal rainfall variability has a significant impact on the choice of riskiness of crop portfolio of farm households.[11]

Table 4. Regression Results: Determinants of Crop Riskiness per Farm Household Using Risk Ranking Measure

	Random effects specification			Mundlak-Chamberlain random effects specification		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Age	0.0002	0.0001	0.0001	-0.001	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sex	-0.069***	-0.062***	-0.062***	-0.058***	-0.053***	-0.053***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Number of male adults in household	0.032***	0.036***	0.038***	-0.027**	-0.007	0
	(0.007)	(0.007)	(0.007)	(0.013)	(0.013)	(0.012)
Number of female adults in household	0.025***	0.030***	0.031***	0.019	0.034***	0.038***
	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)
(Ability to) write	0.048***	0.047***	0.049***	0.042***	0.043***	0.045***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)

[11] In addition to rainfall variability measures based on long-term observations, we also analyzed the effect of rainfall variability based on the rainfall values corresponding only to the production season/year. The results were far less consistent, indicating that farmers base their decisions on observations of long-term trends rather than current rainfall patterns.

Number of livestock	0.009***	0.007***	0.009***	-0.001	-0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of oxen	0.021***	0.027***	0.017**	0.015**	0.022***	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Total land area by household	0.049***	0.057***	0.060***	0.050***	0.057***	0.059***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Avg_red soil	-0.008	-0.003	0.001	-0.01	-0.006	-0.002
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Avg_white soil	-0.002	0.018	0.023	-0.004	0.017	0.021
	(0.063)	(0.062)	(0.062)	(0.062)	(0.062)	(0.061)
Avg_flat slope	-0.128***	-0.101***	-0.094**	-0.126***	-0.103***	-0.096**
	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)	(0.038)
Avg_medium slope	-0.164***	-0.134***	-0.120***	-0.159***	-0.133***	-0.121***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Avg_fertile soil	-0.009	-0.023	-0.013	-0.005	-0.019	-0.01
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Mean_female				0.001	-0.014	-0.018
				(0.015)	(0.015)	(0.015)
Mean_male				0.075***	0.052***	0.046***
				(0.014)	(0.014)	(0.014)
Mean_ox				-0.024***	-0.023***	-0.022***
				(0.004)	(0.004)	(0.004)
Mean_livestock				0.024***	0.023***	0.022***
				(0.004)	(0.004)	(0.004)
Uncertainty	-0.900***	-0.919***	-1.317***	-1.004***	-0.976***	-1.335***
	(0.062)	(0.061)	(0.077)	(0.065)	(0.065)	(0.079)
Su_uncertainty		-2.440***	-2.419***		-2.279***	-2.288***
		(0.221)	(0.219)		(0.225)	(0.223)
Sp_uncertainty			-0.706***			-0.661***
			(0.085)			(0.085)
Constant				1.495***	1.939***	2.517***
	(0.062)	(0.075)	(0.105)	(0.062)	(0.075)	(0.105)
Wald chi2(24)	1044.91	1117.4	1127.63	1108.94	1109.40	1109.64
Prob >chi2	0	0	0	0	0	0
Sigma_u	0.069591	0.082852	0.082673	0.069943	0.07043	0.083074
Sigma_e	0.272266	0.268769	0.26877	0.272266	0.27115	0.26877
Rho	0.061324	0.086781	0.086439	0.061908	0.063204	0.087206

Notes: Significance levels: * = 10%, ** = 5%.

Village level dummies are used as controls for differences in village level characteristics.

Overall, these results are in line with the findings by Haile (2007) and Dercon et al. (1996), in that crop choice is highly responsive to risk environments in Africa. Comparing our results with Haile (2007), the coefficients of rainfall are much higher, perhaps due to the fact that Haile's analysis does not take into account the intercrop dependencies the way our study does.

4. Conclusions

Ethiopia's agriculture is almost exclusively rain fed, so rainfall variability comprises an important source of uncertainty in agricultural production decisions. Better understanding of production risk and its management is important to help farmers make informed and critical decisions about their crops because their welfare depends on their ability to withstand the risk of crop loss. In line with this, our paper explores the choice of a combination of crops as an ex ante risk management mechanism, when crop insurance is limited or non-existent. Our central premise is that in a multiple-crop system, the combination of crops chosen is likely to be sensitive to weather risk, measured by annual, summer, and spring rainfall variability.

Although several studies have assessed the link between weather variability (and change) and crop productivity, their analyses have been limited to assessment of single crops, which leaves out the intercropping effects on a farm, or ad hoc aggregation of multiple crops which represents the intercropping effects inaccurately,. To partially fill this gap in the literature, we compute riskiness of crop portfolios chosen by farm households using the single-index method and explore its link to weather variability.

Based on a rich plot-level panel data set from Ethiopia, the results indicate that the level of riskiness of crop portfolios is partly motivated by rainfall variability, both annual and seasonal. In the context of our case study, we find that moisture-sensitive crops specifically tend to have high beta coefficients. This finding may be driven in large part by households' proclivities to rely on less moisture-sensitive crops in times of rainfall shortages, and vice versa. The relatively narrow dispersion of the risk index, at the farm household level, points to the predisposition of households to combine risky and less-risky crops, and to the importance of taking into account crop interdependencies when analyzing overall riskiness at a farm level.

As long as availability of crop insurance remains limited or non-existent, crop and technology choices remain an efficient way for farm households to shield themselves from weather-related production risks. However, the costs associated with traditional agricultural risk programs may be high. Future research that investigates the costs of using such mitigation mechanisms against exogenous insurance coverage would shed light on the proper risk management needs of farmers operating in extreme risk environments.

Our findings that crop riskiness at a farm level is highly responsive to rainfall variability and that the choice of high risk-high return crops is hampered by weather uncertainty have important policy implications. First, development initiatives aimed at encouraging investment and accumulation of assets needs to look into credit access and off-farm employment policies as well as weather insurance policies. Furthermore, given the impacts of climate change on small holder agriculture and increasing efforts to mainstream climate change policy, crop insurance may be one area where climate policy can be linked effectively to development policy. Second, agro-biodiversity conservation efforts can effectively target areas where rainfall patterns are uncertain.

The riskiness of crops is supposed to increase expected yield and the overall income of households. However, actually quantifying to what extent riskiness of crops leads to a gain in productivity (and to what extent that gain is compromised by weather uncertainty) merits further analysis. Furthermore, there will be costs associated with different portfolios, if households decide to change their crop composition in response to weather variability or other reasons, such as acquiring new seeds, learning new techniques, and adapting their plots and cultivation methods to new crops. Further studies need to look into the quantitative relationships between the gains in productivity and the costs of such adjustments. In addition, extending this analysis to include investment (such as livestock) and non-farm income choices should provide a more comprehensive understanding of income diversifications.

Appendix. The Single Index Method Measuring the Riskiness of Crop Portfolios at a Household Level

Equation (A1) specifies the relationship between the reference portfolio revenue and the individual crop revenue:

$$S_K = \sum_{i=1}^{n} x_i \, S_i \ , \tag{A1}$$

where S_k is the reference portfolio, d_i is the weight of enterprise (crop) i, and S_i stands for the stochastic revenue of crop i.

Similarly, the revenue variance and covariance relationships between the reference portfolio revenue and the individual crop revenues are given by:

$$z_K^2 = \sum_{j=1}^{m} \sum_{i=1}^{n} d_i \, d_j z_{ij} \ , \tag{A2}$$

where z_K^2 is variance of the revenue corresponding to the reference portfolio z_{ij} and the covariance of the individual crop revenues. This equation captures the essence of the single index method, where the portfolio risk measures the proportionate contribution of an individual enterprise's risk to the variance of the underlying index.

From equation (A2), the marginal risk-the contribution that each crop makes to portfolio variance is computed as:

$$\frac{\partial V_K^2}{\partial x_i} = 2 \sum_{j=1}^{n} d_i \, V_{ij} \ . \tag{A3}$$

Our parameter of interest, the anticipated changes in the revenues of a commodity in response to changes in portfolio returns, beta, is given in equation (A4):

$$\beta_i = \frac{z_{ij}}{z_k^2} \ . \tag{A4}$$

This parameter is retrieved from regressions of S_{ih} on the underlying reference portfolio S_{kh}, which are the characteristic equations that determine systematic and non-systematic risk:

$$S_{ih} = \alpha_i + \beta_i S_{kh} + e_{ih} \ , \tag{A5}$$

where α_i is the intercept, β_i is the regression coefficient, and e_{it} is the error term. For simplicity, the weights d_i are kept to 1 (equal weights).

The beta parameter estimated then measures the riskiness of each crop. Averaging over the beta coefficients estimated for each crop within the household gives the riskiness of the overall crop portfolio of the household.

Turvey (1991) estimated equation (5a), using time-series data for each county to estimate a county-beta. Hence, the unit of analysis in that study is the county. In our case, because we set out to estimate the beta for each crop within the household, our unit of analysis is essentially the plot (crop type) within each household, for which we have a plot-level data with observations for about 1,500 households over four survey years. As a result, unlike Turvey et al. (1991), which is an ordinary least squares estimation of equation (5a) using time series data, our estimation is a panel-data estimation (time subscripts representing years are suppressed for convenience). In order to take advantage of the panel feature of our data (and to circumvent the effect of the beta coefficient picking up the effect of variations across households), we estimate equation (5a), using a household fixed-effects estimator.

In sum, while we have the advantage of larger observations across households, our panel is short, making time series estimation impossible. It should be noted that using time series data for such estimations is difficult in our setting and we are not aware that any such data exists at a plot level (in a multiple-crop farm context) in Ethiopia. Even our dataset, which contains detailed plot-level information collected over four rounds, is very rare. As this is the first step in trying to measure riskiness using this methodology, future studies need to explore using much richer data.

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