Risk Preferences and Environmental Uncertainty: Implications for Crop Diversification Decisions in Ethiopia

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Risk Preferences and Environmental Uncertainty: Implications for Crop Diversification Decisions in Ethiopia*

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Abstract

To the extent that diversifying income portfolio is used as a strategy for shielding against production risk, both individual risk preferences and weather uncertainty could affect crop diversification decisions. This paper is concerned with empirically assessing the effects of risk preferences and rainfall variability on farm level diversity. Unique panel data from Ethiopia consisting of experimentally generated risk preference measures combined with rainfall data are employed in the analysis. The major contribution of this study is its explicit treatment of individual risk preferences in the decision to diversify, simultaneously controlling for environmental risk in the form of rainfall variability. Covariate shocks from rainfall variability are found to positively contribute to an increased level of diversity with individual risk aversion having a positive but less significant role. We find that rainfall variability in spring has a greater effect than rainfall variability summer—the major rainy season. This finding is in line with similar agronomic-meteorological studies. These results imply that *in situ* biodiversity conservation could be effective in areas with high rainfall variability. However, reduction in risk aversion, which is associated with poverty reduction, is likely to reduce *in situ* conservation.

Keywords: Crop diversity; Experimental risk preferences; Rainfall; Uncertainty
JEL Classification: Q57; Q56; C33; C35

1 Introduction

Risk exposure and risk management are inherent to agricultural activities. Farmers face various forms of risks, ranging from natural environmental uncertainty such as vagarious climatic conditions (drought, flood, etc.), pests and pathogens, to market-related factors like price volatility. In the presence of efficient insurance

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markets, farmers may insure themselves against these risks. However, in the absence of perfect insurance markets–as is often the case in developing countries–exposure to such risks is likely to affect the *ex ante* production choices (Fafchamps 1992; Chavas and Holt 1996; Kurosaki and Fafchamps 2002).

The empirical literature suggests that farmers in developing countries are generally risk averse (Binswanger 1980 and 1981, Wik and Holden 1998, and Yesuf and Bluffstone 2009). For instance, in a series of studies measuring the risk aversion of a sample of Indian farmers using an experimental gambling approach, Binswanger (1980, 1981) finds that farmers exhibit decreasing absolute risk aversion as well as increasing partial relative risk aversion preferences. That is, farmers are more reluctant to engage in risky behavior the lower their wealth levels and the greater the payoff for a specific lottery. Risk attitudes affect farmers' production choices: for example, crop diversification may be a strategy to insure against production risk. Comparing three competing models of choice under uncertainty (expected utility, safety first and expected profit models), Lin *et al.* (1974) investigate which is best suited to explain farmers' diversification strategies. Their findings suggest that farmers tend to be risk averse and that risk aversion determines their diversification strategies.

A growing body of research suggests that agro-biodiversity contributes to increased agricultural crop yield, and to reduced production risk (Smale *et al.* 1998; di Falco and Chavas 2006, 2008; di Falco *et al.* 2010). Exploring the link between crop genetic diversity and wheat productivity in Pakistan's Punjab, Smale *et al.* (1998) find a positive correlation with the mean yield and a negative correlation with the variance of the yield. This finding has been confirmed by, among others, di Falco and Perrings (2005) and di Falco and Chavas (2006). Furthermore, using a moment-based approach to estimate the mean, variance and skewness of a stochastic crop production function, di Falco and Chavas (2009) maintain that agro-biodiversity enhances farm-level productivity and reduces the risk of crop failure ("downside risk exposure" measured by the skewness) in Tigray, even when diversity has a variance-enhancing effect.[1]

These findings also bolster ecologists' earlier arguments that greater diversity is associated with increased biomass (Tilman and Downing 1994; Tilman, Wedin and Knops 1996) and productivity of ecosystems (Tilman, Polasky, and Lehman 2005). These findings may be explained by two different channels: the "sampling effect" hypothesis posits that a collection of species of diverse productivity will more likely include high productivity species; and the "niche differentiation effect" states that as a collection contains more diverse species, ecological niches are likely to be better utilized.

Recent studies have also found that the effect of diversity on productivity depends on rainfall so that agro-biodiversity has a larger impact at lower precipitation levels (di Falco and Chavas 2008; di Falco *et al.* 2010). This means that farmers' strategies in regard to conserving agro-biodiversity are even more crucial in a water-stressed environment. This result implies that diversity may constitute an even greater insurance mechanism for those farmers facing production risk (crop failure) due to the vagaries of the weather. This is crucial in a country such as Ethiopia which has suffered severe droughts over the past few decades.

In addition to rainfall as an important determinant of crop diversity, standard economic theory also emphasizes that the tendency to diversify income portfolio is driven by the individual risk preferences of the

[1]The variance-enhancing effect of diversity is at odds with the findings cited above. However, di Falco and Chavas (2009) show that what really matters, as far as risk exposure is concerned, is to establish which, between the variance and the skewness, dominates.

decision makers.[2] A review of the literature relating individual risk preferences to optimal portfolio choice is too broad and beyond the scope of this paper. We will merely mention a few relevant contributions. For instance, Kapteyn *et al.* (2002) show that the optimal portfolio of households in the context of incomplete portfolio are explained by measured individual risk preferences. In analyzing workers' share holdings, Blasi *et al.* (2008) argue that diversification of each worker's entire portfolio is most efficient when in line with individual risk preferences. Finally, Heaton and Lucas (2000) show that the presence of background risks dictates differences in portfolio holdings in terms of stocks versus safe securities.

In agriculture, Fafchamps (1992) argues that exposure to risk affects farmers' *ex ante* production choices, and optimal crop allocation depends, amongst other things, on farmers' attitudes toward risk. Despite the importance of risk exposure in the economic literature on agro-biodiversity, only a few papers investigate the effect of farmers' idiosyncratic risk preferences on their choice of diversity. This paper sets out to extend existing analyses on the determinants of crop diversity using risk preferences and rainfall patterns as key factors.

The analysis starts out by setting up a simple theoretical framework that generates testable hypotheses regarding the role of individual risk preferences and environmental risk in relation to crop diversification decisions. The empirical analysis employs Poisson random effects and quasi-fixed effects specifications to empirically assess these relationships. The rationale for examining alternative specifications is to explore the potential unobserved heterogeneity that our panel data enables us to control for.

The data source employed in this analysis is the Sustainable Land Management Survey conducted in 2005 and 2007 in two Zones of the Amhara National Regional State of Ethiopia. The data includes experimentally generated risk preference measures combined with rainfall data from the Ethiopian Meteorological Authority.

The findings of the analysis suggest that both rainfall variability and individual risk aversion contribute to an increased level of crop diversity, although the effect of risk preference is less significant compared to rainfall variability. In addition, we find that rainfall variability during the spring season (minor or short rainy season) is more important in determining farmers' crop diversification decisions than rainfall availability or rainfall variability in summer (major rainy season).

The paper is structured as follows: Section 2 discusses the background literature on risk and crop diversification. A simple theoretical model between diversity and its key determinants is presented in Section 3. Section 4 presents the empirical methodology while section 5 provides the data and statistical analysis. Results are reported and discussed in section 6. Finally, section 7 concludes the paper.

2 Background to Risk and Diversity

Insurance markets are conspicuously missing in the agricultural sector in many developing countries (Fafchamps 1992; Dercon 1996). Since farmers are unable to transfer the risk they face to a third party, they must find

[2] It should be noted that individual risk preferences could differ across decision makers even when the overall riskiness of the decision-making environment is constant. In the case we are studying, farmers living in the same village, while exposed to the same rainfall patterns could still have differing individual risk preferences.

both risk-management and risk-coping strategies to hedge against potential adverse shocks. For instance, diversifying land allocation thereby increasing crop agro-biodiversity, or growing less risky crops, are typical risk-management strategies. The extent to which these strategies are adopted may depend on farmers' risk aversion (Fafchamps 1992).

Farmers' motives for investing in agro-biodiversity have traditionally been explored within the so-called household models. Those models seek to establish the main determinants of crop variety choice (Fafchamps 1992) and agro-biodiversity using a utility maximizing farm household framework (Herath *et al.* 1982; Adesina and Zinnah 1993; Barkley and Porter 1996; Van Dusen 2000; Smale *et al.* 2001; Benin *et al.* 2004). Households are both consumers (of finished goods or rental of labor) and producers—using their endowments, labor, land and capital, to grow crops. The choice variables of interest are typically land allocation (shares of land area devoted to specific crops) or production levels. These decisions generally depend on a number of parameters—namely prices (including wages), income levels, and various socio-economic, physical and geographical characteristics—which in turn affect the level of agro-biodiversity as diversity indices are often constructed from the area shares (Van Dusen 2000; Benin *et al.* 2004). This allows applied economists to estimate agro-diversity as a function of these choice variables. For example, using the Margalef index of richness (number of species or varieties) or the Shannon index of evenness and the count index as a measure of diversity, Benin *et al.* (2004) find that households with more male labor, more oxen or larger farms grow more diverse cereal crops, while di Falco *et al.* (2010) suggest that the level of rainfall and household endowments tend to govern crop diversity decisions rather than plot or other household characteristics.

These models, surprisingly, do not generally explicitly include farmers' risk preferences. Lin *et al.* (1974) and later Fafchamps (1992) are among the rare studies that link risk, farmers' risk attitudes and farm diversification strategies—although they are not particularly concerned with agro-biodiversity *per se*. Investigating why large-scale farmers in the developing world tend to allocate larger shares to cash crops than small-scale farmers, Fafchamps (1992) highlights an interesting relationship between farmers' crop portfolio diversification, idiosyncratic risk aversion and consumption preferences. He develops a dynamic model in which he shows that the effect of risk aversion on crop portfolio is *a priori* ambiguous and results from the combination of a direct portfolio effect, and a consumption effect by which a risk averse farmer will insure himself against potential price risk by weighing his crop allocation in favor of the crops with a high consumption price. The overall direction of the effect will hinge upon the parameters of the model.

However, measures of risk preferences in low income countries are fairly rare. The existing literature has relied either on a production data approach or an experimental approach (Binswanger 1980; Wik and Holden 1998; Yesuf and Bluffstone, 2009) to estimate farmers' risk attitude. Both methods however have weaknesses. The production data method has a serious limitation in that risk behavior is confounded with other factors (Eswaran and Kotwal 1990) while the experimental approach suffers from hypothetical bias.

More recently, Baumgärtner and Quaas (2008) touch on the very issue of the link between agro-biodiversity and risk preference at a rather theoretical level. Their main motivation is to understand how farmers manage their agro-biodiversity portfolio to insure themselves against income risk, and how the availability of financial insurance may have an impact on their management decisions. They develop an interesting ecological-economic model of a farmer's choice of biodiversity in the presence of a financial insurance sector—unlike most of the literature dealing with missing insurance markets in developing countries. They show that agro-biodiversity is used by farmers as a natural insurance mechanism (as opposed to financial insurance) and increases with risk aversion in an unambiguous manner. In a companion paper, Baumgärtner and Quaas (2010) explore the implications of investing in diversity when agro-biodiversity provides both private and social benefits. They show that even without regulation, agro-biodiversity may, under some conditions, enhance welfare by acting as a powerful natural insurance mechanism when environmental risks increase.

The choice variable in these two papers differs from the earlier contributions cited above in that the farmer does not choose the crop allocation which in turn is associated with agro-biodiversity. Instead, in Baumgärtner and Quaas (2008), the farmer chooses the level of biodiversity, which is clearly a more abstract control variable. In our paper, we combine insights from both Baumgärtner and Quaas's modeling and the crop choice household models to suggest a simple model that will be used to analyze the relationship between crop diversity, environmental risk and farmers' risk preferences.

3 Simple model

The purpose of this section is to provide a simple model that relates crop diversity to risk preferences and environmental risk. Assume a farmer endowed with wealth w grows $i = 1,...,n$ different crops in a risky environment (e.g. due to weather conditions, diseases or pests) so that crop yield q_i is a random variable. The farmer may impact the distribution of the crop yield and therefore his income by choosing the area of land L_i allocated to each crop i, with $\sum_{i=1}^{n} L_i = \bar{L}$ where $\bar{L}$ denotes the total land area. Let X represent the other forms of inputs required to grow crops. It is also assumed that the mean $\mu_i(L_i,X)$ and variance $\sigma_i^2(L_i,X)$ of the crop yield depends on land allocation L_i and X such that:

Assumption 1.

$$\mathbb{E}(q_i) = \mu_i(L_i,X), \ \frac{\partial \mu_i}{\partial L_i}(L_i,X) > 0, \ \frac{\partial^2 \mu_i}{\partial L_i^2}(L_i,X) < 0 \tag{1}$$

$$Var(q_i) = \sigma_i^2(L_i,X) = \frac{1}{2}\sigma_0^2 L_i^2, \ \frac{\partial \sigma_i^2}{\partial L_i}(L_i,X) > 0, \ \frac{\partial^2 \sigma_i^2}{\partial L_i^2}(L_i,X) > 0 \tag{2}$$

Assumption 1 indicates that the mean of the yield increases in land allocation and is concave, while the variance increases with land allocation and is convex.[3] For simplicity, we assume $\sigma_i^2(L_i,X) = \frac{1}{2}\sigma_0^2 L_i^2$, where σ_0^2 represents environmental risk and as such is common to all crops in the farm.[4] Given common environmental risk, the variability associated with the yield of crop i increases with land allocation. We also assume that the direct and opportunity costs of production $C_i(L_i,X)$ are increasing and convex.

[3] The assumption on the second derivatives ensures that we have a concave problem when we maximize the certainty equivalent.

[4] This is a reasonable assumption since we consider rainfall as our measure of environmental risk in the empirical section.

The farmer's income is therefore given by $y = Q - C(L,X)$, where $Q = \sum_{i=1}^{n} q_i(L_i,X)$ and $C(L,X) = \sum_{i=1}^{n} C_i(L_i,X)$. Here, we assume that crop yield q_i, is measured in monetary units, thus neglecting influences from market prices on the mean and variance of the yield.[5]

The farmer is non-satiated and risk-averse with respect to income. His preferences are represented by a von Neumann-Morgenstern expected utility function $U = \mathbb{E}[u(w+y)]$, where $u(.)$ is a Bernoulli utility function assumed to be increasing ($u' > 0$) and strictly concave ($u'' < 0$). The farmer's problem is therefore given by:

$$\begin{cases} \max\limits_{L_i,X} & \mathbb{E}\left[u\left(w+y\right)\right] \\ \text{s.t.} & y = \sum\limits_{i=1}^{n} \left[q_i(L_i,X) - C_i(L_i,X)\right] \\ & \sum\limits_{i=1}^{n} L_i = \bar{L} \end{cases} \tag{3}$$

Maximizing the expected utility is equivalent to maximizing the certainty equivalent $CE = \mathbb{E}(w+y) - \pi$ (see Chavas 2004):

$$\begin{cases} \max\limits_{L_i,X} & CE = \mathbb{E}(w+y) - \pi \\ \text{s.t.} & y = \sum\limits_{i=1}^{n} \left[q_i(L_i,X) - C_i(L_i,X)\right] \\ & \sum\limits_{i=1}^{n} L_i = \bar{L} \end{cases} \tag{4}$$

where the risk premium $\pi \equiv \pi(A, \sigma_y^2)$, interpreted as the implicit cost of bearing risk, depends both on the farmer's risk preference (denoted A, the Arrow-Pratt measure of risk aversion) and the income risk he faces (denoted σ_y^2). The latter function is given by:

$$\sigma_y^2 = \sigma_y^2\left(L,X\right) = \sigma_0^2 \left[\frac{1}{2}\sum_i L_i^2 + \sum_{i<j} \rho_{ij} L_i L_j\right] \tag{5}$$

where ρ_{ij} is the correlation between the yield of crop i and j.

If we re-write the certainty equivalent as:

$$CE = w + \sum_{i=1}^{n} \left[\mu_i(L_i,X) - C_i(L_i,X)\right] - \pi\left(A, \sigma_y^2\right) \tag{6}$$

then the optimal choice of land use for each crop i is derived from the following first order condition:[6]

[5] Since the focus of our analysis is production risk, we do not include price risk in our analysis. Prices, while important, are less of interest for two reasons. First, given that in our sample farmers mostly practise subsistence agriculture, price responsiveness is very low. Second, because the production data involves nearly 40 different crops, adding price analysis could result in unnecessary distraction.

[6] The first order conditions with respect to X are not of interest so we do not compute them.

$$\frac{\partial \mu_i}{\partial L_i}(L_i^\star, X) - \frac{\partial C_i}{\partial L_i}(L_i^\star, X) - \frac{\partial \pi}{\partial L_i} = 0 \tag{7}$$

Or equivalently

$$\frac{\partial \mu_i}{\partial L_i}(L_i^\star, X) = \frac{\partial C_i}{\partial L_i}(L_i^\star, X) + \frac{\partial \pi}{\partial \sigma_y^2}(A, \sigma_y^2)\frac{\partial \sigma_y^2}{\partial L_i}(L_i^\star, X) \tag{8}$$

The first order condition says that the optimal land allocation for crop i should be such that the expected marginal product of land is equal to the marginal cost plus the implicit marginal cost of bearing risk.

Assumption 2.

1) $\frac{\partial \pi}{\partial A} > 0$*: Farmers with a higher level of risk aversion are willing to pay a greater premium to avoid risk.*

2) $\frac{\partial \pi}{\partial \sigma_y^2} > 0$ *and* $\frac{\partial^2 \pi}{\left(\partial \sigma_y^2\right)^2} \geq 0$*: Enhanced income risk raises the risk premium at an increasing rate.*

3) $\frac{\partial^2 \pi}{\partial A \partial \sigma_y^2} > 0$*: Enhanced income risk raises the risk premium at an increasing rate with risk aversion.*

Assumption 2 suggests that the implicit cost of bearing risk, in other words the risk premium, rises with the level of risk aversion and income risk, and is convex in income risk. In addition, the marginal cost of bearing risk with respect to income risk increases with the level of risk aversion.

Lemma.

Given Assumptions 1 and 2, the effect of risk aversion (A) and environmental risk (σ_0^2) on cropland allocation is characterized by:

1) $$\frac{\partial L_i^\star}{\partial A} \begin{cases} < 0 & \text{if } L_i > -\sum_{i<j} \rho_{ij} L_j \\ \\ > 0 & \text{if } L_i < -\sum_{i<j} \rho_{ij} L_j \end{cases}$$

2) $$\frac{\partial L_i^\star}{\partial \sigma_0^2} \begin{cases} < 0 & \text{if } L_i > -\sum_{i<j} \rho_{ij} L_j \\ \\ > 0 & \text{if } L_i < -\sum_{i<j} \rho_{ij} L_j \end{cases}$$

Proof: See Appendix A.1.

Given $L_i^\star$, the optimal share of land allocated to crop i is given by $l_i^\star = l_i^\star\left(A, \sigma_0^2\right) = L_i^\star\left(A, \sigma_0^2\right)/\bar{L}$ and depends on the farmer's risk preference. This decision will in turn affect agro-biodiversity as diversity indices are constructed from these area shares (Benin *et al.* 2004).

$$D = D\left(l_i^\star\left(A, \sigma_0^2\right)\right) \tag{9}$$

The effect of risk aversion A and environmental risk σ_0^2 on crop diversity is given by

$$\frac{\partial D}{\partial A} = D'(l_i^\star)\frac{\partial l_i^\star}{\partial A} \tag{10}$$

$$\frac{\partial D}{\partial \sigma_0^2} = D'(l_i^\star)\frac{\partial l_i^\star}{\partial \sigma_0^2} \tag{11}$$

Proposition.

Given Assumptions 1, 2, and $D' > 0$, the effect of risk aversion (A) and environmental risk (σ_0^2) on diversity is characterized by:

1) $$\frac{\partial D}{\partial A}\begin{cases} < 0 & \text{if } L_i > -\sum\limits_{i<j}\rho_{ij}L_j \\ > 0 & \text{if } L_i < -\sum\limits_{i<j}\rho_{ij}L_j \end{cases}$$

2) $$\frac{\partial D}{\partial \sigma_0^2}\begin{cases} < 0 & \text{if } L_i > -\sum\limits_{i<j}\rho_{ij}L_j \\ > 0 & \text{if } L_i < -\sum\limits_{i<j}\rho_{ij}L_j \end{cases}$$

Our model suggests that an increase in individual risk aversion or in environmental risk leads to the increase in both the optimal level of land allocated to crop i and the level of diversity so long as the yield of crop i is negatively correlated with the yield of the other crops j *on aggregate* (i.e. $\sum\limits_{i<j}\rho_{ij}L_j < 0$) and L_i is sufficiently small so that $L_i < -\sum\limits_{i<j}\rho_{ij}L_j$. Conversely, increased individual risk aversion or environmental risk leads to the decrease in both the optimal level of land allocated to crop i and the level of diversity if $L_i > -\sum\limits_{i<j}\rho_{ij}L_j$. This condition is satisfied if either 1) the yield of crop i is positively correlated with the yield of the other crops j *on aggregate* (i.e. $\sum\limits_{i<j}\rho_{ij}L_j > 0$); or 2) if the yield of crop i is *on aggregate* negatively correlated with the yield of the other crops j and L_i is sufficiently large; or 3) if the aggregate negative correlation between the yield of crop i and the yield of the other crops j is sufficiently small.

4 Empirical Methodology

This paper will investigate the relationship between agro-biodiversity, risk preferences and environmental risk using evidence from Ethiopia. As is the case in many low-income countries, agriculture accounts for a large share of the Ethiopian economy: namely, 40% of the GDP, 90% of exports, and 85% of employment (di Falco *et al.* 2010). Ethiopian agriculture relies almost exclusively on rainfall. During the last thirty years, droughts, incidences of pests, as well as animal and human disease have been recurrent events (Dercon 2004). These events have culminated in increased vulnerability of rural households and reduced food security. In extreme cases, they have resulted in large scale famine as happened in the 1980s.

In this section we model the decision of a farming household to diversify its crop allocation using a limited dependent variable framework. Our dependent variable, D_{ht}, represents household h's farm-level diversity in time t, where $h = 1,...,H$ and $t = 1,...,T$. It is measured in terms of count diversity, i.e. the number of crops grown per farm.[7] Equation (12) describes the relationship between the factors affecting the household's decision to diversify and the level of diversity at farm level:

$$\mathbb{E}(D_{ht}|\mathbf{x}_{ht}, \sigma^2_{\mathbf{0}\,ht}, \mathbf{A}_{ht}, \alpha_h) = G\left(\beta\mathbf{x}_{ht} + \gamma\sigma^2_{\mathbf{0}\,ht} + \varphi\mathbf{A}_{ht} + \alpha_h\right) \tag{12}$$

where $\mathbf{x}_{ht}$ denotes a vector of observable household socioeconomic characteristics and farm physical characteristics, $\sigma^2_{\mathbf{0}\,ht}$ represents a vector of rainfall variables, and $\mathbf{A}_{ht}$ represents household risk preferences. The coefficients β, γ and φ denote the respective vectors of parameter estimates and α_h represents the possible existence of unobserved farm-level heterogeneity. G is the mean function which most commonly takes an exponential functional form in a Poisson estimation of a count variable (Wooldridge 2001).

Given that the observed covariates in equation (12) may not account for all the systematic variation in D_{ht}, two alternative approaches are suggested in the literature; fixed effects and random effects estimators. First, the fixed effects estimator takes α_h to be a group specific constant term and uses a transformation to remove these effects prior to estimation. In addition, the fixed effects estimator allows for arbitrary correlation between α_h and the explanatory variables in any time period (Wooldridge 2001).

Second, the random effects estimator has a similar specification to the fixed effects estimator. However, it does not rely on the removal of time-invariant explanatory variables along with α_h (Wooldridge 2001) required by the fixed effects estimator. Conversely, the random effects model requires the regressors to be uncorrelated with the individual effects α_h. So long as this assumption is satisfied, the random effects estimator will be a consistent and efficient estimator (Baltagi 2001; Mundlak 1978).

A violation of the exogeneity assumption underlying the random effects model leads to biased parameter estimates. To remedy this, Mundlak (1978) suggests modeling explicitly the relationship between time varying regressors $\mathbf{z}_{ht} = (\mathbf{x}_{ht}, \sigma^2_{\mathbf{0}\,ht}, \mathbf{A}_{ht})$ and the unobservable effect α_h in an auxiliary regression. In particular, α_{ht} can be approximated by a linear function:[8]

[7] There are a number of diversity measures used in empirical agricultural studies. These include : (i) the Count index which measures species richness on a given farm; (ii) the Margalef Index which measures richness but accounts for land area; (iii) the Shannon Index which measures richness and relative abundance; and (iv) the Berger Parker Index which measures relative abundance (Benin *et al.* 2004). The Count index is the most commonly used index.

[8] Similar approaches are proposed by Hausman and Taylor (1981) and Baltagi *et al.* (2001).

$$\alpha_{ht} = \omega \mathbf{s}_{ht} + \theta \mathbf{z}_{ht} \tag{13}$$

where $\mathbf{s}_{ht}$ represents a vector of explanatory variables and ω is a vector of parameters to be estimated. Averaging over time t for a given household h yields $\alpha_h = \omega \bar{s_h} + \theta \bar{z_h}$, so that substituting the resulting expression into (12) gives:

$$\mathbb{E}(D_{ht}|\mathbf{x}_{ht}, \sigma^2_{\mathbf{0}\,ht}, \mathbf{A}_{ht}, \bar{s_h}, \bar{z_h}) = G\left(\beta \mathbf{x}_{ht} + \gamma \sigma^2_{\mathbf{0}\,ht} + \varphi \mathbf{A}_{ht} + \omega \bar{s_h} + \theta \bar{z_h}\right) \tag{14}$$

Controling for these sources of unobserved heterogeneity by adding the means of time varying observed covariates is commonly known as the pseudo-fixed effects or the Mundlak-Chamberlain's Random Effects Model.

We start our analysis with the strong assumption that there is no unobserved heterogeneity in the diversity equation. Given the discrete nature of D_{ht}, we opt for a random effects Poisson model specification. Once we allow for arbitrary correlation between the covariates and the household-specific effects, we estimate equation (14) since the pseudo-fixed effects estimation removes the possible source of endogeneity associated with unobserved heterogeneity.

5 Data

The data source employed in this analysis is the Sustainable Land Management Survey. The survey was conducted in 2005 and 2007 in the Amhara National Regional State of Ethiopia. A total of 14 villages were included in the study, seven from the East Gojjam Zone and seven from the South Wollo Zone. The dataset contains information on household socio-economic characteristics, farms' physical characteristics, production, and risk preferences. Table 1 describes the variables used in the estimation while Table 2 reflects the summary statistics.

The dependent variable Our dependent variable, farm level diversity, is defined as the number of crops grown by the household. This diversity index is also known as *count index*. Information on the level of farm diversity shows that there has been a moderate change in the level of diversity over time.

Risk preference measures A hypothetical risk preference experiment was conducted with all the respondents of the main survey using a lottery choice experiment. The structure of the experiment follows Binswanger (1980) and Yesuf and Bluffstone (2009). The experiment consists in offering farmers a choice between six pairs of farming systems. Each choice consists of a pair of good and bad outcomes, each outcome occurring with a probability of 50%.[9] This enables the calculation of the expected gains (the average

[9] A bad harvest ranges from 0 to 100 kg, while a good harvest ranges between 100 and 400 kg. An *"extreme"* outcome consists of an expected gain of 100 kg and a spread of 0 kg, while a *"neutral"* outcome consists of an expected gain of 200 kg and a spread of 400 kg.

of the two outcomes), and the spread (the difference between the two outcomes). The choice of any alternative classifies farmers into a risk aversion class (Binswanger, 1980). Farmers are typically assumed to be risk averse in cases where a certain outcome with a lower payoff is preferred over an uncertain outcome with a higher expected payoff. In contrast, risk-seeking behavior occurs when individuals consistently choose a gamble over a certain payoff with a higher payoff value (Teklewold and Kohlin, 2008). Accordingly the extreme risk aversion category represents households who are willing to take the smallest spread in gains and losses, followed by severe, moderate, intermediate, and slight risk aversion categories, while the neutral risk aversion category corresponds to respondents willing to take the biggest spread in gains and losses. Table 3 shows the complete choice sets presented to the respondents.[10]

The fact that higher expected returns could only be realized at the cost of higher variance implies that the risk aversion classes vary with expected income. To obtain a measure of risk aversion that is fixed regardless of the level of payoffs, we follow Binswanger (1980) and construct a constant partial risk aversion coefficient corresponding to each risk aversion class (See table 1).[11] To obtain unique measures of partial risk aversion associated with the indifference points between two alternatives, we use a constant partial risk aversion function of the form $U = (1-A)w^{1-A}$, where w is the certainty equivalent of the prospect and A the constant partial risk aversion coefficient (Binswanger 1980; Sillers 1980). We follow Binswanger (1980) and Yesuf and Bluffstone (2009) in adopting two approaches in measuring risk aversion. One measure of risk is the constant partial risk aversion coefficient while the other measure is captured by a set of dummy variables representing various categories of risk aversion revealed by the experiment.[12] The fifth column of Table 3 shows the end points of the constant partial risk aversion coefficients implied by each possible choice.

Environmental risk Environmental risk is proxied using two measures of rainfall: the mean and the coefficient of variation of rainfall. The latter is an indication of rainfall variability and is computed as the

[10]Our experimental risk preferences measures are hypothetical. The distribution of preferences across the choice categories is similar to the pattern found in earlier studies that relied on hypothetical games (Yesuf and Bluffstone 2009). Typically, highly risk averse individuals (extremely and severely risk averse respondents) tend to be rare (less than 10% percent) in hypothetical games. However, categories of high risk aversion become more important as the stakes are real (as opposed to hypothetical) and higher. For instance, up to 29% of the choices fall in the severe/extreme risk aversion categories with real payoff games even when the actual stakes are small. In addition, Yesuf and Bluffstone (2009) find that households that stand to lose as well as gain are significantly more risk averse than households playing gains-only games. They also find that even without the possibility of losses households are much more averse to risk when stakes are high.

[11]It should be noted that, the constant partial risk aversion is chosen in our study and previous similar studies (Binswanger, 1980; Yesuf and Bluffstone, 2009) because it gives a fixed measure of risk that does not vary with wealth levels or is not sensitive to the scale of the game. However, evidence in both studies shows that individual farm households are more risk averse as the size of the game increases, which is consistent with increasing partial risk aversion (Yesuf and Bluffstone, 2009; Binswanger, 1980). However, with increasing partial risk aversion, indifference points will not be unique and will depend on the rate at which partial risk aversion increases i.e. on the choice paths across the game scale (Binswanger, 1980).

[12]Given the tree structure of the experiment, households first make choices relevant to the intermediate risk preference category. This original choice then splits households into more or less risk averse categories. Households who choose a more risk averse option will further branch out to severe and extreme categories, depending on the subsequent choices they make. Similarly, households who choose a less risky option will branch out into the slight and neutral categories. Because of the tree structure of the experiment, some categories tend to be redundant. As a result, controlling for all the risk aversion categories (but one) did not yield statistically significant results. Hence, in our regression models, we chose to control only for the two largest risk aversion categories, i.e. the neutral and slight risk aversion categories—which represent up to 75% of the respondents.

ratio of the standard deviation to the mean of monthly rainfall in a given season. Because the effective risk faced by farmers lies in the uncertainty about the amount of rainfall during the rainy seasons, our rainfall variables pertain to the rainy seasons only. Ethiopia has two rainy seasons: the *Belg* (spring) or minor rainy season which extends from February to May; and the *Meher* (summer) or major rainy season which runs from June to September. There are reasons to believe that the *Belg* season rainfall may be a more crucial determinant of crop agro-diversity than the *Meher* rainfall. Indeed, although the crops grown during the *Belg* season represent less than 10% of the total annual production, the *Belg* season rainfall is essential for seed-bed preparation for short and long-cycle *Meher* crops such as maize, millet and sorghum[13]; and planting of long-cycle cereal crops (Eggenberger and Hunde, 2001). This is vital since long-cycle crops have considerably higher yield than short-cycle ones (Eggenberger and Hunde, 2001).

Eggenberger and Hunde (2001) maintain that in recent years, the *Belg* rains have been erratic, occurring very late or failing outright in most regions. Besides, Yemenu and Chemeda (2010) find that the variability of the length of the growing period during the *Belg* season is extremely high, resulting in weather uncertainty and frequent occurrences of dry spells and drought events. Therefore, to cover likely food gaps during the *Meher* season, farmers adjust their planting by sowing *Belg* crops late, or could suffer total *Belg* crop loss due to poor *Belg* rains. On the other hand, the *Meher* season rainfall is usually well above the threshold limit so that crop harvesting is less likely to be affected by moisture stress.

Because farmers choose their crop allocation based on historical rainfall patterns, the rainfall variables are measured for the year prior to the observed planting season, making them *ex ante* measures for the farmers. We also use the *lag* of the rainfall seasonal mean and coefficient of variation.

As mentioned, Table 2 summarizes the descriptive statistics for the variables used in the regression analyses. The average summer rainfall remains fairly constant (731 mm in 2005 compared to 735 mm in 2007). On the other hand, rainfall variability in summer has increased (0.42 in 2005 compared to 0.49 in 2007). Most importantly, rainfall variability in spring is considerably larger than in summer (1.15 in spring versus 0.42 in summer 2005) and has changed by a wider margin over time (+16% in summer compared to -50% in spring). These figures indicate that there is considerable seasonal variation in rainfall within a given year and between years.

Household characteristics Following the literature, numerous household characteristics are controled for in our analysis. The typical average household is composed of 1.7 adult males and 1.6 adult females, suggesting that there is adequate supply of both male and female labor. Households are typically headed by males, aged 50, with a low education levels: only a third of them are able to write. Female headed households represent less than 20% of the sample. Regarding wealth measures, the sampled households own, on average, between 1.7 and 2 oxen.

The physical characteristics of the farms provide us with additional key information we want to control for. The average size of holdings is about 1.5 hectares and contains on average 0.14 infertile plots and 0.7 flat slopped plots with little variation between 2005 and 2007.

[13] The *Meher* season crops harvested in September-December make up the bulk of food production (90-95%).

Since the original data are collected at the plot level, and since our primary interest is in farm level diversity, we have computed annual variables focusing on the socioeconomic characteristics of the household head.[14]

6 Results

The empirical analysis investigates the relationship between farm level diversity, risk preferences and rainfall patterns. We estimate this relationship using the two models discussed in section 4: the standard random effects Poisson model and the pseudo-fixed effects Poisson model which controls for possible unobserved heterogeneity at household/farm level. The explanatory variables of interest are the risk preference variables and the seasonal rainfall measures. The coefficient estimates and associated standard errors for the two models are presented in Table 4 to Table 7.

Tables 4 and 5 present the results of the standard random effects models. In Table 4, we use dummy variables to categorize the farmers' risk preferences while in Table 5, risk attitude is measured by the coefficient of constant partial risk aversion. In column (1), we control for risk preferences and households characteristics without including rainfall variables. We find that the "neutral risk aversion" variable is negative and significant, indicating that crop diversity is reduced as farmers are less risk averse. The other measure for risk preferences, "slight risk aversion", is also negatively associated with diversity but statistically insignificant. In Column (2), we control simultaneously for risk preferences and environmental risk (namely rainfall variability in summer). The coefficient of "neutral risk aversion" remains negative and statistically significant. In addition, the coefficient of variation in summer is positive but statistically insignificant. However, the square of the coefficient of variation is significant and negative suggesting that the impact of the coefficient of variation on diversity has diminishing marginal effects.

As discussed in section 5, spring rainfall could play a crucial role in determining future yields and hence *ex ante* planting decisions and farm level diversity. Accordingly in Column (3) we include rainfall variability in spring in addition to risk preferences and summer rainfall variables. The results show that the coefficient of variation in spring is positively associated with crop diversity and statistically significant at the 1% level whereas rainfall variability in summer becomes even more insignificant.[15] This suggests that farmers' decision to diversify their crop portfolios is driven by spring rainfall patterns rather than summer rainfall patterns. In addition, the lag of the coefficient of variation for both seasons is significant, indicating that past rainfall variability affects the farmers' decision to diversify their crop portfolios. In other words, rainfall history matters in that farmers take past years' seasonal rainfall patterns into account when deciding upon current crop choice patterns. The coefficient of the lag of summer rainfall variability is positive and significant at the 5% level, suggesting that households are likely to increase the spectrum of crops in the face of past increased summer rainfall uncertainty. On the other hand, the lag of spring rainfall variability is negative and highly significant, indicating that past rainfall variability actually leads to a lower tendency to diversify the crop portfolio in the current season. While this appears counter-intuitive, it could be explained by the nature of cropping patterns in the spring season, compared to the summer season.

[14] Such approaches are common in agricultural household studies.

[15] Rainfall variability in summer is now estimated with less precision as the magnitude of the coefficient decreases substantially (0.927 in Column (2) as opposed to 0.545 in Column (3)) while the standard error increases from 0.637 to 0.649.

As discussed in section 4, the *Belg* season covers both the short and long season crops while only the long season crops are grown in the summer season. This indicates that summer crops are more or less similar year to year while *Belg* season crops, particularly those sensitive to moisture timing and availability, change from year to year. In his study of the patterns of inter-annual variability in productions of the six major cereals cultivated in the Amhara region, Bewket (2009) shows that crops whose production is more strongly correlated with *Belg* rainfall, exhibit the highest fluctuation in yield. Besides, pulse crops, the short cycle crops planted in the spring, are nitrogen fixers and are the major rotation and intercropping crops with cereals, whose planting hinges upon rainfall timing and availability. Examples include common bean intercropped with maize (Tamado et al., 2007), and sweet potatoes planted along with wheat and barley (Shank and Yesus, 1995). The implication is that moisture sensitive short cycle crops are grown with such inter annual variability that the spring cropping patterns are much less uniform than the summer cropping patterns. Hence, the negative impact of the lag coefficient of variation of the *Belg* season rainfall could be capturing the effect of variation in planting patterns.

Regarding risk attitudes, Column (3) shows that the neutral risk preference variable is negative and significant, while the slight risk preference variable remains negative and statistically insignificant.

The impact of the mean summer rainfall—which represents about half of annual precipitations—is insignificant as shown in column (4). This could be due to: the relative importance of rainfall variability compared to actual rainfall levels, and the possible correlations between mean and variability of summer rainfall.[16]

In sum, spring rainfall patterns are more important in explaining diversity than summer (the major rainy season) rainfall patterns. Furthermore, the coefficient of variation of rainfall in spring has a greater explanatory power than the mean available rainfall in summer. This is because summer rainfall is more stable and comes at a later stage of the growing season than spring rainfall, making spring rains critical in the early growing stages of the crops.

The importance of the lag rainfall values is also highlighted by previous similar studies. Di Falco *et al.* (2010) use the lagged value of mean annual rainfall and find that while rainfall availability increases productivity, it is the lag rainfall availability that has a more crucial impact on diversity. In particular, their findings show that mean rainfall availability negatively affects diversity. It should be noted, however, that in their analysis, it is mean annual rainfall that is controlled for, and not variability or seasonal measures.

Table 5 shows that the constant partial risk aversion coefficient is positive across the board but not statistically significant. Overall, rainfall variables have stronger explanatory power than the risk preference variables.

Of the socio-economic characteristics, age and number of adult males and females in the household are not significantly associated with the level of diversity. However, education, measured as the ability of the household head to write, as well as wealth, measured in terms of ownership of oxen, are significant determinants of greater crop diversity.[17] With respect to low-income agriculture, Benin *et al.* (2004) note that wealth might positively affect the decision to diversify as greater wealth makes farmers more willing to

[16]Indeed, the coefficient of variation is the ratio of the standard deviation to the mean of monthly rainfall in a given season. In light of this, we controlled for the interaction between the risk preference variables and the coefficient of variation of summer rainfall. We found that the results were insignificant.

[17]In most agricultural studies on Ethiopia, it is common to use livestock as a proxy for wealth.

use opportunities to diversify—in turn increasing their income. Female headed households are less likely to diversify than their male-headed counterparts.

Regarding the physical characteristics of farms, farmers with larger farms tend to select more diverse crops. This finding is in line with Benin *et al.* (2004). In addition, farms with more infertile plots have a positive and statistically significant relationship with diversity.

It should be noted that while village level and agro-ecological level variables may have a significant impact on the decision to diversify, we are not able to directly control for them because of their correlation with the rainfall variables.

Tables 6 and 7 present alternative estimates of the diversity regressions using the pseudo-fixed effects model. In addition to the variables controled for in Tables 4 and 5, we include the mean of the following time varying household covariates: oxen, adult male labor, adult female labor, and farm size. We find similar results both in terms of the direction of the relationships and the magnitudes. Furthermore, the mean oxen and the mean farm size are statistically significant, indicating the presence of unobserved fixed effects. However, due to the presence of these unobserved fixed effects the neutral risk aversion is now only marginally significant at the 12% level.

7 Conclusion

This study analyzes the links between farm-level crop diversification decisions and risk factors using a combination of farm household data from the central highlands of Ethiopia, experimental measures of risk aversion and rainfall data. Previous empirical analyses of the decision for crop diversification have focused on household and farm characteristics and, to some extent, on rainfall variability. However, to our knowledge, no other study has looked into the impact of individual risk aversion on crop diversification decisions using measures of risk preferences. Our major objective is to investigate whether diversity is responsive to individual households' risk preferences, and whether it is more responsive to rainfall patterns—a proxy for covariate risks.

This study develops a framework for assessing the impact of households' attitudes toward risk and rainfall on the decision to diversify their crop portfolios, using measures of risk aversion. Our findings suggest that both rainfall variability and risk aversion tend to increase the level of diversified crop portfolio. In particular, in Ethiopia, the variability of rainfall in spring (the minor rainy season) is crucial and more relevant to the choice of crop diversification than the variability or availability of summer rainfall (the major rainy season). This is because summer rainfall is fairly predictable and comes at a later stage of the growing season, making spring rains critical in the early growing stages of the crops. Farmers' expectations with regard to rainfall is shaped by their observations of the previous seasons' rainfall patterns. That is, history also matters in this instance. The link between the seasonal rainfall patterns and diversification is consistent with the literature that assesses rainfall patterns and agricultural productivity in Ethiopia. This link could be explored further.

We also find weak evidence that risk aversion is an important determinant of crop diversity, although to a lesser extent than rainfall variability. These results are robust to the inclusion of fixed effects to the Poisson regressions.

Empirical studies on farm level diversification decisions have also focused largely on crop diversity. Extending the risk-diversification interactions to all farm enterprises including livestock production and off-farm employment may further illuminate our understanding of the role of covariate and idiosyncratic risk in enterprise choice.

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References

[1] Aguirre Gómez, J.A., Bellon, M.R. and Smale, M. (2000): A regional analysis of maize biological diversity in Southeastern Guanajuato, Mexico. *Economic Botany*, 54(1): 60–72.

[2] Adesina, A. and Zinnah, M. (1993): Technology Characteristics, Farmer Perceptions and Adoption Decisions: A Tobit Model Application in Sierra Leone. *Agricultural Economics*, 9: 297–311.

[3] Baltagi, B.H. (2001). Econometric Analysis of Panel Data (Second Edition), New York, Wiley.

[4] Barkley, A. and Porter, L. (1996): The Determinants of Wheat Variety Selection in Kansas, 1974 to 1993. *American Journal of Agricultural Economics*, 78: 202–211.

[5] Baum, C. F., Schaffer, M. E., Stillman, S. and Wiggins, V. (2006): 'Overid: Stata module to calculate tests of overidentifying restrictions after ivreg,ivreg2, ivprobit, reg3', http://ideas.repec.org/c/boc/bocode/s396802.html.

[6] Baumgärtner, S. (2007): The insurance value of biodiversity in the provision of ecosystem services. *Natural Resource Modeling*, 10(1): 87–127.

[7] Baumgärtner, S. and Quaas, M. (2008): Agro-biodiversity as natural insurance and the development of financial insurance markets, pp. 293–317, in Eds. Kontoleon A., Pascual, U. and Smale, M. , *Agrobiodiversity, Conservation and Economic Development*, Routledge.

[8] Baumgärtner, S. and Quaas, M. (2010): Managing increasing environmental risks through agrobiodiversity and agrienvironmental policies. *Agricultural Economics*, 41(5): 483-496.

[9] Bewket, W. (2009): Rainfall variability and crop production in Ethiopia: Case study in the Amhara region. *Proceedings of the 16th International Conference of Ethiopian Studies*, ed. by Svein Ege, Harald Aspen, Birhanu Teferra and Shiferaw Bekele, Trondheim 2009.

[10] Bellon, M.R. and Taylor, J.E. (1993): Folk soil taxonomy and the partial adoption of new seed varieties. *Economic Development and Cultural Change*, 41: 763–786.

[11] Benin, S., Smale, M., Gebremedhin, B., Pender, J. and Ehui, S. (2004): Determinants of cereal crop diversity on farms in the Ethiopian Highlands. *Agricultural Economics*, 31: 197–208.

[12] Binswanger, H.P. (1981): Attitudes toward risk: Theoretical implications of an experiment in rural India. *Economic Journal*, 91: 867–890.

[13] Binswanger, H. P. (1980): Attitudes toward risk: Experimental measurement evidence in rural India. *American Journal of Agricultural Economics*, 62: 395–407.

[14] Blasi J. R. , D. L. Kruse, H. M. Markowitz (2008): Risk and Lack of Diversification under Employee Ownership and Shared Capitalism. *NBER Working Paper* No. 14229

[15] Brush, S., Taylor, J.E. and Bellon, M.R. (1992): Biological diversity and technology adoption in Andean potato agriculture. *Journal of Development Economics*, 39: 365–387.

[16] Carroll, R. J., Ruppert, D. and Stefanski, L. A. (1995): *Measurement Error in Nonlinear Models*. Chapman & Hall.

[17] Chavas, J.-P. (2004): *Risk Analysis in Theory and Practice*. Academic Press, Elsevier.

[18] Chavas, J.P., and Holt, M.T. (1996): Economic behavior under uncertainty: A joint analysis of risk preferences and technology. *Review of Economics and Statistics*, 78: 329–335.

[19] Davidson, R. and MacKinnon, J.G. (1993): *Estimation and Inference in Econometrics*. Oxford University Press, New York, NY.

[20] Dercon, S. (1996): Risk, crop choice, and savings: Evidence from Tanzania. *Economic Development and Cultural Change*, 44(3): 485–513.

[21] Dercon, S. (2004): Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics*, 74(2): 309–329.

[22] Di Falco, S. and Perrings, C. (2005): Crop biodiversity, risk management and the implications of agricultural assistance. *Ecological Economics*, 55: 459–466.

[23] Di Falco, S., and Chavas, J-P. (2008): Rainfall shocks, resilience and the dynamic effects of crop biodiversity on the productivity of the agroecosystem. *Land Economics*, 84(1): 83-96.

[24] Di Falco, S. and Chavas, J-P. (2009): On crop biodiversity, risk exposure and food security in the highlands of Ethiopia. *American Journal of Agricultural Economics*, 91(3): 599–611.

[25] di Falco, S., Bezabih, M. and Yesuf, M. (2010): Seeds For Livelihood: Crop Biodiversity and Food Production in Ethiopia. *Ecological Economics*, 69 (8): 1695-1702.

[26] Eggenberger, W. and Hunde, M. (2001): 2001 Belg Season in North-Central Ethiopia: Rains late but farmers remain optimistic. Report of a joint UN-EUE/MoA/FAO mission undertaken from 19 — 29 March 2001, http://www.africa.upenn.edu/Hornet/belg0301.html" (last accessed February 2011).

[27] Eisgruber, L.M. and Schuman, L.S. (1963): The Usefulness of Aggregated Data in the Analysis of Farm Income Variability and Resource Allocation. *Journal of Farm Economics* 45: 587–591.

[28] Eswaran, M., and Kotwal, A. (1990): Implications of credit constraints for risk behaviour in less developed economies. *Oxford Economic Papers*, 42(2): 473–482.

[29] Fafchamps, M. (1992): Cash crop production, food price volatility, and rural market integration in the Third World. *American Journal of Agricultural Economics*, 74(1): 90–99

[30] Hagedoorn, J. and Hesen, G. (2009): Contractual complexity of R&D alliances: A two-dimensional analysis of the determinants of contractual complexity. *SSRN Working Papers*. http:/ssrn.com/abstract=1367530.

[31] Hardin, J., Schmiediche, H. and Carroll, R. (2003): Instrumental variables, bootstrapping, and generalized linear models. *The Stata Journal*, 3(4): 351–360.

[32] Hausman, J.A. and Taylor, W.E. (1981): Panel data and unobservable individual effects. *Econometrica*, 49(6): 1377–1398.

[33] Heaton, J. and Lucas, D. (2000): Portfolio choice in the presence of background risk. *Economic Journal*, 110 (1): 1–26.

[34] Herath, H., Hardaker, J.B. and Anderson, J.R. (1982): Choice of varieties by Sri Lanka rice farmers: comparing alternative decision models. *American Journal of Agricultural Economics*, 64(1): 87–93.

[35] Kapteyn, R. and F. Teppa, 2002. Subjective measures of risk aversion and optimal portfolio choice. Rand Labor and Population Program. *Working Paper Series*, 02-03 Tilburg University.

[36] Kurosaki, T. and Fafchamps, M. (2002): Insurance market efficiency and crop choices in Pakistan. *Journal of Development Economics*, 67(2): 419–453.

[37] Lin, W., Dean, G.W. and Moore, C.V. (1974): An empirical test of utility vs. profit maximization in agricultural production. *American Journal of Agricultural Economics*, 56: 497–508.

[38] Mundlak, Y. (1978): On the pooling of time series and cross-section data. *Econometrica*, 46: 69–85.

[39] Pope, R.D. and Prescott, R. (1980): Diversification in Relation to Farm Size and Other Socioeconomic Characteristics. *American Journal of Agricultural Economics*, 62: 554–59.

[40] Shank, R. and Yesus, A.H. (1995): Assessment of Belg Cropping and Meher Planting Prospects in East/West Hararghe, United Nations Development Programme, Emergencies Unit for Ethiopia (UNDP-EUE).

[41] Smale, M., Hartell, J., Heisey, P.W. and Senauer, B. (1998): The contribution of genetic resources and diversity to wheat production in the Punjab of Pakistan. *American Journal of Agricultural Economics*, 80: 482–493.

[42] Smale, M., Bellon, M. and Aguirre, A. (2001): Maize diversity, variety attributes, and farmers' choices in Southeastern Guanajuato, Mexico. *Economic Development and Cultural Change*, 50(1): 201–225.

[43] Smale, M., Meng, E., Brennan, J.P. and Hu, R. (2002): Determinants of spatial diversity in modern wheat: Examples from Australia and China. *Agricultural Economics*, 28(1):13–26.

[44] Schurle, B. (1996): The Impact of Size on Yield Variability and Crop Insurance Premiums, *Review of Agricultural Economics*, 18(3): 415–422.

[45] Tilman, D. and Downing, J.A. (1994): Biodiversity and stability in grasslands. *Nature*, 367: 363–365.

[46] Tilman, D., Wedin, D. and Knops, J. (1996): Productivity and sustainability influenced by biodiversity in grassland ecosystems. *Nature*, 379: 718–720

[47] Tilman, D., Polasky, S. and Lehman, C. (2005): Diversity, productivity and temporal stability in the economies of humans and nature. *Journal of Environmental Economics and Management*, 49(3): 405–426.

[48] Tamado, T., Fininsa, C., and Worku, W. (2007): Agronomic performance and productivity of common bean (*Phaseolus vulgaris* L.) varieties in double intercropping with maize (*Zea mays* L.) in Eastern Ethiopia, *Asian Journal of Plant Sciences*, 6(5): 749–756.

[49] Van Dusen, E. (2000). *In Situ Conservation of Crop Genetic Resources in the Mexican Milpa System*. PhD Dissertation, University of California, Davis.

[50] Wik, M., and Holden, S. (1998): Experimental studies of peasant's attitudes toward risk in Northern Zambia. *Discussion Paper D-14*, Department of Economics and Social Sciences, Agricultural University of Norway.

[51] Wooldridge, J.M. (2001): *Econometric Analysis of cross section and panel data*. MIT Press, Cambridge, MA, USA: Massachusetts Institute of Technology.

[52] Williams, R. (2006): Generalized ordered logit/partial proportional-odds models for ordinal dependent variables. *Stata Journal*, 6: 58–82.

[53] Wagstaff, A. and Lindelow, M. (2008): Can insurance increase financial risk? The curious case of health insurance in China. *Journal of Health Economics*, 27 (2008) 990–1005.

[54] Yemenu, F. and Chemeda, D. (2010): Climate resources analysis for use of planning in crop production and rainfall water management in the central highlands of Ethiopia, the case of Bishoftu district, Oromia region. *Hydrology and Earth System Sciences*, 7(3): 3733-3763.

[55] Yesuf, M., and Bluffstone, R. (2009): Poverty, Risk aversion and path dependence in low income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics*, 91(4):1022–1037.

Table 1: Description of variables

Variables	Description
Dependent variable	
Diversity	Count Diversity (number of crops grown per farm)
Risk preference variables	
Neutral risk aversion	Household classified as neutral in risk aversion (dummy)
Slight risk aversion	Household classified as slightly risk averse (dummy)
Intermediate risk aversion	Household classified as intermediately risk averse (dummy)
Moderate risk aversion	Household classified as moderately risk averse (dummy)
Severe risk aversion	Household classified as severely risk averse (dummy)
Extreme risk aversion	Household classified as extremely risk averse (dummy)
Constant Partial Risk Aversion coefficient	Constant Partial Risk Aversion coefficient. (See Table 3)
Rainfall variables	
Seasonal mean rainfall	Sum of the monthly rainfall observations in a given season. It is measured for the year prior to the observed planting season
Rainfall variability	Coefficient of variation of the monthly rainfall observations: ratio of the standard deviation to the mean of monthly rainfall in a given season. It is measured for the year prior to the observed planting season
Socioeconomic and Physical Farm Characteristics of the household	
Age head	Head's age (years)
Gender head	A dummy variable representing the gender of the household head (1=female;0=male)
Household head able to read	Household head is able to read
Household head able to write	Household head is able to write
Adult male labor	The number of male working-age family members of the household
Adult female labor	The number of female working-age family members of the household
Number of oxen	The number of oxen of the household
Farm size	Total farm size (ha)
Number of infertile plots	Average number of infertile plots
Number of flat plots	Average number of flat slopped plots

Table 2: Summary Statistics

Variables	2005		2007	
	Mean	Std. Dev.	Mean	Std. Dev.
Diversity	3.931	1.747	4.225	1.939
Neutral risk aversion	0.490	0.500	0.469	0.499
Slight risk aversion	0.246	0.430	0.218	0.413
Intermediate risk aversion	0.160	0.367	0.232	0.422
Moderate risk aversion	0.10	0.295	0.061	0.239
Severe risk aversion	0.017	0.130	0.006	0.079
Extreme risk aversion	0.010	0.101	0.015	0.121
Constant Partial Risk Aversion coefficient	0.380	0.810	0.430	0.916
Rainfall variability–Summer	0.422	0.120	0.491	0.191
Lag Rainfall variability–Summer	0.459	0.226	0.488	0.146
Rainfall variability squared–Summer	0.193	0.105	0.277	0.163
Seasonal mean rainfall–Summer	731.225	110.579	734.671	121.101
Rainfall variability–Spring	1.150	0.347	0.564	0.191
Lag Rainfall variability–Spring	1.085	0.387	0.486	0.220
Age head	50.543	15.579	51.229	14.956
Gender head (1=Female; 0=Male)	0.159	0.366	0.191	0.393
Household head able to read	0.059	0.235	0.075	0.264
Household head able to write	0.381	0.486	0.333	0.471
Adult male labor	1.671	1.078	1.644	1.099
Adult female labor	1.657	0.920	1.578	0.892
Number of oxen	1.695	1.545	2.002	0.072
Farm size (in hectare)	1.507	0.943	1.655	1.092
Number of infertile plots	0.143	0.251	0.135	0.226
Number of flat plots	0.668	0.354	0.714	0.288

Table 3: Choice sets for the risk preference experiment and risk index

	Bad harvest	Good harvest	Expected mean	Spread	CPRA Coefficient	Risk Classification
Choice Set 1	100	100	100	0	∞ to 7.5	Extreme
Choice Set 2	90	180	105	90	7.5 to 2	Severe
Choice Set 3	80	240	160	160	2 to 0.812	Moderate
Choice Set 4	60	300	180	240	0.812 to 0.316	Intermediate
Choice Set 5	20	360	190	360	0.316 to 0	Slight
Choice Set 6	0	400	200	400	0 to $-\infty$	Neutral

The numbers in Column 2 to 5 represent output in kg.

Table 4: Determinants of Diversity (Naive-Poisson random effects): Ordinal Risk Aversion Categories

	(1)		(2)		(3)		(4)	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Slight risk aversion	-0.012	(0.024)	-0.012	(0.025)	-0.011	(0..025)	-0.010	(0.025)
Neutral risk aversion	-0.037*	(0.021)	-0.036*	(0.021)	-0.036*	(0.021)	-0.036*	(0.021)
Rainfall variability–Summer			0.927	(0.637)	0.557	(0.649)	0.537	(0.649)
Lag Rainfall variability–Summer			-0.097	(0.065)	0.176**	(0.076)	0.176**	(0.076)
Rainfall variability squared–Summer			-1.247*	(0.724)	-0.995	(0.738)	-0.962	(0.738)
Seasonal mean rainfall–Summer							0	(0.000)
Rainfall variability–Spring					0.214***	(0.042)	0.208***	(0.043)
Lag Rainfall variability–Spring					-0.268***	(0.036)	-0.262***	(0.037)
Age head	0	(0.001)	0	(0.001)	0	(0.001)	0	(0.001)
Gender head	-0.105***	(0.029)	-0.101***	(0.029)	-0.097***	(0.029)	-0.097***	(0.029)
Household head able to read	0.037	(0.035)	0.04	(0.035)	0.048	(0.035)	0.05	(0.035)
Household head able to write	0.047**	(0.021)	0.047**	(0.021)	0.053**	(0.021)	0.054**	(0.021)
Adult male labor	0.008	(0.009)	0.008	(0.010)	0.01	(0.010)	0.01	(0.010)
Adult female labor	0.005	(0.010)	0.007	(0.010)	0.009	(0.010)	0.009	(0.010)
Number of oxen	0.020**	(0.008)	0.023**	(0.008)	0.023**	(0.008)	0.023**	(0.008)
Farm size (in hectare)	0.135***	(0.009)	0.130***	(0.009)	0.135***	(0.009)	0.134***	(0.009)
Number of infertile plots	0.218***	(0.036)	0.184***	(0.038)	0.128**	(0.039)	0.129***	(0.039)
Number of flat slope plots	0.039	(0.029)	0.038	(0.029)	0.037	(0.029)	0.035	(0.029)
Ethiopian year	0.075***	(0.018)	0.122***	(0.027)	0.081**	(0.035)	0.079**	(0.035)
Constant	1.040***	(0.049)	0.937***	(0.129)	0.948***	(0.139)	0.901***	(0.151)
Number of observations	3120		3072		3072		3072	
LR Chi2	471.62		476.73		535.60		536.19	
P-Value: Prob>Chi2	0.000		0.000		0.000		0.000	
Log likelihood	-6018.05		-5914.13		-5884.69		-5884.39	

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The variable Ethiopian year controls for yearly variations. The positive coefficient means that, all else equal, there is more diversity in 2007 than in 2005.

Table 5: Determinants of Diversity (Naive-Poisson random effects): Constant partial risk aversion

	(1)		(2)		(3)		(4)	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant partial risk aversion	0.012	(0.010)	0.011	(0.011)	0.009	(0.011)	0.009	(0.011)
Rainfall variability–Summer			0.985	(0.640)	0.575	(0.652)	0.555	(0.652)
Lag Rainfall variability–Summer			-0.094	(0.066)	0.180**	(0.076)	0.179**	(0.076)
Rainfall variability squared–Summer			-1.317*	(0.727)	-1.008	(0.740)	-0.976	(0.740)
Seasonal mean rainfall–Summer							0	(0.000)
Rainfall variability–Spring					0.222***	(0.042)	0.216***	(0.043)
Lag Rainfall variability–Spring					-0.261***	(0.036)	-0.254***	(0.037)
Age head	0	(0.001)	0	(0.001)	0	(0.001)	0	(0.001)
Gender head	-0.108***	(0.029)	-0.103***	(0.029)	-0.099***	(0.029)	-0.099***	(0.029)
Household head able to read	0.038	(0.035)	0.04	(0.035)	0.048	(0.035)	0.05	(0.035)
Household head able to write	0.046**	(0.021)	0.045**	(0.021)	0.051**	(0.021)	0.052**	(0.021)
Adult male labor	0.008	(0.009)	0.008	(0.010)	0.01	(0.010)	0.01	(0.010)
Adult female labor	0.006	(0.010)	0.007	(0.010)	0.009	(0.010)	0.009	(0.010)
Number of oxen	0.019**	(0.008)	0.022**	(0.008)	0.022**	(0.008)	0.022**	(0.008)
Farm size (in hectare)	0.136***	(0.009)	0.132***	(0.009)	0.136***	(0.009)	0.135***	(0.009)
Number of infertile plots	0.223***	(0.036)	0.190***	(0.039)	0.133**	(0.040)	0.133**	(0.040)
Number of flat slope plots	0.038	(0.029)	0.037	(0.029)	0.037	(0.029)	0.036	(0.029)
Ethiopian year	0.076***	(0.018)	0.124***	(0.027)	0.09**	(0.035)	0.089**	(0.035)
Constant	1.019***	(0.049)	0.903***	(0.130)	0.902***	(0.139)	0.855***	(0.151)
Number of observations	3098		3050		3050		3050	
LR Chi2	472.14		476.75		533.48		534.10	
P-Value: Prob>Chi2	0.000		0.000		0.000		0.000	
Log likelihood	-5975.49		-5871.82		-5843.46		-5843.15	

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The variable Ethiopian year controls for yearly variations. The positive coefficient means that, all else equal, there is more diversity in 2007 than in 2005.

Table 6: Determinants of Diversity (Mundlak's pseudo fixed effects): Ordinal Risk Aversion Categories

	(1)		(2)		(3)		(4)	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Slight risk aversion	-0.005	(0.024)	-0.006	(0.025)	-0.004	(0.025)	-0.003	(0.025)
Neutral risk aversion	$-0.031^{\#}$	(0.021)	$-0.032^{\#}$	(0.021)	$-0.031^{\#}$	(0.021)	$-0.031^{\#}$	(0.021
Rainfall variability–Summer			0.734	(0.640)	0.356	(0.652)	0.336	(0.652)
Lag Rainfall variability–Summer			-0.043	(0.066)	0.234**	(0.076	0.233**	(0.076)
Rainfall variability squared–Summer			-1.01	(0.728)	-0.741	(0.740)	-0.708	(0.741)
Seasonal mean rainfall–Summer							0	(0.000)
Rainfall variability–Spring					0.223***	(0.042)	0.217***	(0.043)
Lag Rainfall variability–Spring					-0.265***	(0.036)	-0.258***	(0.037)
Age head	0	(0.001)	0	(0.001)	0	(0.001)	0	(0.001)
Gender head	-0.087***	(0.029)	-0.084***	(0.029)	-0.080***	(0.029)	-0.080***	(0.029)
Household head able to read	0.034	(0.035)	0.034	(0.035)	0.041	(0.035)	0.043	(0.035)
Household head able to write	0.043**	(0.021)	0.042**	(0.021)	0.048**	(0.021)	0.049**	(0.021)
Adult male labor	0.013	(0.011)	0.015	(0.011)	0.016	(0.012)	0.016	(0.012)
Adult female labor	0.003	(0.014)	0.004	(0.014)	0.005	(0.014)	0.005	(0.014)
Number of oxen	-0.005	(0.010)	-0.002	(0.010)	-0.002	(0.010)	-0.002	(0.010)
Farm size (in hectare)	0.056***	(0.016)	0.058***	(0.016)	0.063***	(0.016)	0.062***	(0.016)
Number of infertile plots	0.205***	(0.036)	0.179***	(0.039)	0.122***	(0.040)	0.122***	(0.040)
Number of flat slope plots	0.033	(0.029)	0.034	(0.029)	0.035	(0.029)	0.034	(0.029)
Mean male labor	0.013	(0.011)	0.015	(0.011)	0.016	(0.012)	0.016	(0.012)
Mean female labor	-0.004	(0.012)	-0.002	(0.012)	-0.001	(0.012)	0	(0.012)
Mean number of oxen	0.070***	(0.020)	0.069***	(0.020)	0.067***	(0.020)	0.068***	(0.020)
Mean Farm size	0.107***	(0.019)	0.099***	(0.020)	0.099***	(0.020)	0.098***	(0.020)
Ethiopian year	0.086***	(0.018)	0.121***	(0.027)	0.087**	(0.035)	0.086**	(0.035)
Constant	0.905***	(0.059)	0.810***	(0.133)	0.803***	(0.143)	0.752***	(0.156)
Number of observations	3120		3072		3072		3072	
LR Chi2	520.58		518.65		577.47		578.13	
P-Value: Prob>Chi2	0.000		0.000		0.000		0.000	
Log likelihood	-5982.39		-5881.99		-5852.58		-5852.25	

Standard errors in parentheses. $^{\#}$ $p < 0.13$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Determinants of Diversity (Mundlak's pseudo fixed effects): Constant Partial Risk Aversion

	(1)		(2)		(3)		(4)	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant partial risk aversion	0.009	(0.010)	0.009	(0.011)	0.007	(0.011)	0.007	(0.011)
Rainfall variability–Summer			0.789	(0.642)	0.381	(0.654)	0.362	(0.654)
Lag Rainfall variability–Summer			-0.039	(0.066)	0.237**	(0.077	0.235**	(0.077)
Rainfall variability squared–Summer			-1.076	(0.730)	-0.764	(0.742)	-0.733	(0.743)
Seasonal mean rainfall–Summer							0	(0.000)
Rainfall variability–Spring					0.231***	(0.042)	0.225***	(0.043)
Lag Rainfall variability–Spring					-0.258***	(0.036)	-0.251***	(0.037)
Age head	0	(0.001)	0	(0.001)	0	(0.001)	0	(0.001)
Gender head	-0.090**	(0.029)	-0.086**	(0.029)	-0.082**	(0.029)	-0.082**	(0.029)
Household head able to read	0.034	(0.035)	0.035	(0.035)	0.041	(0.035)	0.043	(0.035)
Household head able to write	0.042**	(0.021)	0.041*	(0.021)	0.047**	(0.021)	0.047**	(0.021)
Adult male labor	-0.011	(0.013)	-0.012	(0.013)	-0.011	(0.013)	-0.011	(0.013)
Adult female labor	0.003	(0.014)	0.004	(0.014)	0.005	(0.014)	0.005	(0.014)
Number of oxen	-0.006	(0.010)	-0.003	(0.010)	-0.002	(0.010)	-0.003	(0.010)
Farm size (in hectare)	0.057***	(0.016)	0.059***	(0.016)	0.063***	(0.016)	0.063***	(0.016)
Number of infertile plots	0.210***	(0.037)	0.185***	(0.039)	0.127**	(0.040)	0.127**	(0.040)
Number of flat slope plots	0.032	(0.029)	0.034	(0.029)	0.036	(0.029)	0.035	(0.030)
Mean male labor	0.013	(0.011)	0.015	(0.012)	0.016	(0.012)	0.016	(0.012)
Mean female labor	-0.004	(0.012)	-0.002	(0.012)	-0.001	(0.012)	0	(0.012)
Mean number of oxen	0.069***	(0.020)	0.068***	(0.020)	0.066***	(0.020)	0.068***	(0.020)
Mean Farm size	0.107***	(0.019)	0.100***	(0.020)	0.100***	(0.020)	0.099***	(0.020)
Ethiopian year	0.086***	(0.018)	0.124***	(0.027)	0.097**	(0.035)	0.095**	(0.035)
Constant	0.884***	(0.058)	0.775***	(0.133)	0.756***	(0.143)	0.706***	(0.156)
Number of observations	3098		3050		3050		3050	
LR Chi2	520.52		518.45		575.41		576.05	
P-Value: Prob>Chi2	0.000		0.000		0.000		0.000	
Log likelihood	-5940.12		-5839.80		-5811.32		-5811.00	

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The variable Ethiopian year controls for yearly variations. The positive coefficient means that, all else equal, there is more diversity in 2007 than in 2005.

8 Appendix A.1. Proof Lemma

The land use choice for each crop i is derived from the following first order condition:

$$\frac{\partial \mu_i}{\partial L_i}(L_i^\star, X) = \frac{\partial C_i}{\partial L_i}(L_i^\star, X) + \frac{\partial \pi}{\partial \sigma_y^2}(A, \sigma_y^2)\frac{\partial \sigma_y^2}{\partial L_i}(L_i^\star, X, \sigma_0^2) \tag{15}$$

Let us now assume that the second order condition holds strictly so that:

$$\frac{\partial^2 \mu_i}{\partial L_i^2}(L_i^\star, X) - \frac{\partial^2 C_i}{\partial L_i^2}(L_i^\star, X) - \frac{\partial^2 \pi}{\partial L_i^2} < 0 \tag{16}$$

Then, using the implicit functions theorem, we can determine two key comparative statics:

$$\frac{\partial L_i^\star}{\partial A} = \frac{\dfrac{\partial^2 \pi}{\partial A \partial \sigma_y^2}\dfrac{\partial \sigma_y^2}{\partial L_i}}{\dfrac{\partial^2 \mu_i}{\partial L_i^2} - \dfrac{\partial^2 C_i}{\partial L_i^2} - \dfrac{\partial^2 \pi}{\partial L_i^2}} \tag{17}$$

$$\frac{\partial L_i^\star}{\partial \sigma_0^2} = \frac{\dfrac{\partial^2 \pi}{\left(\partial \sigma_y^2\right)^2}\dfrac{\partial \sigma_y^2}{\partial \sigma_0^2}\dfrac{\partial \sigma_y^2}{\partial L_i} + \dfrac{\partial \pi}{\partial \sigma_y^2}\dfrac{\partial^2 \sigma_y^2}{\partial \sigma_0^2 \partial L_i}}{\dfrac{\partial^2 \mu_i}{\partial L_i^2} - \dfrac{\partial^2 C_i}{\partial L_i^2} - \dfrac{\partial^2 \pi}{\partial L_i^2}} \tag{18}$$

Since the denominator is strictly negative by the second order condition, the sign of expression (17) is determined by the sign of the numerator. From Assumption 2, we know that $\dfrac{\partial^2 \pi}{\partial A \partial \sigma_y^2} > 0$. In addition, it is straightforward to establish from equation (5) that $\dfrac{\partial \sigma_y^2}{\partial L_i} = \sigma_0^2 \left[L_i + \sum_{i<j} \rho_{ij} L_j \right] \gtreqless 0$ if $L_i + \sum_{i<j} \rho_{ij} L_j \gtreqless 0$. Hence:

$$\frac{\partial L_i^\star}{\partial A} \begin{cases} < 0 & \text{if } L_i + \sum_{i<j} \rho_{ij} L_j > 0 \\ \\ > 0 & \text{if } L_i + \sum_{i<j} \rho_{ij} L_j < 0 \end{cases} \tag{19}$$

Our task now is to determine how optimal land allocation reacts to environmental risk. To do so, we need to determine the sign of the numerator of equation (18).

Assumption 2 ensures that $\frac{\partial \pi}{\partial \sigma_y^2} > 0$ and $\frac{\partial^2 \pi}{\left(\partial \sigma_y^2\right)^2} > 0$. In addition, $\frac{\partial \sigma_y^2}{\partial \sigma_0^2} = \frac{1}{2}\sum_i L_i^2 + \sum_{i<j} \rho_{ij} L_i L_j$ is also positive, since the income variance $\sigma_y^2 = \sigma_0^2 \left[\frac{1}{2}\sum_i L_i^2 + \sum_{i<j} \rho_{ij} L_i L_j\right]$ must be positive by definition. In addition, since $\frac{\partial^2 \sigma_y^2}{\partial \sigma_0^2 \partial L_i} = L_i + \sum_{i<j} \rho_{ij} L_j$, it has the same sign as $\frac{\partial \sigma_y^2}{\partial L_i}$. That is $\frac{\partial^2 \sigma_y^2}{\partial \sigma_0^2 \partial L_i} \gtrless 0$ if $L_i + \sum_{i<j} \rho_{ij} L_j \gtrless 0$.

If $L_i > -\sum_{i<j} \rho_{ij} L_j$ then $\frac{\partial \sigma_y^2}{\partial L_i}$ >0 and $\frac{\partial^2 \sigma_y^2}{\partial \sigma_0^2 \partial L_i} > 0$. It follows that the numerator of equation (18) is positive and therefore $\frac{\partial L_i^\star}{\partial \sigma_0^2} < 0$.

On the other hand, if $L_i < -\sum_{i<j} \rho_{ij} L_j$ then $\frac{\partial \sigma_y^2}{\partial L_i} < 0$ and $\frac{\partial^2 \sigma_y^2}{\partial \sigma_0^2 \partial L_i} < 0$. As a result, the numerator is unambiguously negative and therefore $\frac{\partial L_i^\star}{\partial \sigma_0^2} > 0$. Hence:

$$\frac{\partial L_i^\star}{\partial \sigma_0^2} \begin{cases} < 0 & \text{if } L_i + \sum_{i<j} \rho_{ij} L_j > 0 \\ \\ > 0 & \text{if } L_i + \sum_{i<j} \rho_{ij} L_j < 0 \end{cases} \tag{20}$$

■