ON CROP BIODIVERSITY, RISK EXPOSURE, AND FOOD SECURITY IN THE HIGHLANDS OF ETHIOPIA

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This paper investigates the effects of crop genetic diversity on farm productivity and production risk in the highlands of Ethiopia. Using a moment-based approach, the analysis uses a stochastic production function capturing mean, variance, and skewness effects. Welfare implications of diversity are evaluated using a certainty equivalent, measured as expected income minus a risk premium (reflecting the cost of risk). We find that the effect of diversity on skewness dominates its effect on variance, meaning that diversity reduces the cost of risk. The analysis also shows that the beneficial effects of diversity become of greater value in degraded land.

Key words: barley, diversity, Ethiopia, food security, land degradation, risk.

Production risk is one of the quintessential features of agriculture. Unpredictable weather can expose farm households to significant production uncertainty and serious hardship. Under harsh climatic and agroecological conditions, this can result in food insecurity and famine. The highlands of Ethiopia are a prime example of such environment. During the last forty years, Ethiopia has experienced many severe droughts,[1] leading to production levels that fell short of basic subsistence levels for many farm households (Relief Society of Tigray (REST) and NORAGRIC at the Agricultural University of Norway 1995, p. 137). Harvest failure due to drought is the most important cause of risk-related hardship of Ethiopian rural households, with adverse effects on farm household consumption and welfare (Dercon 2004, 2005). When facing prospects of harvest failure, *ex-ante* farm production decisions, such as crop or varietal choice, remain a part of risk management strategies (Just and Candler 1985; Fafchamps 1992; Chavas and Holt 1996; Dercon 1996; Smale et al. 1998).[2]

We argue that, in dry environments, farmers' reliance on crop biodiversity is an essential part of *ex-ante* risk management strategies. Diversity in genetic resources embedded in crop seeds can support productivity and help manage risk (Smale et al. 1998). Ethiopia is a recognized global center of genetic diversity for several crops, including barley (Vavilov 1949; Harlan 1992). The majority of varieties grown in Ethiopia are farmers' varieties or "landraces," which exhibit significant genetic heterogeneity.

This paper investigates how crop genetic diversity contributes to farm productivity and affects risk exposure. The analysis relies on a moment-based specification of the stochastic production function (Antle 1983). The approach captures the effects of biodiversity on the mean, variance, and skewness of production. The evaluation of the mean and variance effects is now standard (e.g., Just and Pope 1979). However, the variance does not distinguish between unexpected bad events and unexpected good ones. On that basis, it seems important to consider skewness in risk analysis. An increase in skewness of yield means a reduction in downside risk exposure (e.g., a decrease in the probability of crop failure). The paper contributes to the existing literature by investigating three questions. First, how does risk exposure affect the incentive to use crop biodiversity as a means of reducing the cost of risk bearing? Second, what is the relative

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[1] Ethiopia experienced droughts in 1965, 1974, 1983, 1984, 1987, 1990, 1991, 1999, 2000, and 2002.

[2] In this environment, management options are somewhat restricted. Insurance and risk coping mechanisms often function poorly because of credit constraints, information asymmetries, and commitment failures (Deaton 1989; Fafchamps 1992; Kurosaki and Fafchamps 2002). Safety nets typically provide only limited support (Dercon and Krishnan 2000; Dercon 2004). Off-farm, noncovariant income is limited in remote rural areas. In this context, few options exist for implementing income or activity diversification.

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importance of crop failure in the valuation of farmer's welfare under uncertainty? Third, does the role of crop diversity vary with land quality?

The analysis relies on data from a farm survey undertaken in 1999–2000 in the Tigray region of Ethiopia. To our knowledge, this is the only available database recording Ethiopian farm-level information on crop varieties and thus on crop biodiversity.[3] Ethiopian rural households face high weather variability. Significant spatial variations exist in agroecological conditions, including topography, soil type, temperature, and soil fertility (Hagos, Pender, and Gebreselassie 1999). Different landraces of barley can perform differently across agroecological and microclimatic conditions. This poses three specific challenges for our analysis. First, we need to quantify the role of farm-specific agroecological conditions that affect both productivity and risk exposure. Second, we need to control for the effects of unobservable factors (e.g., differences across villages due to location and institutional factors). Third, we need to analyze the interplay between the farm-specific characteristics that are under farmer's control versus those that affect risk exposure.

Our analysis involves a refined econometric estimation of the production process under risk. Special attention is given to the effects of local environmental conditions and managerial decisions. Controlling for such effects is important in order to reduce the potential biases arising from omitted variables (Sherlund, Barrett, and Adesina 2002). This provides a framework to study the influence on productivity of soil quality, crop biodiversity, and their interactions (Bellon and Taylor 1993), with implications for risk management.

The econometric estimates of the stochastic production function are used to assess the welfare effects of biodiversity on production risk. Under risk aversion, risk exposure makes farmers worse off, implying a positive cost of risk (as measured by a risk premium; see Pratt 1964). Most decision makers exhibit both risk aversion and downside risk aversion (e.g., Menezes, Geiss, and Tressler 1980; Binswanger 1981; Antle 1983; Chavas and Holt 1996). Aversion to downside risk indicates that farmers have an incentive to grow crop cultivars or varieties that affect positively the skewness of the distribution of returns (thereby reducing their exposure to crop failure in drought situations). This raises the question: how important is skewness (compared with variance) in the evaluation of diversity effects on the cost of risk?

Applied to the Tigray region in Ethiopia, our analysis provides evidence on how crop biodiversity affects farm productivity, risk exposure, and household welfare and how such effects vary with soil fertility. We find several important results. First, our estimates show that biodiversity increases farm productivity in Ethiopia. Second, we uncover evidence that higher biodiversity increases variance but decreases downside risk exposure (by increasing skewness). Third, our analysis shows that the skewness effect dominates the variance effect so that higher biodiversity tends to reduce the cost of risk (as measured by the risk premium). Finally, we find that the risk benefit of biodiversity becomes larger under less fertile soils. This provides empirical evidence that biodiversity can help farmers deal with harsh climatic conditions, especially in degraded lands.

Conceptual Framework

Consider a farm producing output y using inputs x under risk. The production technology is represented by the stochastic production function $y = g(x, v)$, where v is a vector of random variables reflecting uncontrollable factors affecting output (e.g., rainfall). The farm output y can either be consumed by the household or be marketed: $y = c_1 + m$, where c_1 is the part of farm output consumed by the household, and m is the marketed surplus that can be marketed at price p_1. In general, m is unrestricted in sign. The marketed surplus can be positive ($m > 0$) when the farm household produces more than it consumes, or negative ($m < 0$) when the household produces less than it consumes. The household also consumes another good c_2 that it can purchase at price p_2. For simplicity, assume that all prices are normalized such that $p_2 = 1$. The household income is: $p_1 m + N(x)$, where $p_1 m$ is the income generated from the marketed surplus, and $N(x)$ denotes the net income from other activities (net of the cost of inputs x). Given $p_2 = 1$, the household budget constraint is: $c_2 \leq p_1 m + N(x)$, where

[3] The survey generated cross-section data. Note that the cross-section nature of the data does not allow an analysis of the dynamic aspects of farm-level management decisions. Panel data would be required to explore such issues. Unfortunately, although farm-level panel data exist in Ethiopia (e.g., from the Ethiopia Rural Household Survey, conducted by IFPRI, Addis Ababa University, and the University of Oxford), such data do not include information on farm household crop varieties.

$m = y - c_1 = g(x, v) - c_1$. Assuming that it is binding, the budget constraint becomes: $c_2 = N(x) + p_1\,[g(x, v) - c_1]$. Let $U(c_1, c_2)$ be a von Neumann–Morgenstern utility function representing household preferences under risk. Under the expected utility model, the household makes decisions so as to solve the optimization problem

$$(1) \qquad \text{Max}\{EU(c_1, N(x) + p_1[g(x, v) - c_1])\}$$

where E is the expectation operator based on the subjective probability distribution of the uncertain variables facing the decision maker. Under nonsatiation in c_2 (where $\partial U/\partial c_2 > 0$), the choice of x in (1) can be written in terms of the "certainty equivalent" (CE), which satisfies

$$(2) \quad U(c_1, CE - p_1 c_1) = EU(c_1, N(x) + p_1[g(x,\ v) - c_1]).$$

Letting $\pi = N(x) + p_1\,[g(x, v)]$ and following Pratt (1964), equation (2) can be alternatively expressed as

$$(2') \qquad U(c_1, E(\pi) - R - p_1 c_1) = EU(c_l, \pi - p_1 c_1)$$

where $E(\pi)$ is expected income, and R is a risk premium measuring the cost of private risk bearing. The risk premium R in (2′) measures the decision maker's willingness to pay for an insurance scheme that would replace the random variable π by its mean. Combining equations (2) and (2′) implies that the CE can be decomposed into two additive parts:

$$(3) \qquad CE = E(\pi) - R.$$

By definition, risk aversion corresponds to a positive risk premium, with $R > 0$. Then, equation (3) implies that risk preferences affect behavior and welfare. In general, under risk aversion, risk exposure tends to lower the CE and make the decision maker worse off. As shown by Pratt (1964), risk aversion can be assessed "locally" using the Arrow–Pratt risk aversion coefficient $r_2 \equiv -(\partial^2 U/\partial \pi^2)/(\partial U/\partial \pi)$. With $(\partial U/\partial \pi) > 0$, risk aversion corresponds to $R > 0$, $\partial^2 U/\partial \pi^2 < 0$, and $r_2 > 0$. Pratt (1964) also defined decreasing absolute risk aversion (DARA) as situations in which increasing mean income tends to reduce the risk premium R. Thus, DARA implies that increasing expected income behaves as a substitute for "insurance motives." Pratt (1964) showed that $\partial r_2/\partial \pi < 0$ under DARA. The empirical evidence shows that most decision makers exhibit risk aversion and DARA risk preferences (e.g., Binswanger 1981; Chavas and Holt 1996).

Risk-averse decision makers have an incentive to reduce their risk exposure. Crop genetic diversity is one of the inputs in x. This raises the question: how does genetic diversity affect farm productivity and risk exposure? The effects of diversity on the variance of production have been analyzed in previous literature (e.g., Smale et al. 1998). However, it is of interest to go beyond just variance effects. Because $\partial r_2/\partial \pi = -(\partial^3 U/\partial \pi^3)/(\partial U/\partial/\pi) + r_2^2$, note that DARA implies $\partial^3 U/\partial \pi^3 > 0$, corresponding to aversion to unfavorable "downside risk" (see Menezes, Geiss, and Tressler 1980). Under "downside risk aversion,"[4] decision makers are adversely affected by downside risk (e.g., the risk of crop failure) and try to implement strategies that reduce exposure to such risk (Menezes, Geiss, and Tressler 1980; Antle 1983). This raises the question of how maintaining biodiversity affects the third central moment (skewness) of the distribution of revenue. In general, farmers exhibiting downside risk aversion have incentives to develop management strategies that affect positively the skewness of the distribution of yields (e.g., by reducing the probability of crop failure). This indicates a need to go beyond a mean–variance analysis in the investigation of the effects of crop genetic diversity.

Below, we investigate the role of production uncertainty v as represented by the stochastic production function $y = g(x,\ v)$. How can we assess the probability distribution of $g(x, v)$? Following Antle (1983), we explore the moment-based approach to this assessment. Consider the following econometric specification for $g(x, v)$:

$$(4) \qquad g(x, v) = f_1(x, \beta 1) + u$$

where $f_1(x,\ \beta_1) \equiv E[g(x,\ v)]$ is the mean of $g(x, v)$, and $u \equiv g(x, v) - f_1(x, \beta_1)$ is a random variable with mean 0. The higher moments of $g(x, v)$ are given by

$$(5) \qquad E\{[g(x, v) - f_1(x, \beta_1)]^k \mid x\} = f_k(x, \beta_k)$$

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[4] Increasing downside risk means increasing the asymmetry (or skewness) of the risk distribution toward low outcomes, holding both the mean and the variance constant (Menezes, Geiss, and Tessler 1980). By definition, a downside risk-averse decision maker is made worse off by such a change.

for $k = 2, 3, \ldots$. Equations (4) and (5) give the central moments of the distribution of $g(x, v)$, including the first moment (the mean) $f_1(x, \beta_1)$, the second central moment (the variance) $f_2(x, \beta_2) > 0$, and the third central moment (measuring skewness) $f_3(x, \beta_3)$.[5] This provides a flexible representation of the impacts of inputs x on the distribution of output under production uncertainty.[6] It goes beyond standard mean–variance analysis by considering the effects of skewness and downside risk exposure. As such, the specifications (4)–(5) expand on previous studies of crop genetic diversity (Smale et al. 1998; Widawsky and Rozelle 1998; Di Falco and Perrings 2005).

In general, one expects the mean output function $f_1(x, \beta_1)$ in (5) to be increasing and concave in inputs x. However, the effects of inputs x on the variance and skewness of output is largely an empirical issue. For example, from (5), the ith input can be variance increasing, variance neutral, or variance decreasing as $\partial f_2/\partial x_i > 0$, $=0$, or <0, respectively. Similarly, the ith input can affect downside risk exposure through its effect on skewness $f_3(x, \beta_3)$. The ith input would contribute to decreasing (increasing) downside risk exposure when $\partial f_3/\partial x_i > 0$ (<0). Of special interest are the effects of genetic diversity on the variance and skewness of production.

To help evaluate the importance of these effects on the cost of private risk bearing, consider the definition of the risk premium R in ($2'$). Under risk aversion, the risk premium R depends on all the relevant moments of the profit distribution. In general, given $\pi = N(x) + p_1 g(x, v)$, we expect to find a close relationship between the moments of income π and the corresponding moments of production $g(x, v)$. Below, we will focus our attention on the simple case in which output price is known; that is, where each moment of profit π is a linear function of the corresponding moment of output $g(x, v)$. Then the linkages between the cost of private risk bearing and the moments of outputs can be assessed using equations (4) and (5).

As shown by Pratt (1964), the risk premium R in ($2'$) can be approximated as follows. Taking a Taylor series approximation on both sides of equation ($2'$) evaluated at point $E(\pi)$ gives

$$\begin{aligned} &U(c_1,\ E(\pi) - p_1c_1) - (\partial U/\partial \pi)R \\ &\quad \approx U(c_1, E(\pi) - p_1c_1) + 1/2(\partial^2 U/\partial \pi^2) \\ &\qquad \times E[\pi - E(\pi)]^2 + 1/6(\partial^3 U/\partial \pi^3) \\ &\qquad \times E[\pi - E(\pi)]^3. \end{aligned}$$

This yields the following approximation to the risk premium

$$(6) \qquad R_a = 1/2 r_2 M_2 + 1/6 r_3 M_3$$

where $M_k = E[\pi - E(\pi)]^k$ is the kth central moment of the distribution of profit, $r_2 = -(\partial^2 U/\partial \pi^2)/(\partial U/\partial \pi)$ is the Arrow–Pratt coefficient of absolute risk aversion, and $r_3 = -(\partial^3 U/\partial \pi^3)/(\partial U/\partial \pi)$, all evaluated at $E(\pi)$. Equation (6) can be alternatively written as

$$(6') \qquad R_a = R_{a2} + R_{a3}$$

where $R_{a2} = 1/2 r_2 M_2$ and $R_{a3} = 1/6 r_3 M_3$. Equations (6) and ($6'$) decompose the risk premium R_a into two additive parts: $R_{a2} = 1/2 r_2 M_2$ reflecting the effect of the variance M_2, and $R_{a3} = 1/6 r_3 M_3$ reflecting the effect of skewness M_3 on the cost of risk. When $M_3 = 0$, equation (6) reduces to the standard Arrow–Pratt approximation, establishing that the approximate risk premium R_a is (locally) proportional to the variance of profit M_2, with $r_2/2$ as the coefficient of proportionality (Pratt 1964). It gives the intuitive result that, under risk aversion (when $\partial^2 U/\partial \pi^2 < 0$ and $r_2 > 0$), any increase in the variance of profit tends to increase the private cost of risk bearing. Equation (6) extends this result to show how the third central moment M_3 (the skewness) affects the risk premium. It indicates that $\partial R_a/\partial M_3 = 1/6 r_3$, that is, that the risk premium tends to decrease with a rise in skewness under downside risk aversion (when $\partial^3 U/\partial \pi^3 > 0$ and $r_3 < 0$). In this case, a rise in skewness associated with a decrease in downside risk exposure (e.g., a reduction in the probability of crop failure) would reduce the private cost of risk bearing.

This raises two questions related to risk management. How does risk exposure affect the incentive to use inputs (e.g., crop biodiversity) as a means of reducing the cost of risk bearing? And what is the relative importance of the variance effect versus skewness effect in

[5] Note that u in (4) could be written in general as $u = [f_2(x, \beta_2) - (f_3(x, \beta_3)/k)^{2/3}]^{1/2} e_2(v) + [f_3(x, \beta_3)/k]^{1/3} e_3(v)$, where $(f_2)^3 \geq (f_3/k)^2$, and the random variables $e_2(v)$ and $e_3(v)$ are independently distributed and satisfy $E[e_2(v)] = E[e_3(v)] = 0$, $E[e_2(v)^2] = E[e_3(v)^2] = 1$, $E[e_2(v)^3] = 0$, and $E[e_3(v)^3] = k > 0$. In this context, if we treat the distribution of $e_2(v)$ and $e_3(v)$ as given, then the three moments $f_1(x, \beta_1)$, $f_2(x, \beta_2)$, and $f_3(x, \beta_3)$ are sufficient statistics for the distribution of $g(x, v)$ in (4).

[6] Note that the stochastic production function approach has been criticized by Chambers and Quiggin (2000), who suggested the adoption of a state–contingent approach to model production uncertainty.

the valuation of the cost of private risk bearing? Answering these questions requires evaluating the risk premium R. This can be done using the risk premium R_a given in equations (6) and (6′).

We will also be interested in exploring the farmer's CE given in (3). This can help assess the relative importance of the cost of private risk bearing R compared with expected net revenue $E(\pi)$. Substituting the risk premium in (6) into the CE (3) gives

$$\text{(7)} \qquad CE_a = E(\pi) - R_a$$
$$= E(\pi) - 1/2r_2M_2 - 1/6r_3M_3.$$

This decomposes the CE into three additive parts: expected return $E(\pi)$, the variance component of the risk premium $R_{a2} = 1/2r_2M_2$, and the skewness component of the risk premium $R_{a3} = 1/6r_3M_3$ (with $R_a = R_{a2} + R_{a3}$ from (6′)). We provide an empirical assessment of these three components below, with a focus on the effects of diversity.

Background and Data Information

There are at least two common hypotheses in the literature about on-farm crop genetic resources that relate the diversity of crop varieties to the mean and variance of yields. The first is that farmers match different varieties to the microenvironments in their farms, enhancing overall yield levels and possibly reducing yield variability. A second is that planting more varieties diversifies risk, spreading risk spatially as in an investment portfolio solution. In the first, variety richness leads to more optimal resource use. In the second, variety richness substitutes, to some extent, for other offsetting sources of income or insurance. For example, in the study by Smale et al. (1998), various indicators of genetic, spatial, or temporal diversity in modern wheat varieties had mixed effects in high-potential and low-potential environments of Pakistan's Punjab. The variability effect was more evident in the low-potential environments. Equation (7) provides a convenient way to investigate hypotheses concerning the effects of crop diversity on expected income and the cost of risk bearing.

Barley is a staple food in the highlands of Ethiopia. Along with teff and wheat, it is the most widely grown and consumed grain in the regional state of Tigray (Pender, Place, and Ehui 1999). In almost every household, barley is used to make different types of bread, dough, porridge, beer, and gruel (Asfaw 1990). Barley production represents around 20% of the total national cereal production. From the sample information, we calculated that more than 40% of total farmland is allocated to barley. Remarkably, over 90% of the barley is produced by subsistence farmers using landraces (Alemayehu 1995) with very little external inputs. Thanks to its ecological plasticity, barley is cultivated from 1,500 to over 3,000 m above sea level. Ethiopia is an important center of diversity for barley. This crop was brought to Ethiopia at least 5,000 years ago (Harlan 1968; Frost 1974). Through selection over centuries, barley has developed high genetic diversity (Engels 1991). Ethiopian barley is considered as an isolated line that evolved independently from the mainstream of world barley evolution (Harlan 1968).

In the barley farms surveyed and analyzed below, 10 different landraces were grown. Among these 10, the landraces called *white*, *karkaera*, *sasera*, and *kuntsbe* were widely used. Genetic variation is remarkable and is reflected by the differences in morphogenetic traits among landraces. The genetic characteristics and resistance of Ethiopian barley have been widely studied (Asfaw 2000). In crop genetic resources conservation, Ethiopian barley has been identified as a priority crop since 1920s, and extensive germplasm collections have been deposited in gene banks throughout the world (Negassa 1985; Asfaw 2000). Therefore, the barley of Ethiopia is an important source of genes for resistance and protein quality and many lines have been used as donors of resistance to commercial varieties in North America and Europe (Qualset and Moseman 1966; Qualset 1975; Negassa 1985; Alemayehu 1995; Asfaw 2000).

The data set used in the analysis is from a farm survey conducted in 1999 and 2000 in the highlands (more than 1,500 m above sea level) of Tigray region in Ethiopia by researchers from Mekelle University, the International Food Policy Research Institute (IFPRI), and the International Livestock Research Institute (ILRI). The survey involved a stratified sampling of farm households, with the strata being chosen according to agricultural potential, market access, and population density (Pender, Place, and Ehui 1999). In the Tigray region, peasant associations (PAs) were stratified by distance to the *woreda* town (greater or less than 10 km). Three strata were defined, with 54 PAs randomly selected across the strata. PAs closer to towns and in irrigated areas were selected with a higher sampling fraction to assure adequate representation. Four PAs in the northern part of Tigray could not be studied because of the war with Eritrea. From each of the remaining PAs, two villages were randomly selected, and from each village, five households were randomly selected. A total of 50 PAs, 100 villages, and 500 households were then surveyed. Usable data were available for 96 villages, or kushets. Out of 96 villages, 79 were growing barley. These 79 villages are dispersed throughout the region of Tigray. In the survey year analyzed here, a total of 244 households grew barley on 736 different plots. After controlling for outliers and observations with missing values for relevant variables, 190 household observations remained.[7] These household-level data provide a basis for estimating a stochastic production function for barley, following equations (4) and (5).

Table 1 reports the variable names, definitions, and descriptive statistics. Crop diversity at the farm level is measured by the Margalef index, defined as [(number of barley varieties)/ln(barley area) − 1]. This index captures species richness. Its use is appropriate when "diversity is apparent to farmers" (Meng et al. 1998): the larger is the index, the greater is the number of barley varieties grown in a given farm. The Margalef diversity index has been widely used in the literature (e.g. Smale et al. 1998). Besides crop genetic diversity, the explanatory variables are grouped as conventional inputs (land, labor, animal, urea, and manure), environmental and soil condition variables (erosion, slope, fertility, and altitude), and managerial variables (years of experience in cropping the operated plots and the number of operated barley plots). To control for the role of other crops, we included the amount of land in other crops. Land, labor, and animal are the most important conventional inputs. The average input use for labor and animal is, respectively, 66.46 person-days and 33.09 oxen-days. Both fertilizer and manure are used for maintaining production and enhancing soil fertility. The former is distributed by the agricultural extension and was used by 147 farm households, whereas the latter was used by 155 farms. Environmental and soil conditions are measured via farmers' perception of land fertility, erosion, and steep slope. For instance, the farmers were asked to rank the fertility of each plot (i.e., fertile, moderately fertile, and infertile). The size of the plots ranked as fertile was then divided by total size of land, giving the share of land categorized as fertile.[8] On average, 40% of operated plots were classified as infertile. On average, 5% of the operated plots are affected by severe erosion and water logging problems, and 8% are located on steep slope. On average, nine years were spent cropping the plots (with a maximum of fourteen years and a minimum of one year). Production is quite fragmented. On average, three plots are operated per household.

[7] Outliers were identified by plotting the data. A total of 29 values were found out of the range of other observations. This was due to data entry or transformation errors.

Estimation

Our analysis involves the estimation of the production function for barley. It relies on equations (4) and (5), where the dependent variable y is the quantity of barley produced, with the mean $f_1(x, \beta_1)$, variance $f_2(x, \beta_2)$, and skewness $f_3(x, \beta_3)$. Alternative functional specifications of the mean function f_1 were first explored. They include the quadratic, Cobb–Douglas, and linear-log[9] specifications.[10] Both the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) were used to evaluate the econometric performance of each specification. The AIC criterion was 3,055.4, 4,461.8, and 3,023.0 for the quadratic, Cobb–Douglas, and linear-log specifications, respectively. The corresponding BIC criterion was 3,120.6, 4,513.1, and 3,074.0, respectively. On that basis, the linear-log specification was selected as the preferred model for the mean function.[11] Let (i, j) denote the ith household in the jth location. Assume that $f_1(x_{ij}, \beta_1) = \beta_{0j} + x_{ij}\beta_1$ in (5), where β_{0j} represents unobserved factors influencing farm productivity in the jth location. It follows from (4) that farm production on the ith household in the jth location is

$$(8a) \qquad y_{ij} = \beta_{0j} + x_{ij}\beta_1 + u_{ij}.$$

[8] Farmers' knowledge and perceptions of soil fertility and its implication have been widely documented (Hunting 1976; Haile 1996; Tilahun 1996; and Corbeels, Shiferaw).

[9] The "linear-log" specification means that the dependent variable is linear, whereas the explanatory variables are in logarithms.

[10] The variable "fertilizer" displays many zero values. To include it in the Cobb–Douglas and linear-log specification, we follow Battese (1997), using $[\alpha_0 D + \alpha_1 \ln(\text{Fert} + D)]$, where $D = 1$ if Fert $= 0$, and $D = 0$ if Fert > 0, and α_0 and α_1 are the parameters.

[11] A similar testing procedure was implemented for the variance and skewness functions in (8b). The AIC criterion suggested that the linear-log specification reported in table 3 was appropriate.

Table 1. Variables' List and Definitions of Descriptive Statistics

Variable	Definition	Mean	Std. Dev.	Minimum	Maximum
Urea	Fertilizer use in kilograms	17	20.17	0	131.4
Land	Land for barley in squared meters	2,785.04	2.21	268.87	14,821
Labor	Labor in person days	66.46	1.84	5.9	429
Animal	Animal in oxen days	36.09	1.747	2.99	225
Biodiversity	Margalef index for biodiversity [(number of barley varieties)/ ln(barley area) − 1]	0.168	0.057	0.118	0.407
Altitude	Household altitude	2,341.45	305.05	1,521	2,988
Steep slope	Share of land on steep slope	0.083	0.210	0	1
Severe erosion	Share of land affected by severe erosion and water logging	0.051	0.142	0	0.871
Fertility	Share of land on medium/high fertility	0.60	0.29	0	1
Land in other crops	Land allocated to other crops in squared meters	3,880	1.23	0	18,299
Experience	Number of years of cropping the plots	9.20	2.28	1	14
Fragmentation	Number of operating plots	3.02	1.56	1	11
Manure	Dummy variable for manure use (1 = yes; 0 = no)	0.64	0.48	0	1
Biodiversity × fertility	Interaction between biodiversity and fertility	0.100	0.064	0	0.354
Fertilizer × fertility	Interaction between fertilizer and fertility	11.56	16.58	0	131.40
Fertilizer × severe erosion	Interaction between fertilizer and severe erosion	0.81	2.88	0	19.19

Given the presence of β_{0j} in (8a), we take the mean of u_{ij} to be 0 in each location j.[12] Denote by $\bar{y}_j$ and $\bar{x}_j$ the mean of y_{ij} and x_{ij}, respectively, in the jth location. Then (8a) can be written as

$$(8a') \quad y_{ij} - \bar{y}_{\bar{j}} = (x_{ij} - \bar{x}_j)\beta_1 + u_{ij}.$$

Equation (8a′) involves variables measured as deviations from their location means. In the spirit of Barrett et al. (2004),[13] the specification (8a′) corrects for the effects of factors specific to each location. As such, it controls for the unobservable heterogeneity related to institutional factors and spatial specific conditions. The effects of farm-specific agroecological characteristics are captured by the x's in equations (8) through the measurements of soil quality, fragmentation, and altitude (Sherlund, Barrett, and Adesina 2002). In addition, each farmer's ability is measured by his/her experience. This is particularly relevant in our case as the error term u_{ij} is interpreted as reflecting production uncertainty facing the ith household.

Following Antle (1983), this suggests the following estimation method. First, estimate equation (8a′) to obtain a consistent estimate β_1^e of β_1 and the associated error term $u_{ij}^e = y_{ij} - \bar{y}_j - (x_{ij} - \bar{x}_j)\,\beta_1^e$. Second, from (5), consider the regression specifications

$$(8b) \quad \left(u_{ij}^e\right)^k = f_k(x_{ij}, \beta_k) + w_{ijk}$$

where w_{ijk} is an error term with mean 0, $k = 2, 3$. Estimate (8b) to give consistent estimates

[12] This amounts to the assumption that each farmer learns about the location-specific factors affecting his/her productivity and that such factors are not part of production uncertainty.

[13] Barrett et al. (2004) develop a farm-level fixed effect model using plot-level information. This would not have been appropriate here because our paper attempts to capture synergies at the farm level. A plot-level analysis cannot capture some of the benefits of crop genetic diversity.

of the parameters β_k, $k = 2, 3$ (Antle 1983). However, note that the variance of u_{ij} in (8a′) is $f_2(x_{ij}, \beta_2)$, and the variance of w_{ijkk} in (8b) is $[f_{2k}(x_{ij}, \beta^e_{2k}) - f_k(x_{ij}, \beta^e_k)^2]$, $i = 2, 3$ (Antle 1983). It follows that both equations (8a′) and (8b) exhibit heteroskedasticity, which needs to be taken into consideration in the estimation of the parameters. Heteroskedasticity suggests using a weighted regression approach to capture efficiency gains, in which the optimal weights are given by the inverse of the variance of the error terms.

Both specifications (8a) and (8a′) may be subject to endogeneity bias. This would occur if some of the explanatory variables were correlated with the error term. For example, if the measure for biodiversity (the Margalef index) were correlated with the error term u_{ij} in (8a) or (8a′), then the least-squares estimate of the effects of variety richness on the mean, the variance, and the skewness of output would be biased.[14] In the fixed effects model (8a′), all original variables are expressed in deviation from village means. This removes village-specific unobserved heterogeneity, thus possibly reducing the correlation between explanatory variables and the error term (Hsiao 1986). This indicates that endogeneity bias may be less severe in (8a′) (compared with (8a)). Consider the case in which models (8a) and (8b) are specified in linear-log form. In this context, endogeneity issues are investigated by applying the Wu–Hausman test (see Davidson and MacKinnon 1993; Wooldridge 2002) on both models (8a) (in levels) and (8a′) (with fixed effects). We first identified a set of suitable instruments following both theory and existing literature using the same database (Pender, Place, and Ehui 1999; Benin et al. 2004). The instruments were walking distance from input supplier, walking distance from all-weather road, walking distance from the nearest market town, and lagged values for fragmentation. The choice of the instruments was also scrutinized by testing for their relevance using an F-test of the joint significance of the excluded instruments. We rejected the null hypothesis, indicating that the instruments are relevant. The literature on instruments' relevance indicates that if the F value exceeds 10, then the instruments seem relevant (Stock and Watson 2003). The F value was found to be 28.45. We also tested the overidentification restrictions using a Hansen test.

Table 2. Durbin–Wu–Hausman Endogeneity Test. Comparison Between Model in Levels and Fixed Effects

	Model (8a): (in Levels)	Model (8a′): (Fixed Effects)
Mean	χ^2 test: 10.2 p-value = 0.001	χ^2 test: 0.1 p-value = 0.74
Variance	χ^2 test: 12.82 p-value = 0.0003	χ^2 test:16.23 p-value = 0.00006
Skewness	χ^2 test: 5.4 p-value = 0.01	χ^2 test: 4.7 p-value = 0.02

The test result suggested that the instruments are uncorrelated with the error term. Table 2 reports the endogeneity tests for both the model in levels (8a) and the fixed effects model (8a′). In the former, we found statistical evidence of endogeneity in the mean function, the variance, and the skewness equation. In the latter, we did not find evidence of endogeneity bias in the mean equation. It appears that the elimination of village effects in the fixed effects model removed the main source of correlation between the error term and the biodiversity metric in the mean equation. However, the null hypothesis of exogeneity was rejected in both the variance and the skewness equation. For this reason, we estimated the models using a three-stage least squares (3SLS) estimator, allowing biodiversity to be endogenous in all equations. Optimal weights were used to control for heteroskedasticity effects.

Results

The resulting econometric estimates are reported in table 3. The various tests used to evaluate the validity of the estimates are reported at the bottom of the table. In the mean function (reported in column A, table 3), land and labor have positive and statistically significant effects, whereas oxen use and fertilizer use are not statistically significant. Among the conventional inputs, land is the most effective input. Production elasticity is 0.51 for land and 0.20 for labor. The effect of biodiversity on production is captured through two terms: a linear term and an interaction term with land degradation. Both are found to be statistically significant in the mean function. The estimates show that increasing the number of varieties grown

[14] Possible endogeneity issues were also investigated for land and fertilizer use.

Table 3. Mean, Variance, and Skewness Function: Estimation Results (Three-Stage Least Squares)

	Mean Function (A) $f_1(x, \beta_1)$		Variance Function (B) $f_2(x, \beta_2)$		Skewness Function (C) $f_3(x, \beta_3)$	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Dummy for fertilizer use	71.12	65.74	5,582.80	13,273	7,270.17	5,612.72
Fertilizer	17.90	25.42	−2,494.26	5,732.85	540.21	2,286.90
Land	139.90***	16.68	16,108.78***	3,280.73	3,557.60***	1,080.53
Labor	56.74*	32.09	4,382.74	6,413.50	−786.48	2,170.81
Animal	21.89	37.20	−7,319.92	7,796.62	2,114.03	2,568.50
Biodiversity	1,903***	592.91	552,250***	130,934	181,000***	54,100
Altitude	−0.135***	0.03	−19.44**	8.50	−9.63***	3.45
Fertility	233.72	149.50	76,977.75**	35,608.09	25,300*	13,800
Severe erosion	68.99	96.93	29,211.99	28,005.37	16,700*	8,864
Steep slope	28.15	57.98	−19,431.79*	11,350.91	−4,897.82	3,900.03
Land in other crops	−10.86	10.80	−1,618.35	2,186.15	−687.16	759.42
Experience	8.44	5.86	213.93	1,134.77	35.78	365.72
Fragmentation	45.37***	8.76	4,594.48***	1,758.50	1,201.87**	609.95
Manure	−90.01***	24.11	−13,535.53***	5,023.64	−6,245.51	2,080.94
Biodiversity × fertility	−1,425.38*	805.71	−526,252***	130,934	−180,000***	73,700
Fertilizer × fertility	−14.92	92.21	4,248.82	5,743.40	401.91	2,062.79
Fertilizer × severe erosion	−55.87	43.05	−23,738.68**	12,105.93	−9,390.23**	4,359.33
Constant	350.50***	111.87	−130,948***	49,016	−33,100*	18,900

Note: $N = 190$. $R^2 = 0.615$. Breusch–Pagan test $\chi^2(17) = 93.15$. Mean, variance, and skewness are respectively 280, 20,349, and 1,378,141. Hansen J-test statistic for identification: 0.046 distributed $\chi^2(1)$, p-value $= 0.830$. Test of excluded instruments: $F = 28.42$, p-value $= 0$. Test of independence: $\chi^2(3) = 164.65$, p-value $= 0$. Significance levels are denoted by one asterisk (*) at the 10% level, two asterisks (**) at the 5% level, and three asterisks (***) at the 1% level. The estimated coefficients in the skewness equation have been rescaled and divided by 1,000.

has a large positive effect on barley production. Evaluated at sample means, the elasticity of production with respect to biodiversity is 3.00. Altitude and the dummy variable for manure use are negative and statistically significant. The negative sign can indicate that this variable may capture some unobserved effect or proxy for subsistence or isolated farm. Soil variables are not statistically significant in the mean function. Among the set of managerial variables, only the estimated coefficient for the number of plots is positive and statistically significant. To capture the interplay between fertilizer use and soil conditions, interaction terms were included. The coefficients of these interaction terms, however, are not statistically significant.

The regression results for the variance function are shown in column B of table 3. Diversity is found to be statistically significant both in the linear form and in the interaction with land fertility. Biodiversity increases the variance of output. The negative sign on the coefficient of the interaction term implies that the effect of variety richness is sensitive to the share of fertile land. The marginal impact of biodiversity is found to be positive for the full range of values.

The share of barley production on fertile land contributes positively and significantly to the variability of yield. Increasing land also increases the variance of barley production. Altitude and the interaction term between fertilizer and soil erosion have both a negative and statistically significant effect on the variance of production. Among the managerial variables, plot, the amount of land in alternative crops and experience are not statistically significant. It is important to stress that if the variance were taken to be the only measure of risk, table 3 (column B) suggests that biodiversity and fertility should be considered risk-increasing inputs. As such, they would have a negative effect on the welfare of risk-averse farmers. However, as discussed earlier, the variance does not distinguish between upside and downside risk. These issues are investigated in detail below in the simulation section.

The regression results for the skewness function are shown in column C of Table 3. Biodiversity is positively and strongly related with the skewness of the output. This identifies that increasing the number of grown varieties hedges against the risk of crop failure. In this type of agriculture, greater varietal diversification is desirable as it reduces the exposure to downside risk and helps insure that food production does not fall below some threshold level.

Among the conventional inputs, only land has a positive and statistically significant effect on skewness. Labor use, fertilizer, and oxen are not statistically significant. The total impact (including the interaction with fertilizer) of the share of eroded land is negative. Production fragmentation across multiple plots has a positive and statistically significant effect on the skewness of yields. This may be due to the diversification of production conditions. Land fertility reduces the probability of crop failure. The interaction term between diversity and fertility is negative and significant. This indicates that these two variables behave as substitutes: the benefits of biodiversity in reducing the odds of crop failure are larger in less fertile land.

Implications

To analyze the economic and welfare implications of our econometric results, we present two simulation exercises on the effects of crop biodiversity on risk. The simulations are reported assuming that the decision maker's risk preferences exhibit constant relative risk aversion, with a coefficient of relative risk aversion equal to 2.5.[15] In this context, we use equations (6) and (6′) to evaluate the risk premium R_a and its decomposition into a variance component R_{a2} and a skewness component R_{a3} (the latter capturing the role of crop failure in risk management). Using (7), the effects of diversity on expected income, risk premium, and CE are then investigated under two different scenarios. The first scenario assumes that all variables are evaluated at sample means. The second scenario simulates and compares the role of diversity when land fertility is lower or higher than its sample mean. These simulations shed useful light on the beneficial effect of diversity in reducing risk.

Figure 1 reports the results from the first scenario. Diversity increases the mean revenues for all the range of values. This indicates that diversity plays an important role in supporting agricultural productivity. The risk premium R_a becomes slightly smaller when diversity is higher. Thus, diversity reduces the cost of uncertainty. The risk premium decomposition, $R_a = R_{a2} + R_{a3}$, identifies the role of skewness and downside risk exposure. The effect of diversity on the variance component R_{a2} is positive. However, this effect is dominated by the strong role of diversity in reducing the risk of crop failure. This shows that biodiversity tends to not only increase variance but also decrease downside risk (skewness component) when fertility is at the sample mean. As shown in figure 1, the effect of diversity on the cost of risk is dominated by its favorable skewness component. This is captured also by the CE, which does increase throughout the range of diversity values.

To gain additional insight into the determinants of the cost of risk, figure 2 presents the risk premium along with its variance and skewness components when soil fertility is small versus when it is large. It compares the cost of risk under the following scenarios: one when fertility is below sample mean (40% of the farmland being classified as medium or high fertility); and the other when land fertility is high (80% of the farmland being classified as medium or high fertility). This illustrates how the risk effects differ across scenarios. Qualitatively, the role of biodiversity is consistent under the two scenarios. However, the effect of biodiversity on the skewness component becomes stronger under low fertility. Under the high-fertility scenario, the elasticity of the risk premium with respect to diversity is −0.003, evaluated at sample means, but it is −0.25 under the low-fertility scenario. These effects become stronger when diversity increases. For instance, when the value of the diversity index is 0.30 (which is almost twice the sample mean of.168), the elasticity of the risk premium with respect to diversity is −0.07, but it changes to −0.63 under the low-fertility scenario.

These results document that when the land is more fertile, the contribution of diversity toward reducing crop failure becomes weaker. Alternatively, low fertility means that biodiversity has a stronger effect in reducing downside risk exposure. In turn, this stronger effect contributes to a sharper decline in the cost of

[15] Typical estimates of relative risk aversion have varied between 1 and 5 (e.g., Binswanger 1981; Chavas and Holt 1996; Gollier 2001). A coefficient of 2.5 corresponds to moderate risk aversion.

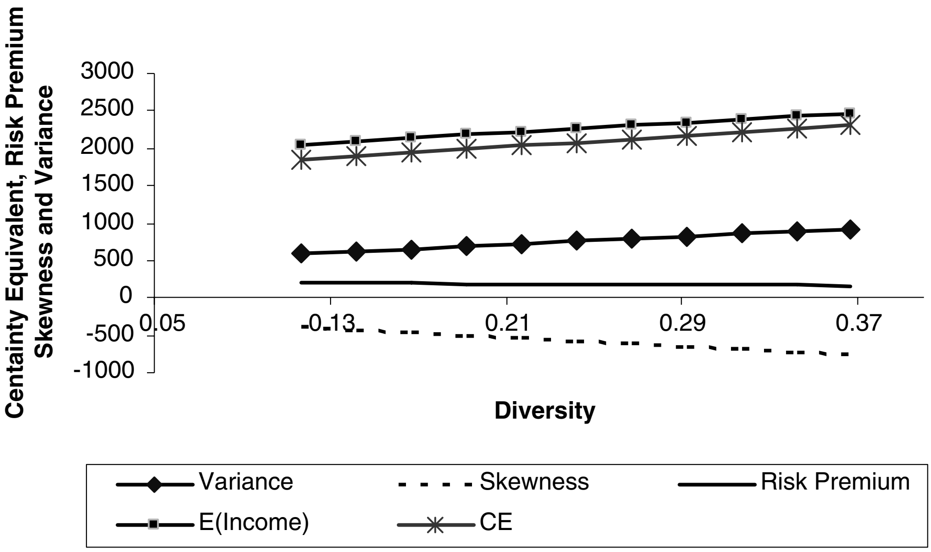

Figure 1. Certainty equivalent, mean revenue and risk premium, and simulation results at sample means. Values are in Birr

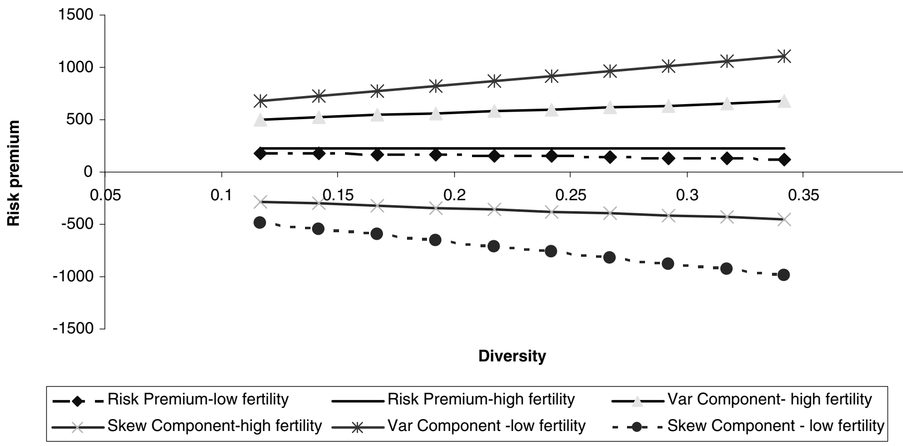

Figure 2. Risk premium decomposition: comparison under high and low levels of fertility. Values are in Birr

risk bearing (as measured by the risk premium R_a). In other words, as far as risk management is concerned, land fertility and diversity behave as substitutes. Although diversity is found to contribute to increased agricultural productivity, its effect on risk (and especially, downside risk) becomes of greater value in degraded land. In this context, diversity is found to deliver important payoff by reducing the cost of risk exposure (especially, the risk of crop failure) in more degraded land.

Conclusion

This paper presented an assessment of the role of crop of biodiversity in risk management. Using data from a survey conducted in the Tigray region of Ethiopia, we analyzed the contribution of barley diversity on the mean, variance, and skewness of production. The effects on the skewness capture the exposure to downside risk (e.g., the probability of crop failure). We found that maintaining a larger number of barley varieties supports productivity and reduces the risk of crop failure. We documented how the skewness effect differs from the variance effect: biodiversity increases variance but reduces downside risk exposure (by increasing skewness). We also found that the skewness effect dominates the variance effect. Thus, for farmers exhibiting both risk aversion and downside risk aversion, reducing the odds of crop failure can be more relevant than reducing yield variance. This indicates that the variance alone would not provide an accurate characterization of risk exposure. Also, we documented how land fertility plays an important role in risk management. We found that, as far as risk management is concerned, land fertility and diversity tend to behave as substitutes. Although diversity contributes to increased agricultural productivity, its beneficial effect on risk (and especially, downside risk) becomes of greater value when farming on degraded land.

These results show that biodiversity is an important asset for sub-Saharan agriculture. In the highlands of Ethiopia, we find that conserving landraces in the field delivers important productive services and allows farmers to mitigate some of the negative effects of harsh weather and agroecological conditions. Therefore, *in situ* conservation of crop biological diversity is one of the strategies that can help improve Ethiopia's poor agricultural performance and alleviate food insecurity. Note, however, that our analysis is based upon data drawn from a one-year survey. This prevented us from addressing issues related to the dynamics of management decisions. Future research is needed to address such issues.

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References

Alemayehu, F. 1995. *Genetic Variation Between and Within Ethiopian Barley Landraces with Emphasis on Durable Resistance*, Ph.D. thesis. Universiteit Wageningen, Landbouw.

Antle, J.M. 1983. "Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach." *Journal of Business and Economic Statistics* 1:192–201.

Asfaw, Z. 1990. "An Ethnobotanical Study of Barley in the Central Highlands of Ethiopia." *Biologisches Zentralblatt* 9:51–62.

——. 2000. "The Barleys of Ethiopia." In S. Brush, ed. *Genes in the Field*. Boca Raton, FL: Lewis Publishers; Ottawa, ON: International Development Research Centre, pp. 77–107.

Barrett, C.B., C.M. Moser, O.V. McHugh, and J. Barison. 2004. "Better Technology, Better Plots, or Better Farmers? Identifying Changes in Productivity and Risk Among Malagasy Rice Farmers." *American Journal of Agricultural Economics* 86:869–88.

Battese, G.E. 1997. "A Note on the Estimation of Cobb–Douglas Production Functions When Some Explanatory Variables Have Zero Values." *Journal of Agricultural Economics* 48:250–52.

Bellon, M.R., and J.E. Taylor. 1993. "Folk Soil Taxonomy and the Partial Adoption of New Seed Varieties." *Economic Development and Cultural Change* 41:763–86.

Binswanger, H.P. 1981. "Attitudes Toward Risk: Theoretical Implications of an Experiment in Rural India." *Economic Journal* 91:867–90.

Chambers, R.G., and J. Quiggin. 2000. *Uncertainty, Production, Choice, and Agency: The State–Contingent Approach*. Cambridge, NY: Cambridge University Press.

Chavas, J.P., and M.T. Holt. 1996. "Economic Behavior Under Uncertainty: A Joint Analysis of Risk Preferences and Technology." *Review of Economics and Statistics* 78:329–35.

Corbeels, M., A. Shiferaw, and M. Haile. 2000. "Farmers' Knowledge of Soil Fertility and Local Management Strategies in Tigray, Ethiopia." Managing Africa's Soils no. 10. Working paper, International Institute for Environment and Development, London, UK.

Davidson, R., and J.G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.

Deaton, A. 1989. "Savings in Developing Countries: Theory and Review." *Proceedings of the Annual World Bank Conference on Development Economics. World Bank Economic Review*, 61–96.

Dercon, S. 1996. "Risk, Crop Choice and Savings: Evidence from Tanzania." *Economic Development and Cultural Change* 44(3):385–415.

——. 2004. "Growth and Shocks: Evidence from Rural Ethiopia." *Journal of Development Economics* 74(2):309–29.

——. 2005. *Insurance Against Poverty*, Helsinki, Finland: World Institute for Development Economics Research, United Nations University.

Dercon, S., and P. Krishnan. 2000. "Vulnerability, Poverty and Seasonality in Ethiopia." *Journal of Development Studies* 36(6):25–53.

Di Falco, S., and C. Perrings. 2005. "Crop Biodiversity, Risk Management and the Implications of Agricultural Assistance." *Ecological Economics* 55:459–66.

Engels, J.M.M. 1991. "A Diversity Study in Ethiopian Barley." In J.M.M. Engels, J.G. Hawkes, and M. Worede, eds. *Plant Genetic Resources of Ethiopia*. Cambridge, NY: Cambridge University Press, pp. 131–39.

Fafchamps, M. 1992. "Cash Crop Production, Food Price Volatility and Rural Market Integration in the Third World." *American Journal of Agricultural Economics* 74:90–99.

Frost, S. 1974. "Three Chemical Races in Barley." *Barley Genetics Newsletter* 4:25–28.

Gollier, C. 2001. *The Economics of Risk and Time*. Cambridge, MA: The MIT Press.

Hagos, F., J. Pender, and N. Gebreselassie. 1999. "Land Degradation in the Highlands of Tigray and Strategies for Sustainable Land Management." Socioeconomic and Policy Research Working paper no. 25. Livestock Analysis Project, International Livestock Research Institute, Addis Ababa, Ethopia.

Harlan, J.R. 1968. "On the Origin of Barley." In *Barley: Origin, Botany, Culture, Winter Hardiness, Genetics, Utilization & Pests*, USDA Agricultural Handbook 338. Washington, DC: USDA, pp. 12–34.

——. 1992. *Crops and Man*, 2nd ed. Madison, WI: American Society of Agronomy and Crop Science Society of America.

Hsiao, C. 1986. *Analysis of Panel Data*. Cambridge, NY: Cambridge University Press.

Hunting. 1976. *Tigray Rural Development Report*. Hemel Hempstead, Hertfordshire, UK: Hunting Technical Service.

Just, R.E., and W. Candler. 1985. "Production Functions and Rationality of Mixed Cropping." *European Review of Agricultural Economics* 12:207–31.

Just, R.E., and R.D. Pope. 1979. "Production Function Estimation and Related Risk Considerations." *American Journal of Agricultural Economics* 61:276–84.

Kurosaki, T., and M. Fafchamps. 2002. "Insurance Market Efficiency and Crop Choices in Pakistan." *Journal of Development Economics* 67:419–53.

Menezes, C., C. Geiss, and J. Tressler. 1980. "Increasing Downside Risk." *American Economic Review*, 70:921–32.

Meng, E.C.H., M. Smale, M.R. Bellon, and D. Grimanelli. 1998. "Definition and Measurement of Crop Diversity for Economic Analysis." In M. Smale, ed. *Farmers, Gene Banks, and Crop Breeding*. Boston: Kluwer, pp. 19–31.

Negassa, M. 1985. "Geographic Distribution and Genotypic Diversity of Resistance to Powdery Mildew of Barley of Ethiopia." *Hereditas* 102:139–50.

Pender, J., F. Place, and S. Ehui. 1999. "Strategies for Sustainable Agricultural Development in the East African Highlands." Environment and Production Technology Division Working paper no. 41, International Food Policy Research Institute, Washington, DC.

Pratt, J.W. 1964. "Risk Aversion in the Small and in the Large." *Econometrica* 32:122–36.

Qualset C.O. 1975. "Sampling Germplasm in a Centre of Diversity: An Example of Disease Resistance in Ethiopian Barley." In O.H. Frankel and G.J. Hawks, eds. *Crop Genetic Resources for Today and Tomorrow*. Cambridge, NY: Cambridge University Press, pp. 81–96.

Qualset, C.O., and J.G. Moseman. 1966. "Disease Reaction of 654 Barley Introduction from Ethiopia." USDA/ARS Progress Report, Unpublished.

Relief Society of Tigray (REST) and NORAGRIC at the Agricultural University of Norway. 1995. "Farming Systems, Resource Management and Household Coping Strategies in Northern Ethiopia: Report of a social and agro-ecological baseline study in central Tigray." Aas, Norway.

Sherlund, S.M., C.B. Barrett, and A.A. Adesina. 2002. "Smallholder Technical Efficiency Controlling for Environmental Production Conditions." *Journal of Development Economics* 69: 85–101.

Smale, M., J. Hartell, P.W. Heisey, and B. Senauer. 1998. "The Contribution of Genetic Resources and Diversity to Wheat Production in the Punjab of Pakistan." *American Journal of Agricultural Economics* 80:482–93.

Stock, J.H., and M.W. Watson. 2003. *Introduction to Econometrics*. Boston: Addison-Wesley.

Tilahun, Y. 1996. "Impacts of Conservation Bunds on Crop Yields in Degua Tembien, Northern Ethiopia." M.S. thesis, Agricultural University of Norway.

Vavilov, N.I. 1949. "The Origin, Variation, Immunity and Breeding of Cultivated Plants." *Chronica Botanica* 13:1–364.

Widawsky, D., and S. Rozelle. 1998. "Varietal Diversity and Yield Variability in Chinese Rice Production." In M. Smale, ed. *Farmers, Gene Banks, and Crop Breeding*. Boston: Kluwer, pp. 159–72.

Wooldridge, J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: The MIT Press.