Rice, Irrigation and Downside Risk:

A Quantile Analysis of Risk Exposure and Mitigation on Korean Farms

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Abstract: This article develops a new quantile approach utilizing partial moments to evaluate risk exposure and illustrate risk valuation, and then applies it to examine the potential importance of 'fat tails', downside risk, and risk mitigation options associated with a highly controlled but stochastic production system − irrigated rice production in Korea. The econometric approach exploits a rich panel dataset to develop consistent and robust econometric estimates of the partial moments needed to implement the quantile-based decomposition of risk outcomes. Our results demonstrate that the costs of downside risk associated with Korean rice production system are quite large, providing an empirical validation of Weitzman's dismal theory.

Keywords: risk, quantile, irrigation, partial moments, downside risk

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1. Introduction

The role of risk and its effects on economic welfare are major themes in an era of uncertainty about global economic and environmental change (e.g., IMF; Stern; UK). Increasing attention is being paid to downside risk exposure or risk associated with unfavorable events, such as climate change and financial shocks (Weitzman; World Economic Forum). Starting with safety first models (e.g., Roy), and in subsequent studies of behavioral aversion to exposure to losses (e.g., Kahneman and Tversky), disappointments (e.g., Gul; Routledge and Zin) or below target returns (e.g., Fishburn), researchers have considered the role of asymmetry in risk exposure and how to characterize and potentially manage downside risk aversion (e.g., Bawa; Menezes et al.; Antle, 1987; Modica and Scarsini; Ang et al.; Crainich and Eeckhoudt; Keenan and Snow, 2002, 2009). In the analysis of climate change, Weitzman argues that the cost of risk associated with catastrophic events can be quite large. In particular, his ‘fat tails’ hypothesis underscores the need for methodological advances and empirical inquiries that estimate downside risk exposure and its economic cost.

This paper makes four contributions to the analysis of risk and downside risk. First, it presents and implements a decomposition of the cost of risk (as measured by the Arrow-Pratt risk premium) into additive components across quantiles of the distribution. Defining downside risk as the risk located in the lower quantile, this provides a basis to evaluate the relative importance of exposure to downside risk. Second, the paper proposes to use partial moments to evaluate risk exposure in each quantile. Partial moments provide a convenient basis to evaluate asymmetry in the payoff distribution.[1] We show how estimates of partial moments can be used to evaluate the cost of exposure to downside risk.

Third, the paper adapts panel data econometric methods to estimate partial moments, thus providing a basis to evaluate empirically the exposure and cost of downside risk, along with the management options available to mitigate risk exposure. Finally, the usefulness of the methodology is illustrated in an application to agriculture, using panel data from Korean irrigated rice farms. To the extent that most of the production risk in Korean agriculture comes from unpredictable weather effects (e.g., temperature, typhoons), this analysis documents the importance of downside risk and fat tails (e.g., as argued by Weitzman) as they relate to climatic shocks and the options for risk management.

The specific application to irrigated rice production is valuable because climatic conditions are the primary source of production risk in agriculture and other natural resource-based goods and services. As such, analyzing both the exposure to risk and levels of downside risk in agriculture is a key component in assessing the welfare effects of climatic changes (e.g., OECD; Hardaker et al.). As noted by Schlenker et al., while irrigation reduces exposure to rainfall risk in agriculture, it does not eliminate overall production risk. Indeed, irrigated rice in Asia remains subject to temperature fluctuations and to potential flooding associated with typhoons. Nonetheless, the longstanding presence of extensive irrigation infrastructure in Asia means a significant reduction in the threat of drought in irrigated rice cultivation (Barker and Herdt; Roumasset et al.), and this leads us to posit that irrigated rice farms in Korea may be close to a "best case scenario" for the investigation of climatic risk in agriculture. To the extent then that we identify the presence of fat tails in the distribution of production risk as well as the relative importance of exposure to downside risk in irrigated rice production, then we would expect those results to be even stronger in other agricultural contexts.

In the empirical analysis, we find strong evidence of ‘fat tails, we analyze the factors that shape risk exposure, and we estimate that about 90% of the cost of risk comes from risk exposure in the first quartile of the distribution. Overall, the article provides evidence that strongly underscores Weitzman's concern with the potential cost of downside risk exposure, especially in situations of fat tails. We also show that management factors can partially mitigate risk exposure outcomes.

The methodological core of the article develops a quantile-based analysis of risk outcomes, where the lower quantile corresponds to downside risk, i.e. unfavorable risk located in the lower tail of the distribution. In section 2, we show how partial moments (partial mean, variance and skewness) in each quantile can be used to assess exposure to risk and downside risk. Section 3 establishes two important results. First, relying on the Arrow-Pratt risk premium as a measure of the cost of risk, the risk premium can be decomposed into components associated with each quantile. Second, we establish linkages between the quantile-decomposition of the risk premium and partial moments, which generalizes previous literature on local risk premiums (Arrow, Pratt, Modica and Scarsin, Crainich and Eeckhoudt, and Keenan and Snow (2002, 2009)). This also shows how partial variance and skewness associated with relevant quantiles can identify the extent and sources of asymmetry in the lower tail of the distribution. Together with risk preferences, these measures provide a basis to evaluate the cost and economics of exposure to downside risk, as well as the potential for risk mitigation through management choices.

The empirical analysis using a panel data set from over 3,000 Korean rice farms covering the period 2003-2008 is presented in section 4. The risk exposure analysis is based on our specification of a multi-output, multi-input production function using robust panel econometric methods, controlling for endogeneity and for unobservable household factors.[2] We document the presence of fat tails in the distribution of production risk and then present quantile-based estimates of partial variance and skewness to evaluate exposure to risk and downside risk. These estimates allow us to evaluate the managerial options for risk mitigation through variations in input use, farmer demographics, and crop rotations.

Section 5 evaluates the implications of our econometric analysis for the cost for risk and downside risk. Our main finding is to show that most of the cost of risk comes from exposure to downside risk (defined as risk located in the lower quartile of the distribution). This points to the importance our approach and the refined empirical assessments of downside risk in the evaluation of climate change effects on agro-ecosystems. Finally, section 6 concludes.

2. Assessing Exposure to Risk and Downside Risk

This section develops a quantile-based decomposition of risk exposure that uses the first three partial moments of a stochastic payoff structure to identify the importance of downside risk. Assume a decision maker facing an uncertain payoff $\pi \in R$. The uncertainty about π is represented by the distribution function $F(c) = \text{Prob}(\pi \leq c)$. We are interested in evaluating the exposure to risk in general, and to downside risk in particular. For that purpose, let $K > 1$ be some finite integer and consider a sequence $\{b_k: k = 1, \ldots, K\}$ satisfying $-\infty \equiv b_0 < b_1 < b_2 < \ldots < b_{K-1} < b_K = \infty$. The b_k's are chosen such that $F(b_k) > F(b_{k-1})$, $k = 1, \ldots, K$. Letting $S_k \equiv (b_{k-1}, b_k]$, $[F(b_k) - F(b_{k-1})]$ is the probability of being in the k-th quantile: $\pi \in S_k$, $k = 1, \ldots, K$. Below, we associate downside risk with unfavorable risk located in the lower quantile: $\pi \in S_1$. In general, knowing the distribution function $F(\cdot)$ across all quantiles provides all the relevant information to evaluate exposure to risk (including downside risk). This distribution function can be evaluated either directly or through the estimation of its moments.[3]

There is an extensive literature that has used moments to evaluate risk exposure (e.g., Markowitz; Fishburn; Bawa; Jorion; Rockefellar and Uryasev; Antle, 2010). Our analysis below focuses on measures relying on partial moments. Throughout the paper, we assume that at least the first three moments of π exist. Denote the mean of π by

$$M_1 = E(\pi) = \sum_{k=1}^{K} \int_{\pi \in S_k} \pi \, dF(\pi), \tag{1a}$$

where E is the expectation operator based on the distribution function $F(\cdot)$. The j-th central moment of π is

$$M_j = E[(\pi - M_1)^j] = \sum_{k=1}^{K} \int_{\pi \in S_k} (\pi - M_1)^j \, dF(\pi), \tag{1b}$$

$j = 2, 3, \ldots$ Given $S_k \equiv (b_{k-1}, b_k]$, denote the partial mean of π in the interval S_k by

$$m_{k1} \equiv \frac{1}{F(b_k) - F(b_{k-1})} \int_{\pi \in S_k} \pi \, dF(\pi), \tag{2a}$$

$k = 1, \ldots, K$. And the j-th partial central moment of π in the interval S_k is

$$m_{kj} = \frac{1}{F(b_k) - F(b_{k-1})} \int_{\pi \in S_k} (\pi - m_{k1})^j \, dF(\pi), \tag{2b}$$

$k = 1, \ldots, K$ and $j = 2, 3, \ldots$ The payoff in the interval S_k can be written as

$$\pi = m_{k1} + e_k, \ \pi \in S_k, \tag{3}$$

where $e_k \equiv [\pi - m_{k1}]$ is a random variable distributed with partial mean zero (when $\pi \in S_k$), $k = 1, \ldots, K$. Below, we consider the following specification for e_k in (3)

$$e_k \equiv [m_{k2} - (m_{k3}/D_k)^{2/3}]^{1/2} \, v_{k2} + [m_{k3}/D_k]^{1/3} \, v_{k3}, \tag{4}$$

where v_{k2} and v_{k3} are independently distributed random variables satisfying $E[v_{k2}] = E[v_{k3}] = 0$, $E[(v_{k2})^2] = E[(v_{k3})^2] = 1$, $E[(v_{k2})^3] = 0$, and $E[(v_{k3})^3] \equiv D_k > 0$, $k = 1, \ldots, K$. These assumptions mean that v_{k2} and v_{k3} in (4) are normalized random variables (i.e., they are each distributed with mean zero and variance =1). In addition, v_{k2} has zero skewness, $E[(v_{k2})^3] = 0$, while v_{k3} has positive skewness, $E[(v_{k3})^3] \equiv D_k > 0$, where D_k is chosen to be large enough to satisfy $[m_{k2} - (m_{k3}/D_k)^{2/3}] > 0$. Note that equation (4) implies that $E(e_k) = 0$, $E[(e_k)^2] = m_{k2}$, and $E[(e_k)^3] = m_{k3}$, $k = 1, \ldots, K$. Thus, m_{k1}, m_{k2} and m_{k3} are the partial central moments of $\pi \in S_k$. It follows from (3)-(4) that, for given distributions of v_{k2} and v_{k3}, the first three moments m_{k1}, m_{k2} and m_{k3} are sufficient statistics for the distribution of $\pi \in S_k$, k = 1, …, K.

When $m_{k3} = 0$ and K = 1, note that equation (4) reduces to the standard two-moment specification commonly found in the literature (e.g., Meyer, 1987). Thus, equation (4) extends this approach in two directions: a) it allows for changes in both variance and asymmetry/skewness of the distribution; and b) when K > 1, it provides a quantile-based representation of the distribution function. The latter direction is particularly useful when one is interested in examining the risk exposure in a specific quantile as in our analysis of downside risk (corresponding to the lower quantile).

From (1a)-(1b) and (2a)-(2b), we have

$$M_j = \sum_{k=1}^{K} [F(b_k) - F(b_{k-1})] \cdot m_{kj}, \tag{5}$$

showing that the overall j-th central moment M_j is the weighted sum of the partial j-th central moments m_{kj} across all K intervals, with $[F(b_k) - F(b_{k-1})]$ as weight for the k-th interval, j = 1, 2, 3, … From equation (3) and (5), it follows that $\{m_{kj}$: k = 1, …, K; j = 1, 2, 3, …$\}$ along with $\{[F(b_k) - F(b_{k-1})]$: k = 1, …, K$\}$ are sufficient statistics for the distribution of π. This provides the basis for the moment-based analysis presented in this paper. Of special interest is the information on downside risk exposure associated with the first interval S_1. The decomposition includes the first three partial central moments (the partial mean m_{11}, the partial variance m_{12}, and the partial skewness m_{13}), and the probability of being in the first quantile, $[F(b_1) - F(b_0)]$. These are the key quantile-based estimates needed to assess downside risk in the lower tail of the distribution of π.

3. A Quantile-Based Evaluation of the Cost of Risk

The valuation of risk depends both on risk exposure and risk preferences. To analyze the cost of risk, we consider the case of a decision maker behaving in a way consistent with the expected utility model,[4] with risk preferences represented by the utility function U: $\Re \rightarrow \Re$. Throughout the paper, we assume that $U(\cdot)$ is strictly increasing. Following Arrow and Pratt, the cost of risk is measured by the risk premium defined as the sure amount R that satisfies

$$E[U(\pi)] = U(M_1 - R),$$

or

$$\sum_{k=1}^{K} \int_{\pi \in S_k} U(\pi)\, dF(\pi) = U(M_1 - R). \tag{6}$$

Equation (6) considers the valuation of a change in risk from π to the overall mean M_1. We want to decompose the risk premium R into parts associated with risk exposure and risk aversion in different intervals S_k, $k = 1, \ldots, K$. Our first result is stated next.

<u>Proposition 1</u> The cost of risk can be decomposed into additive components across quantiles as follows:

$$R = \sum_{k=1}^{K} \Delta R_k, \tag{7a}$$

where ΔR_k is the incremental risk premium associated with risk in the k-th interval. The incremental risk premia ΔR_k satisfy

$$E[U(\pi)] = U(M_1 - \Delta R_1)\,[F(b_1) - F(b_0)] + \sum_{j=2}^{K} \int_{\pi \in S_k} U(\pi - \Delta R_1)\, dF(\pi), \tag{7b}$$

when $k = 1$, and

$$E[U(\pi)] = \sum_{j=1}^{k} U(M_1 - \Delta R_k - \sum_{i=1}^{k-1} \Delta R_i)\,[F(b_j) - F(b_{j-1})]$$
$$+ \sum_{j=k+1}^{K} \int_{\pi \in S_k} U(\pi - \Delta R_k - \sum_{i=1}^{k-1} \Delta R_i)\, dF(\pi), \tag{7c}$$

when $k = 2, \ldots, K$.

Equation (7b) defines ΔR_1 as the decision maker's sure willingness to pay to eliminate the risk in the first quantile, moving it to the mean payoff M_1. And equation (7c) defines ΔR_k sequentially as the incremental willingness to pay to eliminate the risk of the k-th quantile, moving it the mean payoff M_1 while risk has already been eliminated in lower quantiles, k = 2, …, K. When k = K, comparing (7c) with (6) implies that $R = \sum_{k=1}^{K} \Delta R_k$, as given in (7a).

Equation (7a) provides a useful decomposition of the risk premium R into additive parts across the K intervals S_k, k = 1, …, K. This decomposition identifies the role of risk exposure in each of the K quantiles. Of special interest is the contribution of ΔR_1 to the cost of risk R. Indeed, given R > 0, $[\Delta R_1/R]$ measures the proportion of the risk premium due to exposure to downside risk.

Next, we explore how to evaluate the cost associated with terms ΔR_k's in (7). This requires information on both risk exposure and risk preferences. As noted, we focus our attention on a moment-based assessment of risk exposure. Thus, we need to establish linkages between partial moments of the payoff distribution and the risk premium. The following proposition 2 presents those linkages (The proof is presented in Appendix A).

<u>Proposition 2</u>: Assuming that $U(\pi)$ is three times continuously differentiable, the risk premium R can be approximated using a Taylor-series expansion as

$$R = \sum_{k=1}^{K} \Delta R_k, \tag{8a}$$

where

$$\Delta R_k \approx -(1/2)\, \frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot$$

m_{k2}

$$- (1/2)\ \frac{U''(M_1)}{U'(M_1)} \cdot [\int_{\pi \in S_k} (m_{k1} - M_1)^2\ dF(\pi)]$$

$$- (1/6)\ \frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k3}$$

$$- (1/6)\ \frac{U'''(M_1)}{U'(M_1)} \cdot [\int_{\pi \in S_k} (m_{k1} - M_1)^3\ dF(\pi)], \tag{8b}$$

with $U'(\pi) = \partial U/\partial\pi$, $U''(\pi) = \partial^2 U/\partial\pi^2$, and $U'''(\pi) = \partial^3 U/\partial\pi^3$.

Like proposition 1, proposition 2 decomposes the risk premium R into additive parts across the K intervals S_k, k = 1, …, K. Equation (8b) provides an approximate measure of the risk premium in terms of variance and skewness terms associated with each quantile of the distribution. This identifies the relative contributions of each quantile to the risk premium. As such, this is a generalization of previous literature on local measurements of the risk premium (Arrow; Pratt, Modica and Scarsin; Crainich and Eeckhoudt; Keenan and Snow (2002, 2009)).

For the k-th quantile, equation (8b) includes two variance components and two skewness components. The first variance component is: $- (1/2) \frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k2}$, which is proportional to the partial variance m_{k2}, and weighted by the probability of being the k-th interval, $[F(b_k) - F(b_{k-1})]$. This variance component is also weighted by the term $\frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}}$, reflecting risk preferences with respect to variance. Under risk aversion (where $U''(\pi) < 0$; see Arrow and Pratt), this gives the intuitive result that an increase in variance in the k-th quantile tends to increase the cost of risk.

The second variance component in (8b) is: – (1/2) $\frac{U''(M_1)}{U'(M_1)}$ · [$\int_{\pi \in S_k} (m_{k1} - M_1)^2 \ dF(\pi)$], which is proportional to the square deviation of the k-th partial mean from the overall mean $[m_{k1} - M_1]^2$. Under risk aversion (where $U''(\pi) < 0$), it means that an increase in the distance between the partial mean in the k-th interval, m_{k1}, and the overall mean, M_1, tends to increase the cost of risk.

The first skewness component in (8b) is: – (1/6) $\frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}}$ · $[F(b_k) – F(b_{k-1})]$ · m_{k3}, which is proportional to the partial skewness m_{k3}, and weighted by the probability of being the k-th interval, $[F(b_k) – F(b_{k-1})]$. This skewness component is also weighted by the term $\frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}}$, reflecting risk preferences with respect to skewness. Under downside risk aversion (where $U'''(\pi) > 0$; see Menezes et al.), this gives the intuitive result that an increase in skewness in the k-th interval tends to reduce exposure to downside risk and decrease the cost of risk.

Finally, for the k-th quantile, the second skewness component in (8b) is: – (1/6) $\frac{U'''(M_1)}{U'(M_1)}$ · [$\int_{\pi \in S_k} (m_{k1} - M_1)^3 \ dF(\pi)$], which is proportional to the cubed deviation of the k-th partial mean from the overall mean, $[m_{k1} - M_1]^3$. This skewness component is weighted by the term $\frac{U'''(M_1)}{U'(M_1)}$, reflecting risk preferences with respect to skewness (Menezes et al.). Under downside risk aversion (where $U'''(\pi) > 0$), it means that an increase in the cubed deviation of m_{k1} from the mean M_1 tends to reduce exposure to downside risk and decrease the cost of risk.

The following sections develop an empirical approach to estimate the quantile-based partial moments and probabilities that allow us to construct estimates of risk exposure and risk costs, with a focus on the role of downside risk associated with the lower quantile of the payoff distribution.

4. An Empirical Application to Risk Exposure on Korean Farms

Our empirical analysis examines production risk on rice farms in Korea. It is based on a panel dataset of Korean rice farms (Kim et al., 2012). It relies on a survey conducted annually from rice farm households over the period of 2003-2007, which provides information on annual farm inputs and outputs. The Korean National Statistical Office collected these data from a sample of 3,140 farm households surveyed annually from 314 enumeration districts. Summary statistics of the data are reported in Kim et al. (2012).

In a Korean rice production system, major outputs are rice, vegetable, soybean, barley and miscellaneous crops, and potato. Rice is the dominant crop, typically being grown on irrigated paddy land. Non-irrigated land is called "upland" and is suitable for other crops. Reflecting this, the output measures are: rice (prod_rice), vegetables (prod_vegi), soybean (prod_soybean), potato (prod_potato), and barley and other crops (prod_barleymisc). Inputs include land, divided into paddy land (land_paddy) and upland (land_upland), labor measured in hours, capital, fertilizer, pesticides, and seeds.[5] The distinction between paddy land and upland is important: it will provide useful insights on the role of irrigation in risk management. Socio-demographic measures (e.g., age and the level of education: edu1 for elementary school and edu4 for college or above) are also included to control for farm specific heterogeneity in human capital endowments that can matter to management outcomes including risk mitigation. Crop rotations within and across years are a third type of management option that is incorporated via the multi-output, multi-input, panel data analysis developed below.

4.1. Econometric Model of Risk Exposure

To empirically evaluate the presence of fat tails, the extent of downside risk exposure, and the cost of risk using a quantile approach, we need to estimate the partial central moments (m_{k1}, m_{k2} and m_{k3}) of $\pi \in S_k$ and the probability of being in each quantile ($[F(b_k) – F(b_{k-1})]$). In our analysis, the payoff π denotes farm income: $\pi = p\ z$, where $z = (y, x)$, y denotes rice production, x is the vector of farm inputs and other outputs produced, $p = (p_y, p_x)$ is the vector of prices for z, p_y is the price of rice and p_x is the vector of prices for x, elements of p_x being defined as positive for outputs and negative for inputs. Under production uncertainty, the production technology is represented by the production function $y = f(x, \varepsilon)$, where ε is a random variable reflecting production risk (e.g., unpredictable weather effects). After normalizing prices so that $p_y = 1$, farm income is then given by $\pi = f(x, \varepsilon) + p_x\ x$. It follows that the production function $f(x, \varepsilon)$ provides all the relevant information for analyzing risk exposure on Korean farms. In particular, the variance and skewness of π are the same as the corresponding variance and skewness of $f(x, \varepsilon)$. On that basis, we proceed using our Korean data to specify and estimate the moments of $f(x, \varepsilon)$.

Let $E[f(x, \varepsilon)] = [f_1(x, \beta_1) + \alpha]$ be expected production, where E is the expectation operator based on the information available to the farmer, α captures the effects of factors known to the farmer but not to the econometrician, and β_1 is a vector of parameters. It follows that rice production y can be specified as

$$y = f_1(x, \beta_1) + \alpha + e, \tag{9}$$

where $e \equiv y - E[f(x, \varepsilon)]$. When the unobservable effect α is farm-specific, then (9) corresponds to the standard specification used in panel data analysis (e.g., Wooldridge). Then, α can be treated as a "fixed effect" parameter, and e is an error term that captures the uncertainty faced by farmers and satisfies E(e) = 0.

Using appropriate panel data econometrics (further discussed below), we can obtain consistent estimate (β_1^c, α^c) of (β_1, α) in (9). This can generate consistent estimates of the residuals: $e^c = y - f_1(x, \beta_1^c) + \alpha^c$. Based on the sample information, e^c can then be used to evaluate the distribution of e, conditional on x. Following Antle (1983), this can generate consistent estimates of the moments of e, conditional on x (see Antle, 1983, 1987; Antle and Goodger). Since e captures the uncertainty in farmer's payoff (and after controlling for the effects of unobservables given by α in (15)), this provides a basis to estimate all relevant moments of farmer's payoff. This is the approach we follow below, first to evaluate the distribution for the presence of fat tails and then to examine the particular role played by downside risk in overall risk exposure and the costs of risk

Our econometric analysis proceeds working with 4 quantiles of the payoff distribution: K = 4, the four quantiles being quartiles. Let e_k be the part of e associated in the k-th quantile, with corresponding consistent estimate e_k^c, k = 1, …, 4. Denote by $f_{k2}(x, \beta_{k2})$ the variance of e_k conditional on x, where β_{k2} are parameters. Consider the following model specification for the k-th quantile:

$$(e_k^c - m_{k1}^c)^2 = f_{k2}(x, \beta_{k2}) + u_{k2}, \quad k = 1, 2, 3, 4, \tag{10}$$

where m_{k1}^c is a consistent estimate of the partial mean for e_k and u_{k2} is an error term distributed with mean zero. Then, following Antle (1983), consistent estimates β_{k2}^c of the parameters β_{k2} can be obtained from (10). It follows that $f_{k2}(x_{k2}, \beta_{k2}^c)$ is also a consistent estimator of m_{k2}, the partial variance of e_k in the k-th quantile.

Similar arguments apply to the estimation of partial skewness. Denote by $f_{k3}(x, \beta_{k3})$ the skewness of e_k conditional on x, where β_{k3} are parameters. Consider the following model specification for the k-th quantile:

$$(e_k^c - m_{k1}^c)^3 = f_{k3}(x, \beta_{k3}) + u_{k3},\ k = 1, 2, 3, 4, \tag{11}$$

where u_{k3} is an error term distributed with mean zero. Again, consistent estimate β_{k3}^c of the parameters β_{k3} can be obtained from (11). It follows that $f_{k2}(x_{k2}, \beta_{k2}^c)$ is also a consistent estimator of m_{k3}, the partial skewness of e_k in the k-th quantile. This provides a basis to obtain empirical estimates of risk exposure associated with each quantile, as measured by the corresponding partial variance and skewness just discussed.

Next, we need to estimate the probability of being in each quantile, $[F(b_k) - F(b_{k-1})]$. This is done using a multinomial logit model applied across all 4 quantiles. Together with the estimates of partial moments $\{(m_{k2}, m_{k3}$: k = 1, …, 4$\}$, this provides all the information required to evaluate risk exposure reported in equation (8).

Several econometric challenges arise in estimating equations (9)-(11). First, the multi-output multi-input production function $f_1(x, \beta_1)$ needs to be flexible enough to capture the effects of multiple outputs on the productivity of rice, the dominant crop. For this, we introduce five major outputs (rice, vegetable, soybean, barley and miscellaneous, and potato), and specify the mean function as a quadratic form allowing for non-linear relationships between rice production and other output productions. In a way consistent with previous studies (e.g., Antle and Goodger 1986; Groom et al. 2008), this provides a fairly flexible representation of the underlying technology. The following explanatory variables x are used in the specification of the mean function (9). Conventional inputs (paddy land and upland, labor, seed, fertilizer, pesticide, capital) are included in log form to allow for potential non-linear input effects. An index variable (intra) capturing the degree of intra-year double cropping helps to account for the effects of rotation on rice production.[6] We include a series of interaction terms of the non-rice output variables and land types and use to capture the heterogeneous marginal effects of other crops and inter-year rotations on rice. Three examples are suggestive of the full set. One is paddy_prod_vegi, which interacts paddy land and vegetable production; second is upland_prod_vegi, which interacts upland and vegetable production; and third is intra prod_vegi, which interacts intra-year crop rotation and vegetable production. We also include a time trend (t) accounting for the impacts of technological progress on rice production during sample periods, and the age (age) of the household manager accounting for demographic differences that might reflect heterogeneous managerial ability. Regional dummy variables account for potential agro-climatic heterogeneity across production regions. Lastly, the following diversification index variables are included in an effort to capture the effects of possible diversification strategies in a rice production system: (i) a lag value of Herfindahl index (lag_hi), (ii) a lag value of interaction variable between the size of upland and the proportion of soybean production (lag_upland_soybean_share), and (iii) a lag value of interaction variable between the size of upland and the proportion of potato production (lag_upland_potato_share).

We want to stress the importance of the specification of the mean function in (9). Indeed, its error term e in (9) is being used to estimate the parameters of the higher moments given in (10) and (11), and its distribution is used initially to evaluate whether excess kurtosis is present, or whether instead we have a normal distribution (without fat tails). The second partial moment functions (10) are specified as exponential functions to ensure non-negative variance. And the third partial moments (11) are specified as linear to reduce multicollinearity problems.

The second major econometric challenge is addressing potential bias in estimating equations (9)-(11). Potential endogeneity issues associated with farmer's production choices could arise if rice farmers use information that is not available to the econometrician. Then, this information would affect both their input-output choices x and also appear in the error terms in (9)-(11), possibly generating endogeneity bias and inconsistent parameter estimates associated with unobserved heterogeneity when using standard econometric approaches (e.g. least-squares estimation method). Panel data econometrics can deal with both issues (Wooldridge). Below, we utilize a Hausman-Taylor estimator (Hausman and Taylor, 1981) of the mean and higher moment equations in (9)-(11). This instrumental variable estimation method deals with omitted variable issues and endogeneity issues in the context of panel data and controls for the unobserved fixed effects α in (9). It generates consistent estimates of the parameters by using the mean of endogenous variables that are not correlated with individual specific effects and time-invariant regressors as instruments. The panel data structure and appropriate estimation techniques allow us to recover consistent estimates of the error term e in (9) while controlling for unobserved heterogeneity across farm households. This is a crucial step in the estimation of higher partial moment functions in (10)-(11).

Third, the error term e in (9) will likely exhibit heteroscedasticity. This arises when the variance of e is not constant across observations. Also, as showed by Antle (1983, 2010), the error terms in the variance and skewness equations (10)-(11) are also likely to exhibit heteroscedasticity. To deal with heteroscedasticity problems, either a heteroscedastic-consistent estimator or a weighted least squares estimation can be utilized. Below, we report heteroscedastic-consistent standard errors of parameter estimates in higher partial moment functions. This gives a consistent estimate of the variance-covariance matrix which is essential to support hypothesis testing.

4.2. Econometric Estimation

We begin by estimating equation (9) using the techniques described above. Because we are primarily interested in the residual of the estimation, we do not dwell on the standard economic parameters, which Kim et al. report in detail. The estimation results of the mean rice production function are reported in Table B1 in appendix B. In terms of the panel data estimation strategy, we find no strong evidence against the consistency of the Hausman-Taylor estimator (the test statistic = 4.817). This outcome implies that potential endogeneity issues in Korean rice production system were resolved adequately by the use of the Hausman-Taylor approach. Table B1 also shows that most of the estimated coefficients are statistically significant and capture the factors shaping Korean rice production outcomes in an appropriate manner including the importance of output mix and core inputs, such as paddy land, labor, and capital to rice productivity (see Kim et al. 2012 for more on the first moment estimations). As discussed above, the mean estimates give the residuals needed for the quantile-based analysis of risk exposure.

The empirical results discussion starts with an analysis of the kurtosis and skewness properties of the rice yield distribution to test for normality of the error term e^c. The normalized skewness of e^c is 1.09 and the normalized kurtosis is 86.09. Using the Bera-Jarque test, we find that the skewness is statistically different from zero, with a p-value of 0.0001. And e^c is found to exhibit excess kurtosis, with a p-value of 0.0001. This indicates that the distribution of e^c is asymmetric: it is skewed to the right. And it has "fat tails", or at least tails that are significantly "fatter" than the normal distribution (which has a normalized kurtosis equal to 3). We also investigate partial moments of the error term e^c. We find partial variance of both lower and upper tails of the distribution (corresponding to the 1st and 4th quantiles) are much larger than that of the 2nd and 3rd quantiles: they are 1757.9 for the 1st quantile, 28.7 for the 2nd quantile, 30.1 for the 3rd quantile, and 2256.8 for the 4th quantile. For a partial skewness, we find negative partial skewness for the lower tail (= -5.68) and positive partial skewness for the upper tail (= 6.06). These results are consistent with the existence of fat tails in the distribution of production risk on Korean rice farms. This leads us to conjecture that fat tails are likely to be prevalent in agriculture and other activities subject to the vagaries of climatic or ecosystem variation. What are the implications of these fat tails? Below, we examine in more details the relative role of downside risk located in the lower tail of the distribution. In particular, our analysis will explore the cost of downside risk in rice production and the potential for managing that risk through irrigation, input, and rotation choices.

The rest of this section presents the estimation of our empirical model on downside risk exposure. It starts with a discussion of the estimates of the partial moment equations (9)-(11) for each quantile, followed by the multinomial logit model that estimates the probability of being in each quantile, $[F(b_k) – F(b_{k-1})]$. We put special attention on the factors that shape partial moment outcomes in the quantiles, because they provide information on factors shaping risk exposure and management. Then we present hypothesis tests that compare the factors shaping risk exposure and management across the quantiles. These comparisons demonstrate both the importance of downside risk and the potential to mitigate that exposure through certain management choices. In the next section, these estimates are combined with relatively conservative assumptions about risk preferences to estimate the significance of the 'costs' associated with downside risk exposure.

The estimation results of the partial variance functions are presented in Table 1. As in Antle (2010), we test for the presence of asymmetry in production risk, and as in the financial disappointment aversion literature (Butler et al. 2005, Routledge and Zin, 2010) we highlight the potentially significant role that downside risk exposure can play in the management options facing economic agents. Unlike either of these other approaches, we generate estimates of risk exposure that identify the extent of the exposure in different quantiles of the risk distribution. After discussing individual coefficient relationships in the quantile regressions, we do hypothesis testing of the potential asymmetry of these coefficients across quantiles of the distribution.

Overall, we find more significant relationships between explanatory variables and partial variance outcomes for the 1^{st} and 4^{th} quantiles as compared to the 2^{nd} and the 3^{rd} quantiles. This broad finding indicates that characterizing partial variance associated with the lower and upper tails of the distribution of variance (corresponding to the 1^{st} and 4^{th} quantiles, respectively) is relatively easier than it is in the middle quantiles. It also suggests that asymmetry in production risk is concentrated in those outer tails.

As in Antle (2010), we find that labor input has significant positive effects on the lower tail of the 2^{nd} moment distribution. In our case, they vary positively with age when evaluated at the sample mean. This result suggests that younger farmers might have better management abilities when it comes to managing downside risk. In contrast, we find the opposite effects of labor on the 4^{th} quantile of the 2^{nd} moment, i.e., labor input has significant negative effects on the higher tail of the 2^{nd} moment, which vary negatively with age when evaluated at the sample mean of age. This implies again that younger farmers might also be better able to secure the upside risk possibilities.

The coefficients associated with paddy land, capital, and double cropping (evaluated at the sample mean of paddy land) are negatively related with the lower tail of 2^{nd} moment distribution. This implies that paddy land and capital help to manage downside risk as captured by reducing the variance experienced in the lowest quantile of the 2^{nd} moment distribution. We also find that the cost of seed and interaction variable between upland and the lag of soybean share have statistically significant and positive effects on the lower tail of the 2^{nd} moment distribution. These results suggest that new varieties, which are usually more expensive than traditional ones, tend to increase downside risk. This finding might capture risk-bearing ability of traditional varieties compared to new varieties that might be capable of producing better yield at a cost of risk increase. That result would be consistent with many technology adoption studies of high-yielding varieties (Feder et al.). On the other hand, the coefficient of the cost of fertilizer was found to be positively related with the upper tail of the 2^{nd} moment distribution. This suggests that fertilizer input appears to be an upside-risk-increasing input, in that it helps to increase the upside production potential.

Table 3 presents the estimation results of the partial skewness equation. The general lack of significance in coefficient estimates throughout all quantiles suggests the difficulty associated with panel estimation of the 3^{rd} moment functions. Nonetheless, we find relatively more significant relationships between explanatory variables and skewness measures in the 2^{nd} and 3^{rd} quantiles. The coefficient of lag of Herfindahl index variable is positive and significant, implying that concentration in output mix tends to increase the partial skewness corresponding to the 2^{nd} and 3^{rd} quantiles, thus contributing to the shift of distribution to the right. However, the capital variable works the other way. The negative and significant coefficients of capital in the 2^{nd} and 3^{rd} quantiles suggest that capital contributes to a shift of the distribution to the left. Without many significant relationships, these skewness estimates do not tell us much more about the potential for managing risk exposure.

Multinomial logit estimation results for the probability of being in each quantile are presented in two tables: the estimates are presented in Table B2 in Appendix B, and the marginal effects are reported in Table 3. The number of statistically significant coefficient estimates are small compared to those of 2^{nd} moment functions, which again suggests that managing the probability of being in a risk quantile is much harder than managing the amount of risk exposure associated with partial 2^{nd} moments. Given the inherently stochastic nature of risk outcomes, it is not surprising that predicting where producers fall in the distribution without explicit incorporation of weather-related variables proves challenging. Nonetheless, two useful observations emerge from discussing the marginal effect estimates. One is that two measures of intensification strategies, total paddy land (which entails much more input investment per land unit than non-paddy land) and intra (the measure of intra-annual rotations), are positive and statistically significant predictors for being found in the first and fourth quantiles, or the downside and upside intervals of the risk distribution. That makes sense given that intensification strategies can both increase returns and risks. The other useful observation is that fertilizer use is a positive and statistically significant predictor for being in the lower-middle quantile and negative and statistically significant predictor for being in the other quantiles. Thus, fertilizer can be viewed as largely a risk-reducing insurance strategy in rice production, in terms of putting producers in different risk quantiles**.**

We turn next to evaluating potential asymmetry in the effects of other output production and inputs on the 2nd and 3rd partial moments of rice production. Testing the hypothesis of symmetric input effects involves using the separate estimation of equations (10) and (11) for each quantile to produce t-tests of the equality of specific parameter estimates of quantile-based 2nd central moment functions in (10) and quantile-based 3rd central moment functions in ((11). These tests (shown in Table 4) allow us to comment on the significance of different factors in shaping risk exposure and identifying possible mitigation strategies. Table 4 reports these hypothesis test results for the most important input variables (land, labor, capital, fertilizer, pesticide, and seed) for each pair of quantiles of the 2nd and 3rd central moments of rice production.

Test results suggest that the null hypotheses of symmetry in the important management variables (e.g. paddy land, labor, capital, fertilizer, pesticide, and seed) for most pairs of quantiles are rejected for the 2nd central moment function (with the exception for the pair of the 2^{nd} and 3^{rd} quartiles). Notably, asymmetry effects of paddy land and labor input variables are highlighted in the 2^{nd} partial moments of rice production. This result implies that these inputs differ across the quantiles in terms of how they shape risk exposure and management effects in the 2^{nd} central moment of the distribution. In particular, these hypothesis test results reveal strong asymmetric management effects in the pair of the 1^{st} and 4^{th} quantiles, which highlights the potential heterogeneous management effects in dealing with downside versus upside risk exposure. For the 3^{rd} central moment of rice production, we find a lack of significance in the asymmetry of input effects across the quantiles compared to the 2^{nd} central moment test results. This again suggests the difficulty of identifying input effects in characterizing risk exposure and potential management tools when it comes to the 3^{rd} central moment of rice production.

Overall, these econometric results show that our quantile approach for evaluating risk exposure is relevant econometrically. Below we investigate whether the quantile approach is also meaningful in terms of assessing the costs of risk exposure. For this purpose, we develop a quantile-based risk valuation measure under an expected utility example to measure the costs of risk in each quantile. Under some scenarios of non-expected utility, especially those that assume strong disappointment or downside risk aversion, we would expect even stronger results than we find using a relatively conservative set of assumptions on risk preferences.

5. Evaluating the Cost of Risk

In this section, the cost of risk is decomposed using the quantile methodology presented in section 3. Primary focus is given to the cost of downside risk. Using an expected utility framework, we consider the case where risk preferences are given by the constant relative risk aversion (CRRA) utility function $U(\pi) = [\pi^{(1-b)}]/(1 - b)$, where $\pi > 0$ and $b > 0$ is the relative risk aversion coefficient.[7] It satisfies risk aversion (with $U''(\pi) < 0$) and downside risk aversion (with $U'''(\pi) > 0$) (see Arrow, Pratt and Menezes et al.). It follows that, under CRRA preferences, equation (8) gives $R = \sum_{k=1}^{K} \Delta R_k$, where

$$\begin{aligned}\Delta R_k \approx\ & 0.5 \cdot [F(b_k) - F(b_{k-1})] \cdot \Big\{ \frac{b\,(m_{k1})^{-b-1}}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot (m_{i1})^{-b}\}} \cdot m_{k2} \\ & + [b\,(M_1)^{-1}] \cdot [m_{k1} - M_1]^2 \Big\} \\ & + (1/6) \cdot [F(b_k) - F(b_{k-1})] \cdot \Big\{ - \frac{b\,(1+b)\,(m_{k1})^{-b-2}}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot (m_{i1})^{-b}\}} \cdot m_{k3} \\ & - [b\,(1+b)\,(M_1)^{-2}] \cdot [m_{k1} - M_1]^3 \Big\}, \end{aligned} \tag{12}$$

$k = 1, 2, 3, 4$. Equation (12) provides a decomposition of the (approximate) cost of risk associated with the k-th interval S_k under CRRA preferences. It provides an explicit tool for the empirical assessment of the cost of risk measured through the partial mean, partial variance, and partial skewness, and the probabilities of being in each quantile and how it varies with the input choices x_1, x_{k2}, x_{k3}, $k = 1, 2, 3,4$.

Table 5 provides a summary measure of the decomposition results. Using equation (12) and the econometric results from section 4, we decompose the costs of risk by each quantile for two rice farm types, labeled here as type A and type B. On the one hand, type A (identified by evaluating management variables at their sample means) represents a typical rice farm. On the other, type B is consistent with a more specialized rice farm (identified by evaluating management variables at the 75 percentile of the share of rice income). Thus, type B farm relies more on rice in its production system than does a type A farm. We consider these two types of rice farms to investigate the potential effects of irrigation technologies on the management of downside risk in agricultural production. In addition, sensitivity analysis of the decomposition results is done by evaluating the costs of risk at different levels of constant relative risk aversion. We choose scenarios where constant relative risk aversion ranges from moderate (1/b= 2) to modest (1/b = 1). Lastly, we further decompose the costs of risk in each quantile into variance and skewness components. This is done by separating 2^{nd} and 3^{rd} moment effects in the valuation of risk summarized in equation (12).

Our decomposition results show that the costs of risk associated with the lower tail of the distribution (downside risk) are quite large; they account for more than 90% of total risk premium when both 2^{nd} and 3^{rd} moments are taken into consideration. Along with the 'fat tail' of the overall risk distribution, this estimate stresses the economic significance of downside risk exposure. Combined, these make irrigated rice outcomes consistent with the dismal theory (Weitzman, 2009) that focuses on the potentially high the costs of a tail-fattening event (e.g., climate change). Moreover, the costs of risk associated with the upper tail of the distribution (upside risk) seem relatively small compared to downside risk, accounting for about 10% of total risk premium with both variance and skewness components. It is not surprising to find that the costs of risk at the 2^{nd} and 3^{rd} quantiles are negligible in all of the scenarios.

Our results also suggest that 2^{nd} moment information alone is not enough to investigate what happens at the lower and upper tail of distribution. About 70%~80% of risk premium in the lowest quantile is generated by skewness components, implying the importance of 3^{rd} moment information in the valuation of risk premium in the lower tail of distribution. Skewness effects are also shown to be important for the valuation of risk in the upper quantile. The decomposition results also reveal that the risk premium in the lowest quantile for the more specialized farm in rice production (type B) is lower than that of a typical rice farm (type A). This stresses the critical role of irrigation technology in rice production for risk management. When a production system is involved with more rice production, the costs of risk are found to be smaller. This finding is consistent with Schlenker, Hanneman, and Fischer (2005) in highlighting the importance of irrigation systems as a risk management tool in the lower tail of the distribution. Meanwhile, skewness effects in the 4th quantile for both type A and type B are found to be negative. This suggests that the presence of positive skewness contributes to the increase of overall welfare of rice farm households. However, the magnitude of this decrease in the costs of risk associated with the upper tail of distribution in terms of skewness components is small compared to the costs of risk in the lower tail of distribution.

Overall, our results highlight the value of the quantile approach in risk assessment. They provide estimates of the costs of risk in each quantile, identify management strategies relevant to each quantile, and thus show that our quantile approach to risk assessment is relevant and meaningful economically.

6. Concluding Remarks

Weitzman's seminal article on 'Catastrophic Climate Change' stresses the potentially important roles that "fat tails" can play in the assessment of risk and uncertainty associated with low probability, large-downside risk events. This article develops a new quantile approach utilizing first, second, and third partial moments to evaluate risk exposure and illustrate risk valuation, and then applies it to examine the potential importance of 'fat tails', downside risk, and risk mitigation options associated with a highly controlled but stochastic production system − irrigated rice production in Korea. This case provides a conservative choice in the spectrum of agricultural production systems worldwide for an empirical effort to identify ‘fat tails’ and the exposure, value, and management prospects for downside-risk.

The econometric approach exploits a rich panel dataset to develop consistent and robust econometric estimates of the partial moments needed to implement the quantile-based decomposition of risk outcomes. We found that the risk distribution associated with Korean rice production system has fat tails, with most of the risk exposure occurring on the downside, and involving substantial potential for risk management associated with farmer choices. Specifically, the decomposition results demonstrate that the costs of risk associated with the lower tail of distribution (downside risk) are quite large, accounting for more than 90% of total risk premium, providing an empirical validation of Weitzman's dismal theory. Together these findings suggest two critical economic implications deserving of further analysis. First, downside risk outcomes in agriculture are likely to matter a lot to farmers and potentially consumers (especially in more catastrophic situations). Second, at least in the case of irrigated rice, a highly controlled production system, the risks are subject to some mitigation through management choices on the farm, but the probability of landing in the lowest quartile is at best only partially subject to management.

The implications of this article could be deepened by applying the quantile approach to other agricultural and natural resource systems to identify the extent of downside risk exposure and potential for risk mitigation options in other contexts. In our view, finding strong empirical evidence of fat tails and 90% of the cost of risk occurring in the lower quantile among irrigated Korean rice farms is likely to provide lower bounds estimates relative to other contexts. In addition, these risk estimates may be conservative at a social level, because they do not incorporate broader food security concerns of consumers and governments. Finally, there is the obvious need to explore the economics of risk and downside risk in other sectors. These tasks seem critical to advancing scientific discussions on the effects of downside risk on economic welfare and policy discussions on the private and social options for mitigation.

Table 1. Estimation of partial variance equations (dep. var. = variance of rice production)

Variables	1st quantile	2nd quantile	3rd quantile	4th quantile
age	-0.864**	0.200	0.0767	1.328***
	(0.416)	(0.248)	(0.185)	(0.403)
t	0.028	-0.001	0.088	0.425*
	(0.207)	(0.079)	(0.061)	(0.251)
prod_vegi	0.002	-0.026**	-0.012	0.012
	(0.007)	(0.011)	(0.011)	(0.027)
prod_soybean	0.009	-0.019	0.006	0.039
	(0.037)	(0.029)	(0.021)	(0.028)
prod_barleymisc	-0.003	0.008	-0.034	-0.002
	(0.017)	(0.066)	(0.048)	(0.014)
prod_potato	-0.035**	-0.001	-0.010	0.155*
	(0.014)	(0.036)	(0.014)	(0.087)
ln_land_paddy	-1.603**	-0.377	-0.020	-4.951**
	(0.656)	(0.432)	(0.413)	(1.489)
ln_land_upland	0.196	-0.101	0.102	-0.142
	(0.199)	(0.117)	(0.106)	(0.302)
ln_labor	-4.389	2.082	0.745	11.596***
	(3.243)	(2.661)	(2.024)	(3.465)
age_ln_labor	0.121**	-0.032	-0.015	-0.207***
	(0.061)	(0.041)	(0.030)	(0.061)
ln_cost_seed	0.611***	0.072	0.139	-0.161
	(0.190)	(0.116)	(0.124)	(0.247)
ln_cost_fertilizer	-0.418	0.014	-0.088	0.893**
	(0.277)	(0.183)	(0.125)	(0.401)
ln_cost_pesticide	-0.758	-0.307*	0.193*	0.557*
	(0.485)	(0.170)	(0.102)	(0.310)
ln_capital	-1.789**	0.248	-0.319	-0.476
	(0.915)	(0.417)	(0.400)	(0.776)
intra	0.546	-1.681	1.728	-2.719
	(2.951)	(7.033)	(3.254)	(2.695)
intra_paddy	-1.004**	2.639	1.145	-1.053*
	(0.464)	(5.281)	(1.815)	(0.633)
lag_hi	2.556	-0.019	1.011	4.485
	(2.244)	(1.119)	(0.905)	(3.119)
lag_upland_soybean_share	14.655**	-5.442	2.563	8.616
	(6.194)	(5.093)	(5.684)	(7.986)
lag_upland_potato_share	-45.981	3.878	2.388	-68.233
	(31.159)	(8.070)	(9.982)	(54.479)
Constant	57.421***	-11.686	-0.659	-76.786***
	(22.222)	(17.613)	(13.020)	(13.763)
Observations	390	1,558	1,558	389

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 2. Estimation of partial skewness equations (dep. var. = skewness of rice production

Variables	1st quantile	2nd quantile	3rd quantile	4th quantile
age	0.605	-73.009	-33.418	-0.361
	(2.717)	(54.130)	(59.891)	(0.226)
t	-0.764	11.318	11.766	-0.034
	(1.369)	(15.311)	(15.729)	(0.077)
prod_vegi	0.063	0.987	-3.297	0.043**
	(0.062)	(2.129)	(2.249)	(0.025)
prod_soybean	0.951	4.231	2.525	0.027
	(0.657)	(6.972)	(5.335)	(0.017)
prod_barleymisc	-0.116	6.416	-3.229	-0.006*
	(0.138)	(7.013)	(9.937)	(0.004)
prod_potato	-0.026	-4.001	-4.592	0.040**
	(0.138)	(8.167)	(5.969)	(0.021)
ln_land_paddy	11.911	-136.259	-109.119	-0.190
	(8.656)	(87.501)	(87.588)	(0.355)
ln_land_upland	-2.481	91.855**	21.867	0.044
	(1.934)	(52.487)	(13.233)	(0.092)
ln_labor	6.085	-851.818	-365.904	-2.933
	(13.645)	(575.729)	(560.20)	(1.837)
age_ln_labor	-0.066	11.290	3.656	0.048
	(0.405)	(8.760)	(8.395)	(0.030)
ln_cost_seed	-0.610	8.785	-15.552	-0.012
	(1.337)	(18.147)	(28.430)	(0.074)
ln_cost_fertilizer	0.464	-5.636	-72.036***	-0.043
	(1.461)	(14.738)	(28.837)	(0.089)
ln_cost_pesticide	-2.116	6.266	-19.452	0.198*
	(2.738)	(37.027)	(20.291)	(0.119)
ln_capital	2.454	-223.10***	-154.035*	0.594
	(5.962)	(79.795)	(91.229)	(0.385)
intra	25.572	1,023.49	1,170.71	-1.699
	(19.859)	(1,124.30)	(899.37)	(1.235)
intra_paddy	-3.475	-437.298	112.988	0.217
	(3.467)	(703.31)	(378.03)	(0.163)
lag_hi	-14.923	703.672***	582.699***	2.540*
	(16.534)	(215.39)	(180.12)	(1.447)
lag_upland_soybean_share	94.204	-544.569	-305.755	7.331*
	(102.43)	(1,057.46)	(1,274.92)	(3.760)
lag_upland_potato_share	539.076	3,436.13***	1,781.96	-28.090
	(525.22)	(1344.21)	(2,440.28)	(22.758)
Constant	-62.103	6,801.46**	4,225.94	15.566
	(178.02)	(3,718.86)	(3,403.07)	(12.449)
Observations	390	1,558	1,558	389

Note: Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Skewness measures in 1st and 4th quantile are rescaled by dividing by 1,000,000.

Table 3. Marginal effects of multinomial logit estimates

Variables	1st quantile	2nd quantile	3rd quantile	4th quantile
Age	-0.001931	-0.010172	0.011489	0.000614
	(0.004)	(0.007)	(0.008)	(0.004)
prod_vegi	-0.000013	-0.000839*	0.000950**	-0.000099
	(0.000)	(0.000)	(0.000)	(0.000)
prod_soybean	0.001063**	-0.00596***	0.004246***	0.000646
	(0.001)	(0.002)	(0.002)	(0.000)
prod_barleymisc	-0.000390**	-0.000369	0.000933	-0.000174
	(0.000)	(0.001)	(0.001)	(0.000)
prod_potato	-0.000433	-0.000773	0.001452*	-0.000245
	(0.000)	(0.001)	(0.001)	(0.000)
ln_land_paddy	0.067157***	-0.12947***	-0.012327	0.074645***
	(0.013)	(0.023)	(0.022)	(0.012)
ln_land_upland	-0.000807	-0.01913***	0.019543***	0.000394
	(0.003)	(0.006)	(0.007)	(0.002)
ln_labor	-0.006855	-0.070018	0.054576	0.022298
	(0.034)	(0.073)	(0.080)	(0.038)
age_ln_labor	0.000069	0.001677	-0.001484	-0.000262
	(0.001)	(0.001)	(0.001)	(0.001)
ln_cost_seed	0.000307	-0.013472	0.011549	0.001616
	(0.005)	(0.010)	(0.010)	(0.004)
ln_cost_fertilizer	-0.008603	0.073044***	-0.05204***	-0.012401**
	(0.006)	(0.012)	(0.012)	(0.006)
ln_cost_pesticide	0.006961	0.005963	-0.013112	0.000188
	(0.005)	(0.011)	(0.011)	(0.005)
ln_capital	0.017847*	0.027452*	-0.05760***	0.012304
	(0.010)	(0.015)	(0.015)	(0.008)
Intra	0.061125***	-0.19107***	0.053595	0.076352***
	(0.023)	(0.044)	(0.045)	(0.023)
intra_paddy	-0.001618	0.001872	0.006897	-0.007151
	(0.004)	(0.020)	(0.018)	(0.008)
t	0.004898	0.008953	-0.015417*	0.001567
	(0.004)	(0.008)	(0.008)	(0.004)
lag_hi	0.036633	-0.24134***	0.126158*	0.078551**
	(0.033)	(0.063)	(0.064)	(0.033)
lag_upland_soybean_share	-0.035812	0.392265	-0.360758	0.004304
	(0.118)	(0.336)	(0.324)	(0.100)
lag_upland_potato_share	0.107360	-0.113734	-0.154572	0.160946
	(0.142)	(0.333)	(0.354)	(0.108)

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 4. Hypothesis Test Results for Asymmetric Input Effects

Variables	$1^{st}/2^{nd}$	$1^{st}/3^{rd}$	$1^{st}/4^{th}$	$2^{nd}/3^{rd}$	$2^{nd}/4^{th}$	$3^{rd}/4^{th}$
Partial Variance						
ln_land_paddy	1.561	2.042**	2.058**	0.597	2.950***	3.191***
ln_land_upland	1.287	0.417	0.935	1.286	0.127	0.762
ln_labor	1.543	1.343	3.368***	0.400	2.178**	2.704***
age_ln_labor	2.082**	2.001**	3.802***	0.335	2.381**	2.824***
ln_cost_seed	2.421**	2.080**	2.477**	0.395	0.854	1.085
ln_cost_fertilizer	1.301	1.086	2.690***	0.460	1.994**	2.336**
ln_cost_pesticide	0.878	1.919*	2.285**	2.522**	2.444**	1.115
ln_capital	2.026**	1.472	1.094	0.981	0.822	0.180
Partial Skewness						
ln_land_paddy	1.685*	1.375	1.397	0.219	1.555	1.244
ln_land_upland	2.218**	1.002	1.304	1.431	2.161**	0.901
ln_labor	1.489	0.663	0.365	0.605	1.474	0.648
age_ln_labor	0.516	0.525	0.447	0.722	0.485	0.547
ln_cost_seed	0.516	0.525	0.447	0.722	0.485	0.547
ln_cost_fertilizer	0.237	2.511**	0.346	1.718*	0.217	2.497**
ln_cost_pesticide	0.226	0.847	0.844	0.609	0.164	0.968
ln_capital	2.821***	1.713*	0.374	0.570	2.803***	1.695*

Note: t-test statistics for each pair of quantiles are reported: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5. Decomposition of risk premium by quantiles

CRRA coeff.	Total (R) Type A[a]	Total (R) Type B[b]	1st quantile Type A	1st quantile Type B	2nd quantile Type A	2nd quantile Type B	3rd quantile Type A	3rd quantile Type B	4th quantile Type A	4th quantile Type B
Variance + skewness components										
2	30.69	28.636	28.439	26.942	0.216	0.222	0.228	0.23	1.816	1.242
	(1.00)	(1.00)	(0.93)	(0.94)	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.04)
1	9.426	8.32	8.168	7.539	0.11	0.113	0.119	0.121	1.029	0.548
	(1.00)	(1.00)	(0.87)	(0.91)	(0.01)	(0.01)	(0.01)	(0.01)	(0.11)	(0.07)
Variance components only										
2	13.198	9.411	9.013	5.547	0.211	0.215	0.235	0.236	3.74	3.413
	(1.00)	(1.00)	(0.68)	(0.59)	(0.02)	(0.02)	(0.02)	(0.03)	(0.28)	(0.36)
1	5.818	4.333	3.495	2.349	0.107	0.109	0.123	0.124	2.093	1.75
	(1.00)	(1.00)	(0.60)	(0.54)	(0.02)	(0.03)	(0.02)	(0.03)	(0.36)	(0.40)
Skewness components only										
2	17.492	19.225	19.426	21.395	0.005	0.007	-0.007	-0.006	-1.924	-2.171
	(1.00)	(1.00)	(1.11)	(1.11)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.11)	(-0.11)
1	3.608	3.987	4.673	5.19	0.003	0.004	-0.004	-0.003	-1.064	-1.202
	(1.00)	(1.00)	(0.80)	(1.30)	(0.00)	(0.00)	(0.00)	(0.00)	(-0.18)	(-0.30)

Composition ratios of risk premium in each quantile are in parenthesis
a/ “Type A” farm is a typical rice farm.
b/ “Type B” farm is a large-size rice farm (evaluated at 75 percentile of land paddy).

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Appendix A

The proof of proposition 2 requires analyzing the elimination of risk in two steps. The first step involves eliminating the risk in each quantile and moving it the partial mean of the quantile. And the second step involves moving the partial means of each quantile to the overall mean.

We start with the first step. Letting $\underline{\sigma} = (\sigma_1, \ldots, \sigma_K)$, where $\sigma_k \in [0, 1]$, k = 1, …, K, define

$$v(\pi, \underline{\sigma}) \equiv \sigma_k \pi + (1-\sigma_k)\, m_{k1} \text{ when } \pi \in S_k,\ k = 1, \ldots, K. \tag{A1}$$

The parameters $\underline{\sigma}$ in $v(\pi, \underline{\sigma})$ capture a shift in risk. Letting $\underline{0} = (0, \ldots, 0)$ and $\underline{1} = (1, \ldots, 1)$, note that $v(\pi, \underline{1}) = \pi$, and $v(\pi, \underline{0}) = m_{k1}$ when $\pi \in S_k$, k = 1, …, K. It follows that a move of the vector $\underline{\sigma}$ from $\underline{1}$ to $\underline{0}$ reflects a redistribution of risk from π to the partial means of each quantile m_{k1}, k = 1, …, K.

Using (A1) provides a basis to explore the cost of risk associated with different quantiles. For a given $\underline{\sigma}$ in (A1), define $R_a(\underline{\sigma})$ as the sure amount of money satisfying

$$E[U(v(\pi, \underline{\sigma}))] = \sum_{k=1}^{K} \int_{\pi \in S_k} U[v(\pi, \underline{0}) - R_a(\underline{\sigma})]\, dF(\pi), \tag{A2}$$

where $R_a(\underline{\sigma})$ is the amount of money the decision maker is willing to pay to replace $v(\pi, \underline{\sigma})$ by $v(\pi, \underline{0}) = m_{k1}$ when $\pi \in S_k$, k = 1, …, K. Clearly, equation (A2) implies that $R_a(\underline{0}) = 0$. And $R_a(\underline{1})$ measures the willingness-to-pay to replace π by the partial means m_{k1}'s, with m_{k1} occurring with probability $[F(b_k) - F(b_{k-1})]$, k = 1, ..., K.

Next, we consider the second step (where the m_{k1}'s are replaced by the sure overall mean M_1). Given $s \in [0, 1]$, define

$$w(\pi, s) \equiv s\, m_{k1} + (1-s)\, M_1, \text{ when } \pi \in S_k,\ k = 1, \ldots, K. \tag{A3}$$

The parameter $\underline{s}$ in $w(\pi, s)$ captures a shift in risk. Noting that $w(\pi, 0) = M_1$, and $w(\pi, 1) = m_{k1}$ when $\pi \in S_k$, $k = 1, \ldots, K$, it follows that a move of the vector s from 1 to 0 reflects a redistribution of risk from the partial means $\{m_{k1}: k = 1, \ldots, K\}$ to the overall mean M_1.

Using (A3) provides another basis to explore the cost of risk across quantiles. For a given $R_a(1)$ and a given s in (A3), define $R_b(s)$ as the sure amount of money which satisfies

$$\sum_{k=1}^{K} \int_{\pi \in S_k} U[w(\pi, s) - R_a(\underline{1})]\, dF(\pi) = U[w(\pi, \underline{0}) - R_a(\underline{1}) - R_b(s)], \tag{A4}$$

where $R_b(s)$ is the amount of money the decision maker is willing to pay to replace $[w(\pi, s) - R_a(1)]$ by $[w(\pi, 0) - R_a(\underline{1})]$. Clearly, equation (A3) implies that $R_b(\underline{0}) = 0$. And given $w(\pi, 0) = M_1$, $R_b(1)$ measures the willingness-to-pay to replace all m_{ki}'s by the overall mean M_1.

Combining (A2) and (A4), and using equation (6), gives the following result:

<u>Lemma 1</u>:

$$R = R_a(\underline{1}) + R_b(1). \tag{A5}$$

Equation (A5) shows that the risk premium R can be decomposed into two additive parts: $R_a(\underline{1})$ capturing the cost of risk associated with the first step (moving the risk in each interval to the corresponding partial means); and $R_b(1)$ capturing the cost of risk associated with the second step (moving the risk from the partial means to the overall mean). Next, we use (A5) in lemma 1 to prove Proposition 2.

We first derive a moment-based measure of $R_a(\underline{1})$ across quantiles. From equation (A1), let $v_k'(\pi, \underline{\sigma}) \equiv \partial v(\pi, \underline{\sigma})/\partial\sigma_k = \begin{Bmatrix} \pi - m_{k1} \\ 0 \end{Bmatrix}$ when $\pi \begin{Bmatrix} \in \\ \notin \end{Bmatrix} S_k$. Differentiating (A2) with respect to σ_k gives

$$E\{U'[v(\pi, \underline{\sigma})] \cdot [v_k'(\pi, \underline{\sigma})]\} = - R_{ak}'(\underline{\sigma}) \cdot [\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'[m_{i1} - R_a(\underline{\sigma})]\}], \tag{A6}$$

where $U'(v) = \partial U/\partial v$, and $R_{ak}'(\underline{\sigma}) = \partial R_a/\partial\sigma_k$. Evaluated at $\underline{\sigma} = \underline{0}$ and using $R_a(\underline{0}) = 0$, (A6) yields

$$E\{U'[v(\pi, \underline{0})] [v_k'(\pi, \underline{0})]\} = - R_{ak}'(\underline{0}) \cdot [\sum_{i=1}^{K} \{[F(b_i) – F(b_{i-1})] \cdot U'(m_{i1})\}]. \tag{A7}$$

Using $v_k'(\pi, \underline{\sigma}) \equiv \begin{Bmatrix} \pi - m_{k1} \\ 0 \end{Bmatrix}$ when $\pi \begin{Bmatrix} \in \\ \notin \end{Bmatrix} S_k$, $E(v_k'(\pi, \underline{\sigma})) = \int_{\pi\in S_k} (\pi - m_{k1})\, dF(\pi)$, and $v(\pi, \underline{0}) = m_{k1}$ when $\pi \in S_k$, $k = 1, \ldots, K$, (A7) can be written as

$$U'(M_k) \int_{\pi\in S_k} (\pi - m_{k1})\, dF(\pi) = - R_{ak}'(\underline{0}) \cdot [\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}]. \tag{A7'}$$

Since $\int_{\pi\in S_k} (\pi - m_{k1})\, dF(\pi) = 0$, (A7') implies that $R_{ak}'(\underline{0}) = 0$.

Noting that $v_k'(\pi, \underline{\sigma})$ does not depend $\underline{\sigma}$, differentiating (A6) with respect to σ_j gives

$$\begin{aligned} &E\{U''[v(\pi, \underline{\sigma})] \cdot [v_k'(\pi, \underline{\sigma})] \cdot [v_j'(\pi, \underline{\sigma})]\} \\ &\quad = - R_{akj}''(\underline{\sigma}) \cdot [\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'[m_{i1} - R_a(\underline{\sigma})]\}] \\ &\quad\quad + R_{ak}'(\underline{\sigma}) \cdot R_{aj}'(\underline{\sigma}) \cdot [\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U''[m_{i1} - R_a(\underline{\sigma})]\}], \end{aligned} \tag{A8}$$

where $U''(v) = \partial^2 U/\partial v^2$, and $R_{akj}''(\underline{\sigma}) = \partial^2 R_a/(\partial\sigma_k\partial\sigma_j)$. Using $R_a(\underline{0}) = 0$ and $R_{ak}'(\underline{0}) = 0$, evaluating (A8) at $\underline{\sigma} = \underline{0}$ gives

$$E\{U''[v(\pi, \underline{0})] \cdot [v_k'(\pi, \underline{0})] \cdot [v_j'(\pi, \underline{0})]\}$$

$$= - R_{akj}''(\underline{0}) \cdot [\, \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\} \,] . \tag{A9}$$

Using $v_k'(\pi, \underline{\sigma}) \equiv \begin{Bmatrix} \pi - m_{k1} \\ 0 \end{Bmatrix}$ when $\pi \begin{Bmatrix} \in \\ \notin \end{Bmatrix} S_k$, $E(v_k'(\pi, \underline{\sigma})) =$

$\int_{\pi \in S_k} (\pi - m_{k1})\; dF(\pi)$, and $v(\pi, \underline{0}) = m_{k1}$ when $\pi \in S_k$, $k = 1, \ldots, K$, (A9) can be written as

$$0 = - R_{akj}''(\underline{0}) \cdot [\, \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\} \,] \text{, when } k \neq j, \tag{A10a}$$

$$U''(m_{k1}) \cdot [\int_{\pi \in S_k} (\pi - m_{k1})^2 \; dF(\pi)\,]$$

$$= - R_{akk}''(\underline{0}) \cdot [\, \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\} \,] \text{, when } k = j. \tag{A10b}$$

Equations (A10a)-(A10b) imply that

$$R_{akj}''(\underline{0}) = 0 \text{, when } k \neq j, \tag{A11}$$

$$R_{akk}''(\underline{0}) = -\frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [\int_{\pi \in S_k} (\pi - M_k)^2 \; dF(\pi)\,]$$

$$= -\frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k2}, \tag{A12}$$

where $m_{k2} = \dfrac{1}{F(b_k) - F(b_{k-1})} \int_{\pi \in S_k} (\pi - m_{k1})^2 \; dF(\pi)$ is the partial variance of π in the interval S_k.

Noting that $v_k'(\pi, \underline{\sigma})$ does not depend on $\underline{\sigma}$, differentiating equation (A8) with respect to σ_n gives

$$E\{U'''[v(\pi, \underline{\sigma})] \cdot [v_k'(\pi, \underline{\sigma})] \cdot [v_j'(\pi, \underline{\sigma})] \cdot [v_n'(\pi, \underline{\sigma})]\}$$

$$= - R_{akjn}'''(\underline{\sigma}) \cdot [\, \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'[m_{i1} - R_a(\underline{\sigma})]\} \,]$$

$$+ R_{ak}''(\underline{\sigma}) \cdot R_{an}'(\underline{\sigma}) \cdot [\, \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U''[m_{i1} - R_a(\underline{\sigma})]\} \,]$$

$$+ R_{akn}''(\underline{\sigma}) \cdot R_{aj}'(\underline{\sigma}) \cdot [\ \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U''[m_{i1} - R_a(\underline{\sigma})]\}\ ]$$

$$+ R_{ak}'(\underline{\sigma}) \cdot R_{ajn}''(\underline{\sigma}) \cdot [\ \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U''[m_{i1} - R_a(\underline{\sigma})]\}\ ]$$

$$- R_{ak}'(\underline{\sigma}) \cdot R_{aj}'(\underline{\sigma}) \cdot R_{an}'(\underline{\sigma}) \cdot [$$

$$\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'''[m_{i1} - R_a(\underline{\sigma})]\}], \tag{A13}$$

where $U'''(v) = \partial^3 U/\partial v^3$, and $R_{akjn}'''(\underline{\sigma}) = \partial^3 R_a/(\partial\sigma_k \partial\sigma_j \partial\sigma_n)$. Using $R_a(\underline{0}) = 0$ and $R_{ak}'(\underline{0}) = 0$, evaluating (A13) at $\underline{\sigma} = \underline{0}$ gives

$$E\{U'''[v(\pi, \underline{0})] \cdot [v_k'(\pi, \underline{0})] \cdot [v_j'(\pi, \underline{0})] \cdot [v_n'(\pi, \underline{0})]\}$$

$$= - R_{akjn}'''(\underline{0}) \cdot [\ \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}\ ]. \tag{A14}$$

Using $v_k'(\pi, \sigma) \equiv \begin{Bmatrix} \pi - m_{k1} \\ 0 \end{Bmatrix}$ when $\pi \begin{Bmatrix} \in \\ \notin \end{Bmatrix} S_k$, $E(v_k'(\pi, \sigma)) =$

$\int_{\pi \in S_k} (\pi - m_{k1})\ dF(\pi)$, and $v(\pi, \underline{0}) = m_{k1}$ when $\pi \in S_k$, $k = 1, \ldots, K$, (A14) can be

written as $0 = - R_{akjn}'''(\underline{0}) \cdot [\ \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}]$, when $\{k = j = n\}$ does

not hold, (A15a)

$$U'''(m_{k1}) \cdot [\int_{\pi \in S_k} (\pi - m_{k1})^3\ dF(\pi)]$$

$$= - R_{akkk}'''(\underline{0}) \cdot [\ \sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}], \text{ when } k = j = n. \tag{A15b}$$

Equations (A15a)-(A15b) imply that

$$R_{akjn}'''(\underline{0}) = 0, \text{ when } \{k = j = n\} \text{ does not hold}, \tag{A16}$$

$$R_{akkk}'''(\underline{0}) = -\frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [\int_{\pi \in S_k} (\pi - m_{k1})^3\ dF(\pi)]$$

$$= -\frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k3}, \text{ when } k =$$

$j = n$, (A17)

where $m_{k3} = \frac{1}{F(b_k) - F(b_{k-1})} \int_{\pi \in S_k} (\pi - m_{k1})^3 \, dF(\pi)$ is the partial skewness of π in the interval S_k. Using $R_a(\underline{0}) = 0$, $R_{ak}'(\underline{0}) = 0$ and equations (A11), (A12), (A16) and (A17), a third-order Taylor series approximation of $R_a(\underline{1})$ in the neighborhood of $\underline{\sigma} = \underline{0}$ is given by

$$R_a(\underline{1}) \approx R_a(\underline{0}) + \sum_{k=1}^{K} R_{ak}'(\underline{0}) \cdot [1-0] + 0.5 \cdot \sum_{k=1}^{K} R_{akk}''(\underline{0}) \cdot [1-0]^2$$

$$+ (1/6) \cdot \sum_{k=1}^{K} R_{akkk}'''(\underline{0}) \cdot [1-0]^3$$

$$\approx -0.5 \cdot \sum_{k=1}^{K} \left\{ \frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k2} \right\}$$

$$- (1/6) \cdot \sum_{k=1}^{K} \left\{ \frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k3} \right\}. \quad \text{(A18)}$$

Next, we derive a moment-based measure of $R_b(1)$ across quantiles. From equation (A3), we have $w(\pi, 0) = M_1$, $w(\pi, 1) = m_{k1}$ when $\pi \in S_k$, and $R_b(0) = 0$. Let $w'(s) \equiv \partial w/\partial s = m_{k1} - M_1$ when $\pi \in S_k$, $k = 1, \ldots, K$. Assuming differentiability, differentiating equation (A4) with respect to s gives

$$\sum_{k=1}^{K} \int_{\pi \in S_k} U'[w(\pi, s) - R_a(\underline{1})] \, (m_{k1} - M_1) \, dF(\pi) = -R_b'(s) \cdot U'[M_1 - R_a(\underline{1}) - R_b(s)], \quad \text{(A19)}$$

where $U'(w) \equiv \partial U/\partial w$ and $R_b'(s) \equiv \partial R_b/\partial s$. Evaluated at s = 0 and using $R_b(0) = 0$ and $R_a = 0$ (since all risk has been eliminated at s = 0), (A19) gives

$$U'(M_1) \cdot \left[\sum_{k=1}^{K} \int_{\pi \in S_k} (m_{k1} - M_1) \, dF(\pi) \right] = -R_b'(0) \cdot U'(M_1). \quad \text{(A20)}$$

Since $\sum_{k=1}^{K} \int_{\pi \in S_k} (m_{k1} - M_1) \, dF(\pi) = 0$, it follows that $R_b'(0) = 0$. Differentiating (A19) with respect to s gives

$$\sum_{k=1}^{K}\int_{\pi\in S_k} U''[w(\pi, s) - R_a(\underline{1})]\,[(m_{k1} - M_1)^2]\; dF(\pi)$$

$$= -R_b''(s) \cdot U'[M_1 - R_a(\underline{1}) - R_b(s)] + [R_b'(s)]^2 \cdot U''[M_1 - R_a(\underline{1}) - R_b(s)], \qquad \text{(A21)}$$

where $U''(w) \equiv \partial^2U/\partial w^2$ and $R_b''(s) \equiv \partial^2R_b/\partial s^2$. Evaluated at s = 0, and using $R_b(0) = 0$, $R_b'(0) = 0$ and $R_a = 0$, (A21) gives

$$U''(M_1) \cdot \Big[\sum_{k=1}^{K}\int_{\pi\in S_k} (m_{k1} - M_1)^2\; dF(\pi)\Big] = -R_b''(0) \cdot U'(M_1),$$

which implies

$$R_b''(0) = -\frac{U''(M_1)}{U'(M_1)} \cdot \Big[\sum_{k=1}^{K}\int_{\pi\in S_k} (m_{k1} - M_1)^2\; dF(\pi)\Big]. \qquad \text{(A22)}$$

Differentiating (A21) with respect to s gives

$$\sum_{k=1}^{K}\int_{\pi\in S_k} U'''[w(\pi, s) - R_a(\underline{1})]\,[(m_{ka} - M_1)^3]\; dF(\pi)$$

$$\begin{aligned}
&= -R_b'''(s) \cdot U'[M_1 - R_a(\underline{1}) - R_b(s)] \\
&\quad + R_b''(s) \cdot R_b'(s) \cdot U''[M_1 - R_a(\underline{1}) - R_b(s)] \\
&\quad + 2\, R_b'(s) \cdot R_b''(s) \cdot U''[M_1 - R_a(\underline{1}) - R_b(s)] \\
&\quad - [R_b'(s)]^3 \cdot U'''[M_1 - R_a(\underline{1}) - R_b(s)], \qquad \text{(A23)}
\end{aligned}$$

where $U'''(w) \equiv \partial^3U/\partial w^3$ and $R_b'''(s) \equiv \partial^3R_b/\partial s^3$. Evaluated at s = 0, and using $R_b(0) = 0$, $R_b'(0) = 0$ and $R_a = 0$, equation (A23) gives

$$U'''(M) \cdot \Big[\sum_{k=1}^{K}\int_{\pi\in S_k} (m_{k1} - M_1)^3\; dF(\pi)\Big] = -R_b'''(0) \cdot U'(M_1),$$

which implies

$$R_b'''(0) = -\frac{U'''(M_1)}{U'(M_1)} \cdot \Big[\sum_{k=1}^{K}\int_{\pi\in S_k} (m_{k1} - M_1)^3\; dF(\pi)\Big]. \qquad \text{(A24)}$$

Taking a third-order Taylor series expansion of $R_b(s)$ in the neighborhood of s = 0, and using $R_b(0) = 0$, $R_b'(0) = 0$, and equations (A22) and (A24), we obtain

$R_b(1) \approx R_b(\underline{0}) + R_b'(0) \cdot [1 - 0] + 0.5\, R_b''(0) \cdot [1 - 0]^2 + (1/6)\, R_b'''(0) \cdot [1 - 0]^3$

$$\approx -0.5\ \frac{U''(M_1)}{U'(M_1)} \cdot \Big[\sum_{k=1}^{K} \int_{\pi \in S_k} (m_{k1} - M_1)^2\ dF(\pi) \Big]$$

$$- (1/6)\ \frac{U'''(M_1)}{U'(M_1)} \cdot \Big[\sum_{k=1}^{K} \int_{\pi \in S_k} (m_{k1} - M_1)^3\ dF(\pi) \Big]. \qquad \text{(A25)}$$

Substituting equations (A18) and (A25) into (A5) gives

$R = R_a(\underline{1}) + R_b(\underline{1}),$

$$\approx -0.5 \cdot \sum_{k=1}^{K} \Big\{ \frac{U''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k2} \Big\}$$

$$- (1/6) \cdot \sum_{k=1}^{K} \Big\{ \frac{U'''(m_{k1})}{\sum_{i=1}^{K} \{[F(b_i) - F(b_{i-1})] \cdot U'(m_{i1})\}} \cdot [F(b_k) - F(b_{k-1})] \cdot m_{k3} \Big\}$$

$$-0.5\ \frac{U''(M_1)}{U'(M_1)} \cdot \Big[\sum_{k=1}^{K} \int_{\pi \in S_k} (m_{k1} - M_1)^2\ dF(\pi) \Big]$$

$$- (1/6)\ \frac{U'''(M_1)}{U'(M_1)} \cdot \Big[\sum_{k=1}^{K} \int_{\pi \in S_k} (m_{k1} - M_1)^3\ dF(\pi) \Big],$$

which is equation (8).

FOR ONLINE PUBLICATION: Appendix B

Table B1. Estimation of the mean equation (dep. variable = rice production)

Variables	Coefficients (Std errors)	Variables	Coefficients (Std errors)	Variables	Coefficients (Std errors)
age	-1.131**	upland_prod_potato	1.091**	intra_paddy	55.190***
	(0.455)		(0.545)		(5.715)
t	-0.152	upland_prod_potato2	-0.007	lag_hi	-24.823***
	(0.806)		(0.005)		(9.182)
edu0	-1.012	intra_prod_vegi	-0.417	lag_upland_soybean_share	10.823
	(39.423)		(0.427)		(39.641)
edu1	-0.149	intra_prod_vegi2	-0.006***	lag_upland_potato_share	-33.793
	(38.402)		(0.002)		(75.009)
edu2	-5.002	intra_prod_soybean	3.099*	Constant	-257.70***
	(38.718)		(1.687)		(55.530)
edu3	-6.329	intra_prod_soybean2	-0.116**		
	(35.783)		(0.053)	Observations	3,895
edu4	-88.402	intra_prod_barleymisc	-0.963***	Number of households	1,327
	(56.570)		(0.344)		
paddy_prod_vegi	0.203***	intra_prod_barleymisc2	-0.002*		
	(0.036)		(0.001)		
paddy_prod_vegi2	-0.001***	intra_prod_potato	-2.939		
	(0.000)		(2.322)		
paddy_prod_soybean	0.542***	intra_prod_potato2	0.025		
	(0.062)		(0.028)		
paddy_prod_soybean2	-0.003***	prod_vegi_barleymisc	0.008***		
	(0.001)		(0.002)		
paddy_prod_barleymisc	0.072**	prod_vegi_potato	0.003		
	(0.034)		(0.004)		
paddy_prod_barleymisc2	0.000	prod_vegi_soybean	-0.017***		
	(0.000)		(0.003)		
paddy_prod_potato	-0.213	prod_barleymisc_potato	0.019		
	(0.153)		(0.017)		
paddy_prod_potato2	-0.002	prod_barleymisc_soybean	-0.038***		
	(0.002)		(0.011)		
upland_prod_vegi	-0.374***	prod_soybean_potato	0.006		
	(0.115)		(0.018)		
upland_prod_vegi2	0.002***	ln_land_paddy	18.065***		
	(0.000)		(3.618)		
upland_prod_soybean	-0.434	ln_land_upland	-2.267*		
	(0.281)		(1.167)		
upland_prod_soybean2	0.004*	ln_labor	16.118***		
	(0.002)		(2.974)		
upland_prod_barleymisc	-0.240	ln_cost_seed	-0.475		
	(0.170)		(0.994)		
upland_prod_barleymisc2	-0.001***	ln_cost_fertilizer	5.606***		
	(0.000)		(1.158)		
upland_prod_potato	1.091**	ln_cost_pesticide	3.363***		
	(0.545)		(1.236)		
upland_prod_potato2	-0.007	ln_capital	34.288***		
	(0.005)		(3.034)		
intra_prod_vegi	-0.417	intra	-55.039***		
	(0.427)		(15.620)		

Note: Standard errors in parentheses:
*** p<0.01, ** p<0.05, * p<0.1
Regional dummy variable estimates are not reported.

Table B2. Estimation of multinomial logit equations (dependent variable = probability of being in each quantile, base outcome = 2nd quantile)

Variables	1st quantile	3rd quantile	4th quantile
age	-0.003238	0.050304*	0.032808
	(0.061)	(0.029)	(0.065)
prod_vegi	0.001773	0.004153**	0.000472
	(0.002)	(0.002)	(0.002)
prod_soybean	0.028618***	0.023690***	0.023490***
	(0.009)	(0.007)	(0.009)
prod_barleymisc	-0.004570	0.003023	-0.001738
	(0.004)	(0.003)	(0.005)
prod_potato	-0.004228	0.005167	-0.001866
	(0.006)	(0.004)	(0.005)
ln_land_paddy	1.234535***	0.272029***	1.416788***
	(0.222)	(0.094)	(0.217)
ln_land_upland	0.033208	0.089810***	0.050313
	(0.046)	(0.028)	(0.039)
ln_labor	0.067270	0.289344	0.496000
	(0.565)	(0.323)	(0.614)
age_ln_labor	-0.002934	-0.007341	-0.007809
	(0.009)	(0.005)	(0.010)
ln_cost_seed	0.035556	0.058108	0.055444
	(0.073)	(0.042)	(0.072)
ln_cost_fertilizer	-0.28925***	-0.29048***	-0.35504***
	(0.092)	(0.053)	(0.100)
ln_cost_pesticide	0.082948	-0.044300	-0.011035
	(0.083)	(0.046)	(0.088)
ln_capital	0.184437	-0.19753***	0.120236
	(0.152)	(0.061)	(0.135)
intra	1.293701***	0.568174***	1.585362***
	(0.373)	(0.187)	(0.381)
intra_paddy	-0.026849	0.011671	-0.111265
	(0.088)	(0.086)	(0.144)
t	0.047320	-0.056597	0.002637
	(0.061)	(0.035)	(0.060)
lag_hi	1.069853**	0.853432***	1.734969***
	(0.523)	(0.267)	(0.547)
lag_upland_soybean_share	-1.408890	-1.748750	-0.846538
	(2.092)	(1.483)	(1.699)
lag_upland_potato_share	1.757049	-0.094881	2.670661
	(2.266)	(1.527)	(1.831)
Constant	-2.396414	0.822611	-4.362678
	(5.069)	(2.075)	(5.428)

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Log likelihood = -4164.5; pseudo R^2 = 0.104.

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Footnotes

[1] Partial moments have been used to evaluate risk exposure relative to some reference point: higher (lower) partial moments are defined for risky outcomes that are above (below) the reference point (e.g., Markowitz; Fishburn; Bawa; Jorion; Rockefellar and Uryasev; Antle, 2010). Our quantile-based analysis generalizes partial moments to multiple intervals, each interval corresponding to a different quantile.

[2] This modeling approach builds on a companion article (Kim et al., 2012) that examines productivity outcomes in rice farms based on a careful analysis of the gains from specialization/diversification.

[3] One way to estimate the distribution function is using quantile regression (e.g., Kroenker and Bassett; Chernozhukov and Hansen). Another way is to rely on the estimation of partial moments. This paper follows this latter approach.

[4] In this paper, our evaluation of the cost of risk is based on the expected utility model. As discussed below, this provides a good basis to investigate the role of downside risk. Extensions of the quantile approach to non-expected utility model are explored in Chavas and Kim (2012).

[5] The capital variable is constructed by adding agricultural machinery costs, rent, maintenance costs, sub-contract fees, interest paid, and depreciation costs.

[6] Intra is defined as the ratio of the size of intra-year double cropping paddy land to total irrigated paddy land.

[7] When $b \to 1$ and using L'Hôpital's rule, the utility function can be written as $U(\pi) = \ln(\pi)$.