# Self-Protection from Weather Risk using Improved Maize Varieties or Off-Farm Income and the Propensity for Insurance

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# 1 Introduction

In developing countries farmers commonly experience severe income fluctuations due to weather shocks and plant and animal diseases. The absence of formal insurance in these countries leads farmers to resort to non profit maximizing production and technology adoption decisions (Eswaran and Kotwal, 1990; Rosenzweig and Wolpin, 1993) and to rely on imperfect informal risk sharing strategies for managing risk and smoothing income and consumption (Townsend, 1994; Ligon, 1998; Dercon and Krishnan, 2000; Little et al., 2001; Fafchamps and Lund, 2003).

To assist farmers overcome the agronomic and missing market challenges in developing countries, significant resources have been dedicated to a variety of initiatives including improved crop varieties (e.g., drought and disease resistant maize) and weather index based insurance.[1] While an increasing number of studies are reporting significant gains in adoption of improved maize varieties (IMV) (CIMMYT-IITA, 2013; Diiro, 2013), most pilot programs for index insurance have suffered from low demand and under-insurance indicating little chance of scaling-up and sustaining the programs. For example, in a program introduced in Andhra Pradesh and Gujarat in India, only 5-10% of the households purchased coverage even though most of them reported rainfall risk as a major risk they face (Giné et al., 2008; Cole et al., 2013). Further troubling, the authors found demand to be lowest amongst the most risk averse households and that wealthy households were the predominant purchasers.

A wide-range of explanations for the disappointing uptake and performance of weather insurance have been proposed and analyzed. Cai et al. (2009) and Dercon and Christiaensen (2011) argue that poor understanding and lack of trust of insurance instruments are significant impediments to insurance demand. Others including Barnett et al. (2008), Hartel et al.

[1] Weather index based insurance, e.g. rainfall index insurance, insure farm yields within a given radius (say 20 miles) from a local meteorological station and compensate buyers of the policy if the cumulative rainfall over a given window during the crop growing season falls below a certain (trigger) amount which can be different from that observed on individual farms. This form of insurance costs less to administer (since it eliminates the need to assess losses on individual farms) and is not susceptible to moral hazard and adverse selection.

(2006), Hess and Syroka (2006), Molini et al. (2008), and Skees and Barnett (2006) have attributed it to cash and credit constraints faced by farmers in developing nations and the mismatch between insurance payouts and actual losses due to uninsured basis risk. A third explanation put forth by Binswanger-Mikhize (2012) argues that the coverage offered by index insurance is not sufficiently competitive with pre-existing informal sources of insurance provided by risk-sharing networks.

In this study we build upon the previous work investigating the impediments to significant sustained uptake of insurance in developing nations and show that self-protection practices, which farmers have a long history of relying upon to hedge on-farm income, partially explains low insurance demand and underinsurance. Self-protection are actions which reduces the probability of being in a low-wealth state at the expense of reducing wealth in all other states whereas formal insurance helps to transfer wealth from a high utility state to a low utility state. Risk averse individuals have the incentive to adopt practices which positively affect the skewness of their yields, thus reducing the probability of crop failure and downside risk (Binswanger, 1981; Chavas and Holt, 1996). Adoption of improved maize varieties (IMV) and off-farm income can directly or indirectly affect the shape properties of yield distributions and thus the probability of crop failure. A reduction in the probability of crop failure will reduce the private cost of risk and likely cause the premium charged by the insurer to appear higher and unfair, reducing demand. Specifically, we show using data from smallholder maize producers in Uganda that self-protection actions such as the adoption of IMV and diversification of income through pursuits of off-farm work substantially reduces risk premiums, although the magnitude is heterogeneous across different farm and farming characteristics. This result is driven by the effect of self-protection and their interactions on moments of the production function and downside risk.

Our focus and methodological approach is most closely related to the work by Smale et al. (1998) and DiFalco and Chavas (2009). Smale et al. (1998) investigate the effect of genetic diversity on the mean and variance of wheat yields for rain-fed agriculture in Punjab Pakistan using a stochastic production function and found genetic diversity to be positively associated with mean yield and negatively associated with the variance. Extending the approach to account for the skewness of yield distributions, DiFalco and Chavas (2009) investigate the effect of diversity in barley variety on production risk in Ethiopia and found the effect on skewness to dominate that on the variance resulting in a decrease in risk premium. Neither of these studies was motivated by or used to directly explain the exceedingly low and puzzling uptake of index insurance in developing countries, and did not consider off-farm income and IMV. One potential complication with the empirical approach of DiFalco and Chavas (2009), which is considered in our study, is that by considering the skewness without kurtosis, the overall effect of crop diversity on risk is likely overestimated since a change in the tail mass (skewness) of a distribution is often accompanied by change in its peak (kurtosis) (Just and Weninger, 1999; Ramirez et al., 2003) and vice versa. Jointly considering skewness and kurtosis allows a more accurate approximation of the unknown production function (distribution) and its underlined production risks given that the number of potential distributions defined by the moments decreases as higher moments become available. Thus failure to consider all relevant moments could invalidate risk premium and welfare analysis through inaccurate approximation of expected utility maximization.

In order to unbundle the effect of IMV and off-farm income on risk premium, we decompose the cost of risk to explicitly consider the first four moments (mean, variance, skewness and kurtosis). In the first stage of our analysis, we use a unique plot-level panel data for maize production in Uganda to estimate a flexible moment-based production function based on an expanded form of the Johnson $S_U$ family distribution (Johnson et al., 1994; Ramirez, 1997). This procedure is superior to most specifications because it allows us to fully characterize and jointly test the first four moments of the distribution in a full information approach, thus avoiding the 'double jeopardy' problem (Just and Weninger, 1999). Empirical studies have found yield distributions to fit different distributions and at times with contradictory results with regards to the shape (skewness, kurtosis, and all higher moments) of the distribution, suggesting high chances for model misspecification error. Ignoring nonnormality could invalidate approximations of expected utility maximization (Ramirez et al., 2003) producing unreliable estimates of private cost of risk and welfare analysis.

In the second phase of our analysis, we use estimates of the moments to simulate how changes in the share of land under IMV and off-farm income influence risk premiums and the welfare of farmers. Following DiFalco and Chavas (2009), we examine scenarios of joint adoption of IMV with low and high application of inorganic fertilizer through interaction effects. Similarly, we investigate the effect of off-farm income on agricultural productivity and risk premiums when there is high and low supply of farm labor.

Results from our analysis show that both IMV and off-farm income reduce the private cost of risk among smallholder maize farmers in Uganda. The effect of IMV and off-farm income is found to be stronger on farm plots with infertile soil, gentle slope and no exposure to soil erosion than those with fertile soil. In addition, the risk reduction effect of IMV is found to be even stronger with low application of inorganic fertilizer while that for off-farm income was slightly stronger under high supply of farm labor. This implies that self-protection practices may contribute to crowding out index based insurance if the design fails to consider the reduction in the probability of crop failure due to self-protection. In addition, we found that considering skewness but not kurtosis in evaluating the cost of risk overstates the risk component associated with skewness under IMV and off-farm income by 1.54% and 2.42% respectively, and thus the gross risk premiums. While this value appears to be economically insignificant in this study, it reveals that considering skewness while leaving out kurtosis produces biased private cost of risk and index-insurance premiums if its design accounts for self-protection. For resource poor farmers in developing countries, such bias could be high enough to influence their decisions on insurance uptake.

The rest of the study proceeds as follows. In the next section, we develop and relate the framework of the behavioral model under risk and the maize production function. The data is presented in section three, while the model selection is discussed in section four.

The results and discussion are presented in section five, and finally we conclude with policy implications in regards to the design of index insurance.

# 2 Theoretical Framework

The model specification hinges on the standard theory of utility maximization under risk and uncertainty (Pratt, 1964). Let $y$ be the risky quantity of maize produced using inputs $X = \{x_1, x_2\}$, where $x_1$ are inputs not affected by off-farm income ($I$) and $x_2 = g(I)$ represent inputs affected by off-farm income such as farm labor. A production function relating output to inputs can be represented as $y = F(x_1, x_2, v)$ where $v$ is the idiosyncratic error. Letting $c_2$ denote the numeraire bundle of goods with normalized price $p_2 = 1$, and $c_1$ the quantity of farm commodity output consumed by the household, the surplus output $y - c_1$ is marketed at a price $p_1$. We can specify the household budget constraint as $c_2 \leq p_1(y - c_1) + I$. Substituting for $y$ and assuming non-satiation, the budget constraint simplifies to $c_2 = p_1(F(x_1, x_2, v) - c_1) + I$. Letting household preferences under risk be represented by a Von Neumann-Morgenstern utility function, U($c_1$,$c_2$), the household objective function is

$$\underset{c_1, x_1, x_2}{\text{Maximize}} \quad E[U(c_1, p_1(F(x_1, x_2, v) - c_1) + I)]. \tag{1}$$

Defining $\pi$=$p_1 F(x_1, x_2, v) + I$ and expressing the choice of $X$ in equation (1) in terms of the household's certainty equivalent (CE) following Pratt (1964) gives

$$U(c_1, CE - p_1 c_1) = E[U(c_1, \pi - p_1 c_1)], \tag{2}$$

where $CE$, a measure of household welfare under production risk represents the guaranteed amount of income that a household will view as equally desirable as the uncertain income is

$$CE = E(\pi) - R. \tag{3}$$

Where E($\pi$) is the expected income and $R$ is the risk premium (private cost of risk bearing) which is the amount households are willing to pay to replace the random income $\pi$ with a reduced but certain amount (CE). Expanding both sides of the equation (2) using Taylor expansion gives $U(c_1, E(\pi) - R - p_1 c_1) = U(c_1, E(\pi) - p_1 c_1) - RU^{'}(.)$ and $E[U(c_1, \pi - p_1 c_1)] = U(c_1, E(\pi) - p_1 c_1) + \frac{1}{2}U^{''}(.)E[\pi - E(\pi)]^2 + \frac{1}{6}U^{'''}(.)E[\pi - E(\pi)]^3 + \frac{1}{24}U^{''''}(.)E[\pi - E(\pi)]^4$. Equating coefficients of the expansions and solving for $R$ gives an expression for the risk premium capturing the first four moments of the yield distribution:

$$R = \frac{1}{2} r_2 E[\pi - E(\pi)]^2 + \frac{1}{6} r_3 E[\pi - E(\pi)]^3 + \frac{1}{24} r_4 E[\pi - E(\pi)]^4, \tag{4}$$

where $r_2 = -\frac{U^{''}(.)}{U^{'}(.)}, r_3 = -\frac{U^{'''}(.)}{U^{'}(.)}$, $r_4 = -\frac{U^{''''}(.)}{U^{'}(.)}$, and $E[\pi - E(\pi)]^K$ are the $kth$ central moment of the distribution of profit, $r_2$, $r_3$ and $r_4$, all evaluated at E($\pi$). This decomposes the risk premium into three parts; the effect of variance, skewness and kurtosis. When $E[\pi - E(\pi)]^3 = E[\pi - E(\pi)]^4 = 0$, equation (4) reduces to the Arrow Pratt coefficient indicating that the approximate risk premium is proportional to the variance of the profit with the coefficient of proportionality equal to $\frac{r_2}{2}$.[2] Thus, under risk aversion, an increase in the variance of profit will increase the private cost of risk bearing while an increase in skewness (kurtosis) reduces (increases) it under downside risk aversion. Jointly considering both skewness and kurtosis could result in situations where they both reinforce or cancel each other depending on the shape of the yield distribution and how it responds to changes in off-farm income or the proportion of land planted with an improved maize variety. Several outcomes are possible, for example an increase in kurtosis reduces the mass in the tails of the yield distribution making extreme events less likely. In a symmetric distribution, the effects in both end of the tails could cancel out resulting in little effect on downside risk. However, in a skewed kurtotic distribution, the effects at the tails might not cancel out, thus requiring the joint effect on

[2]Risk aversion implies $R > 0$ and $CE < E(\pi)$. Under both constant relative risk aversion (with $R > 1$) and decreasing absolute risk aversion,$U^{'}(.) > 0$, $U^{''}(.) < 0$, $U^{'''}(.) > 0$ and $U^{''''}(.) < 0$, meaning $r_2 > 0$, $r_3 < 0$ and $r_4 > 0$.

both skewness and kurtosis to be considered to fully evaluate the effect on downside risk.[3] Thus an increase in skewness may or may not be associated with a decrease in downside risk exposure. Substituting equation (4) into equation (3) gives

$$CE = E(\pi) - R = E(\pi) - \frac{1}{2}r_2 E[\pi - E(\pi)]^2 - \frac{1}{6}r_3 E[\pi - E(\pi)]^3 - \frac{1}{24}r_4 E[\pi - E(\pi)]^4, \quad (5)$$

a more explicit representation of risk which we use to assess the relative importance of the variance, skewness and kurtosis effect on farmer's welfare.

We evaluate the risk in producing maize in Uganda created by production uncertainty ($v$) using a generalized moment-based production function based on a flexible form of Johnson $S_U$ family distribution (Johnson et al., 1994; Ramirez, 1997; Ramirez et al., 2003). The corn yield distribution for household $i$ on parcel $j$ and plot $k$ at time $t$ following the $S_U$ family can be modified and expanded by a single parameter to obtain a flexible distribution. Dropping the $i$, $j$ and $t$ index for simplicity, this model can be represented as

$$Y_k = \mathbf{X_k}\beta + \frac{[(\frac{\sigma_k^2}{G(\theta,\mu)})^{\frac{1}{2}}(sinh(\theta Z_k) - F(\theta,\mu))]}{\theta}, Z_k \sim N(\mu, 1), \quad (6)$$

where $F(\theta,\mu) = E[sinh(\theta Z_k)] = exp(\frac{\theta^2}{2})sinh(\theta\mu)$, $G(\theta,\mu) = \frac{(exp(\theta^2)-1)(exp(\theta^2)cosh(-2\theta\mu)+1)}{2\theta^2}$, $\mathbf{X_k}$ is a vector of exogenous variables affecting the mean of corn yield, $\beta$ is a vector of parameters, $\sigma_k > 0$, $-\infty < \theta < \infty$ and $-\infty < \mu < \infty$ are parameters responsible for the non-normal shape of the distribution, and *sinh*, *cosh*, and *exp* denote the hyperbolic sine and cosine and the exponential function, respectively. The stochastic component of the distribution ($Z_k$) is assumed to be independent and normally distributed. The first four moments as derived in Johnson et al. (1994) and are given as: $E(Y_k) = \mathbf{X_k}\beta, var(Y_k) = \sigma_k^2$, $skew(Y_k) = S(\theta,\mu)$, and $kurt(Y_k) = K(\theta,\mu)$, respectively, where $S(\theta,\mu)$ and $K(\theta,\mu)$ is a combinations of exponential and hyperbolic sine and cosine functions. In this study, we reparametized $\sigma_k^2$ and $\theta$ to be a

[3] When farmers are loss averse, i.e., strongly prefer avoiding an increase in the probability of lower yields to higher yields, the effects at the tail could still cancel out.

function of the mean taking

$$\sigma_k^2 = \sigma_0^2 + \sigma_1^2(\mathbf{X_k}\beta), \tag{7}$$

and

$$\theta = \theta_0 + \theta_1(\mathbf{X_k}\beta). \tag{8}$$

Thus all variables affecting the first moment also affect the second, third and fourth moments. By so doing, we also fully account for heterogeneity in the data through $\sigma_1^2$ and $\theta_1$. If $\theta \neq 0$ and $\mu$ approaches zero, the distribution becomes symmetric but still kurtotic, while higher absolute values of $\theta$ increases kurtosis. Also, if $\theta \neq 0$ and $\mu > 0$, the distribution is kurtotic and right-skewed, whereas if $\mu < 0$, it is kurtotic and left-skewed. Skewness increases with higher absolute values of $\mu$. Johnson et al. (1994) also showed that both the normal and log-normal are specific cases of the $S_U$ family and that it allows for any combination of skewness-leptokurtosis values below the normal line. This implies that as long as platy-kurtosis can be ruled out, the expanded $S_U$ family is flexible enough to discriminate and approximate an unknown distribution. The log-likelihood function of the distribution (equation (6)) can be obtained as

$$LL = \Sigma_{t=1}^{N} ln(G_k) - 0.5\Sigma_{t=1}^{N} H_k^2, \tag{9}$$

where $G_k = (\frac{\sigma_k}{G(\theta,\mu)(1+R_k^2)})^{\frac{1}{2}}$; $(H_k = \frac{sinh^{-1}(R_k)}{\theta}) - \mu$; and $R_k = (\frac{\theta(Y_k - \mathbf{X_k}\beta)}{(\frac{\sigma_k^2}{G(\theta,\mu)})^{\frac{1}{2}}}) - F(\theta,\mu)$, and $sinh^{-1}(R_k) = ln(R_k + (1+R_k^2)^{\frac{1}{2}})$.

# 3 Data

Farm and yield data used in the analysis comes from the Uganda National Panel Survey (UNPS) made available by the World Bank and the Uganda Bureau of Statistics. The survey was funded by the government of the Netherlands and the World Bank Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) project. It is a multi topic panel built from Uganda's National Household Survey (UNHS) fielded in 2005-2006 in 783 enumeration areas (EAs) in two waves to capture data from the two crop growing seasons. In 2009-2010, the UNPS program tracked and interviewed 3123 households (in two separate waves) from 322 EAs initially interviewed by UNHS in 2005-2006. The most recent version of the surveys was completed in 2010 - 2011 giving a total of six waves with three capturing data for the main growing season and the other three for the minor growing season. Parts of the survey were revised after 2005-2006 to introduce several new variables relevant to this study. Because of this we use only data from the last two panels (2010 - 2011) in our analysis. In addition, because some of the key variables are missing during the minor season we further limit our analysis only to samples based on the main crop growing season. The final sample used in estimation after dropping outliers is made of 516 observations. One unique feature of the data is that the agriculture survey collected data on household farming activities on a plot-by-plot level enabling heterogeneity to be fully modeled.[4]

Table 1 presents explanatory and control variables used in the model, their definition and summary statistics. Yield (kg/hectare) is the output variable. The explanatory (production input) variables are land, labor, use of improved maize seeds and fertilizer (inorganic and/or organic), and value of seeds. The average plot size cultivated with corn is 0.5 hectare and takes about 223 labor days. A very small (3-4) percentage of the farmers use inorganic or organic fertilizer to improve soil fertility, while a third use improved maize seedlings. Fertilizer application is often required with the use of improved seedlings for optimal yield realization which is contrary to what is observed. On average, 22,336 Ugandan shillings (UGX) is spent on corn seedlings and households earn 954,400 UGX from off-farm activities.

We control for plot-specific soil and environmental characteristics that influence agricultural productivity using the survey measures of the share of land on gentle slope, share of the land that is fertile, and share of the land under erosion. About 73% of the land is either on a gentle or flat slope or in a valley. More than half (60%) of the land is regarded as fertile

[4]Plot level geographical coordinates or boundary maps are absent in the data set and makes it impossible to test for spatial correlation or estimate a spatial model.

Table 1: Variable Summary.

| Variable | Definition | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Land | Area (hectares) of land planted with corn | 0.456 | 0.550 | 0.02 | 5 |
| Land squared | Area (hectares) of land planted with corn squared | 0.510 | 1.815 | 0.0004 | 25 |
| Labor | Number of labor days used | 222.726 | 250.616 | 0 | 1567 |
| Improved seeds | Dummy variable for maize variety (1=improve; 0=traditional) | 0.335 | 0.473 | 0 | 1 |
| Inorganic fertilizer | Dummy variable for inorganic fertilizer use (1=yes; 0=no) | 0.031 | 0.174 | 0 | 1 |
| Organic fertilizer | Dummy variable for organic fertilizer use (1=yes; 0=no) | 0.037 | 0.188 | 0 | 1 |
| Gentle slope | Share of land in a valley or with slope described as flat or gentle | 0.733 | 0.372 | 0 | 1 |
| Fertility | Share of fertile land (fertility described as good or fair) | 0.597 | 0.440 | 0 | 1 |
| Erosion | Share of land under erosion | 0.190 | 0.372 | 0 | 1 |
| Improved seeds x Organic fertilizer | Interaction between Improved seeds and Organic fertilizer | 0.012 | 0.107 | 0 | 1 |
| Value of seeds | Amount spent on the purchase of seeds in Uganda Shillings (x $10^3$) | 22.336 | 35.660 | 0.6 | 400 |
| Off-farm income | Income generated from non-farm activities in Uganda Shillings (x $10^5$) | 9.544 | 58.864 | 0 | 1230 |
| Improved seeds x Value of seeds | Interaction between improved seeds and Value of seeds | 11.944 | 32.778 | 0 | 400 |
| Improved seeds x Inorganic fertilizer | Interaction between improved seeds and inorganic fertilizer | 0.021 | 0.145 | 0 | 1 |
| Off-farm income x labor | Interaction between off-farm income and labor | 1603.645 | 8424.786 | 0 | 161280 |
| Age | Overall average age of household members between 9 and 81 years supplying labor | 28.750 | 9.145 | 14.833 | 78 |
| Yield | Corn yield in kg/hectares | 360.992 | 255.394 | 5 | 1000 |

while about 19% is under erosion. Amongst plots planted with improved maize seedlings, 54% are described as gentle slope, flat or in the valley, 43% are fertile, while most (80%) are under little or no erosion. About 33% of the plots planted with improved maize seedlings are fertile, with gentle slope and under very little or no erosion, while 12% are infertile, with gentle slope and under very little or no erosion.

We consider interactions between off-farm income and farm labor days (as the main channel through which off-farm income affects production risk), and between IMV and use of inorganic and organic fertilizer. Age is used as a proxy for experience to account for variability associated to managerial skills. The average age of the household members supplying farm labor is 29 years.

# 4 Model selection and estimation

The first step is to estimate the production function specified in equation 6. As widely reported in the literature, this equation commonly suffers from endogenous bias given that farm input decisions tend be driven by plot specific soil quality and environmental characteristics. Failure to adequately control for the later in the equation will result in correlation between the input variables and the error term producing biased estimates. Our model controls for soil quality and environmental conditions using share of fertile land, share of gentle sloping or flat land, and share of land under erosion.

For completeness of the model selection process, we begin by estimating the base model (mean yield) using Ordinary Least Squares (OLS) and tested for endogenous bias using the Wu-Hausman test.[5] Only the area cultivated (land) was close to being significant at the 15 percent level indicating the plot specific soil quality and environmental variables were effective in controlling for endogeneity in the data. To ease comparison to a standard normal

[5]To test the endogeneity of each production input variable, we use instrumental variable with four instruments; distance to the nearest school in kilometers, time taken to walk to the school in Minutes, distance to the place where health treatment was sought for in kilometers, and how long it took to travel to the nearest major road.

distribution, all explanatory and control variables were standardized before estimation. This step completely eliminate any concern of endogeneity stemming from "land" based on the Wu- Hausman endogeneity test. Recall that following our specification in equation (7) and (8), we allow for heterogeneity in the variance, skewness and kurtosis. In order to determine the correct specification, and to also ensure that only relevant higher moments are included in the model, we implement a step-wise model selection in estimating equation (6).

Specifically, a backward selection process was adopted with an objective to test nonnormality (joint test of skewness and kurtosis avoiding the double jeopardy problem (Just and Weninger, 1999)), and heterogeneity. The null hypothesis for non-normality is that $\mu$ and $\theta$ both equal zero versus the alternative hypothesis that at least one of them is different from zero. We estimated a full model and five restricted models. The full model is a heterogenous nonnormal model with $\mu \neq 0, \theta_0 \neq 0, \theta_1 \neq 0, \sigma_0 \neq 0$ and $\sigma_1 \neq 0$. The sub models are: (i) heterogenous nonnormal ($\mu \approx 0, \theta_0 \neq 0, \theta_1 \neq 0, \sigma_0 \neq 0$ and $\sigma_1 \neq 0$) which is symmetric but still kurtotic, (ii) homogenous nonnormal ($\mu \approx 0, \theta_0 \neq 0, \theta_1 \neq 0, \sigma_0 \neq 0$ and $\sigma_1 = 0$) is also symmetric but still kurtotic, (iii) heterogenous normal ($\mu \approx 0, \theta_0 = \theta_1 = \sigma_0 = 0$ and $\sigma_1 \neq 0$) and (iv) a homogenous normal ($\mu \approx 0, \theta_0 = \theta_1 = \sigma_1 = 0$ and $\sigma_0 \neq$). Where $\mu \approx 0$ we set $\mu = 0.001$.

Note that the model indirectly screens for different specifications of the production function (such as the translog, linear-log, linear, and Cobb-Douglas) since the expanded $S_U$ is flexible enough to correctly approximate any distribution including the normal and lognormal as long as platy-kurtotic distribution is ruled out.[6]

To analyse economic and welfare effects of the use of improved maize on $E(\pi)$, R, and CE, we conduct three sets of simulations. In the first case, using the parameter estimates in the final model in equation (6), we simulate corn yields and revenues while marginally

[6]To further investigate and account for area-level heterogeneity in the data, we estimate and test three separate models weighted by the survey sampling weights. The first model is presented in the text without weighting within sampling strata. This model relies only on the $S_U$ specification to account for heterogeneity. In the second model, we weighted the data by strata using estimated probability weights. In the third model, the weights are truncated above within each strata by setting all weights above a chosen maximum weight (e.g, the 90th percentile) to the chosen maximum weight. There was little gain in using the model with weights, hence our analysis does not involve the survey sampling weights.

increasing the share of land allocated to IMV from 0% to 100% holding all other explanatory and control variables at their sample mean.[7] We use the sample average market price (400 UGX) in generating revenue. Simulated revenues are then used in equation (4) and (5) to decompose and estimate the cost of risk (premium) and conduct welfare analysis. In the next two sets of simulation we separately investigate how the effect of IMV vary under low (25% < sample mean) and high (25% > sample mean) application of inorganic fertilizer while holding all other input and control variables at their sample means. The simulations are conducted for two separate sub samples; the first restricted to plots with fertile soil, gentle or flat slope, and under no erosion which we refer to as Fertile-Flat-NoErosion plots. while the second sample is restricted to plots with infertile soil, gentle or flat slope, and no exposure to erosion, refer to as Infertile-Flat-NoErosion plots.

Similarly, to determine how changes in off-farm income affect productivity, cost of private risk bearing and farmer's welfare, we conduct three sets of simulations. In the first case, we marginally increase average off-farm income from the sample mean up to two standard deviations above the sample mean while holding all other explanatory and control variables at their sample means. In the second and third simulations, we repeat the process but keep the number of labor days worked at 25% below and above the sample mean respectively. The simulations are conducted for two separate sub samples; a sample of Fertile-Flat-NoErosion plots and that of Infertile-Flat-NoErosion plots.

In all the simulations, we assume farmer's risk preferences follow CRRA with a risk aversion parameter of 3 which assumes farmers are moderately risk averse based on existing estimates in the literature. Finally, following a similar approach, we simulate the elasticity of the risk premium associated with use of IMV and off-farm income under all three scenarios.

[7] To simulate yields (1) we use parameter estimates in final model to sequentially estimate $\mathbf{X_k}\beta$, $\sigma_k^2$ and $\theta$, $F(\theta, \mu)$ and $G(\theta, \mu)$; (2) draw 2000 pseudorandom numbers from a standard normal distribution and combine them with the estimates in step (1) as specified in equation (6).

# 5 Results and Discussion

Estimates of the base (mean) model with OLS and robust-OLS are reported in table 2. In both cases, the coefficient on IMV and off-farm income are positive and significant at the 1 percent level indicating that both have a positive effect on corn yield. Other inputs with a significant impact on yields include land and inorganic fertilizer. As expected, the coefficient on the later is positive indicating that inorganic fertilizer positively affects corn yield. The coefficient on land is negative while its square is positive, but not significant at the 10 percent level. The negative sign on land suggests larger farms have lower yields. As expected, the interaction between off-farm income and labor is negative and close to being significant at the 10 percent level indicating that the two variables are behaving as substitutes. Surprisingly, the interaction between IMV and inorganic fertilizer use is negative and close to being significant at the 10 percent level indicating that the two variables are behaving as substitutes instead as complements.

Table 2: OLS estimates of mean yield effect

| | | OLS | | OLS-Robust | |
|---|---|---|---|---|---|
| Variable | Coef. | Std. Err. | $P > \|t\|$ | Std. Err. | $P > \|t\|$ |
| Land | -54.505 | 27.223 | 0.046 | 27.426 | 0.047 |
| Land squared | 33.745 | 25.552 | 0.187 | 27.408 | 0.219 |
| Labor | 9.2495 | 13.469 | 0.493 | 13.412 | 0.491 |
| Improved seed | 42.485 | 14.127 | 0.003 | 14.426 | 0.003 |
| Inorg. fertilizer | 33.279 | 21.092 | 0.115 | 19.148 | 0.083 |
| Org. fertilizer | -12.341 | 14.673 | 0.401 | 9.722 | 0.205 |
| Gentle slope | -3.9912 | 11.574 | 0.730 | 12.024 | 0.740 |
| Fertility | -16.167 | 11.44 | 0.158 | 12.122 | 0.183 |
| Erosion | .8573 | 11.260 | 0.939 | 11.027 | 0.938 |
| Improved seed X Org. fertilizer | 8.9327 | 14.245 | 0.531 | 13.097 | 0.496 |
| Value of seed | 22.932 | 21.286 | 0.282 | 31.866 | 0.472 |
| Off-farm income | 50.213 | 15.844 | 0.002 | 10.747 | 0.000 |
| Improved seed X Value of seed | -13.570 | 22.949 | 0.555 | 30.438 | 0.656 |
| Improved seed X Inorg. fertilizer | -30.712 | 21.104 | 0.146 | 19.229 | 0.111 |
| Off-farm income X Labor | -21.155 | 15.905 | 0.184 | 13.448 | 0.116 |
| Age | -10.017 | 11.194 | 0.371 | 10.311 | 0.332 |
| constant | 360.99 | 10.982 | 0.000 | 10.982 | 0.000 |

R-squared = 0.0755

Table 3 reports estimation results of the full and restricted moment-based models based on the flexible $S_U$ family distribution. These model specifications are the full information heterogenous nonnormal (M1), a reduced heterogenous nonnormal (M3), the homogenous nonnormal (M2 and M4) both symmetric but still kurtotic, heterogenous normal (M6) and the homogenous normal (M5).

Table 3: Method of moment estimates using Johnson *SU* family distribution

| Variables | $M1$ | $M2$ | $M3$ | $M4$ | $M5$ | $M6$ |
|---|---|---|---|---|---|---|
| Constant | 359.37 | 349.98 | 366.28 | 356.08 | 360.99 | 366.61 |
| Land | -67.96 | -73.74 | -59.73 | -50.13 | -55.41 | -38.27 |
| Land squared | 38.44 | 39.81 | 33.98 | 30.25 | 34.55 | 27.82 |
| Labor | 15.55 | -1.86 | 16.46 | 7.54 | 9.03 | 2.43 |
| Improved seeds | 43.77 | 44.79 | 38.97 | 22.49 | 42.44 | 39.09 |
| Inorg. fertilizer | 30.52 | 34.50 | 31.40 | 15.49 | 33.04 | 31.61 |
| Org. fertilizer | -4.92 | -1.12 | -3.60 | -0.33 | -12.14 | -16.52 |
| Gentle slope | -9.48 | -12.58 | -5.92 | -5.41 | -3.96 | -3.13 |
| Fertility | -7.69 | -6.77 | -8.16 | -3.83 | -16.11 | -14.45 |
| Erosion | -4.05 | -2.24 | -3.48 | -5.31 | 0.49 | 0.79 |
| Improved seeds X Org. fertilizer | -4.54 | -5.33 | 0.00 | 3.57 | 8.71 | 1.72 |
| Value of seeds | 14.28 | 12.52 | 8.03 | 2.17 | 22.60 | 69.93 |
| Off-farm income | 64.63 | 46.37 | 80.85 | 51.26 | 50.20 | 111.78 |
| Improved seeds X Value of seeds | -2.60 | -0.58 | -0.00 | -4.33 | -13.24 | -47.78 |
| Improved seeds X Inorg. fertilizer | -25.38 | -29.67 | -28.44 | -13.92 | -30.48 | -36.59 |
| Off-farm income X Labor | -19.00 | -23.23 | -28.09 | -17.70 | -21.07 | 45.00 |
| Age | -8.43 | -8.08 | -7.86 | -4.44 | -10.03 | -4.02 |
| | | | | | | |
| $\sigma_0^2$ | 158.15 | 187.31 | 113.80 | 269.78 | 245.32 | 83.05 |
| $\sigma_1^2$ | 0.32 | / | 0.48 | / | / | 0.45 |
| $\theta_0$ | 1.09 | 0.89 | 0.60 | 0.55 | / | / |
| $\mu$ | 10.75 | 11.72 | 11.20 | 15.59 | / | / |
| $\theta_1$ | -0.15 | -0.17 | / | / | / | / |
| | | | | | | |
| LLH | -3507.92 | -3560.17 | -3511.55 | -3516.74 | -3571.50 | -3565.42 |
| AIC | 7059.84 | 7162.34 | 7065.09 | 7073.48 | 7179.00 | 7168.83 |
| BIC | 6878.42 | 6989.17 | 6891.92 | 6908.56 | 7030.57 | 7012.16 |

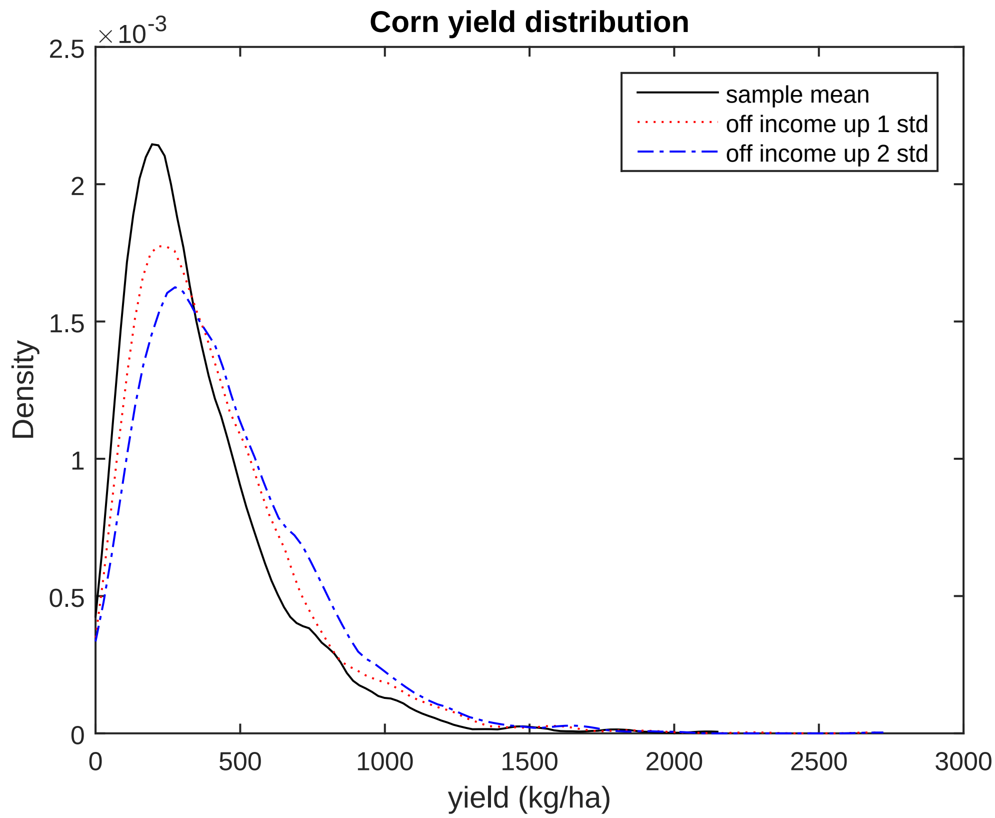
M1=full information heterogenous nonnormal; M3= reduced heterogenous nonnormal; M2, M4=homogenous nonnormal, both symmetric but still kurtotic; M6= heterogenous normal; M5= homogenous normal.

Results based on both Akaike information criterion (AIC), Bayesian information criterion (BIC) and likelihood ratio test (LRT) clearly fail to reduce the full model to any of the sub specifications and thus selects the full heterogenous nonnormal (M1) specification as the best (AIC=7059.84 and BIC=6878.42).[8] More specifically, the joint test of nonnormality (equally the test of skewness and kurtosis) can be inferred by comparing results from the full model (M1) and either of the normal models (M5 and M6). In either case, we reject the null hypothesis in favor of the heterogenous nonnormal specification, thus indicating that skewness and kurtosis are significant and relevant moments of the yield distribution. Also notice that the second best fit is the reduced heterogenous nonnormal model (M3) confirming that the data is highly heterogenous and nonnormal.

More specifically, results presented in table 3 show that the final model is kurtotic and right-skewed ($\theta \neq 0$ and $\mu > 0$). The signs on the parameter estimates are similar to those obtained in the base model using OLS and indicate that IMV, off-farm income, land area, and inorganic fertilizer have a positive effect of corn yield. Thus, any action that increases the right-skewness of the yield distribution reduces downside risk and will be desirable by the farmer. However, a change in skewness is most likely accompanied by a change in the kurtosis. Therefore jointly considering both skewness and kurtosis to assess the effect of off-farm income and the use of IMV on productivity and risk premium is necessary to be able to correctly capture the net effect of the action. Figure 1 illustrates kernel density plots of corn yield simulated using Fertile-Flat-NoErosion plot sample with all explanatory variables held at sample mean, and two other scenarios where off-farm income and use of IMV each is above the sample mean. Figure 2 presents similar results based on Infertile-Flat-NoErosion plot sample. The plots show that corn yield is highly kurtotic and right-skewed and that increasing off-farm income and the use of IMV shifts both the skewness and peakness (kurtosis) of the distribution. Our simulation results below captures the individual effect as well as the net effect of IMV and off-farm income on risk premium resulting from the simultaneous change in skewness and kurtosis.

[8] The P-value for the LRT between M1 & M2, M1 & M3, M1 & M4, M1 & M5 and M1 & M6 are 0.0000, 0.0071, 0.0001, 0.0000 and 0.0000 respectively.

Figure 1: Kernel density of simulated corn yields for levels of IMV and off-farm income for Fertile-Flat-NoErosion soil



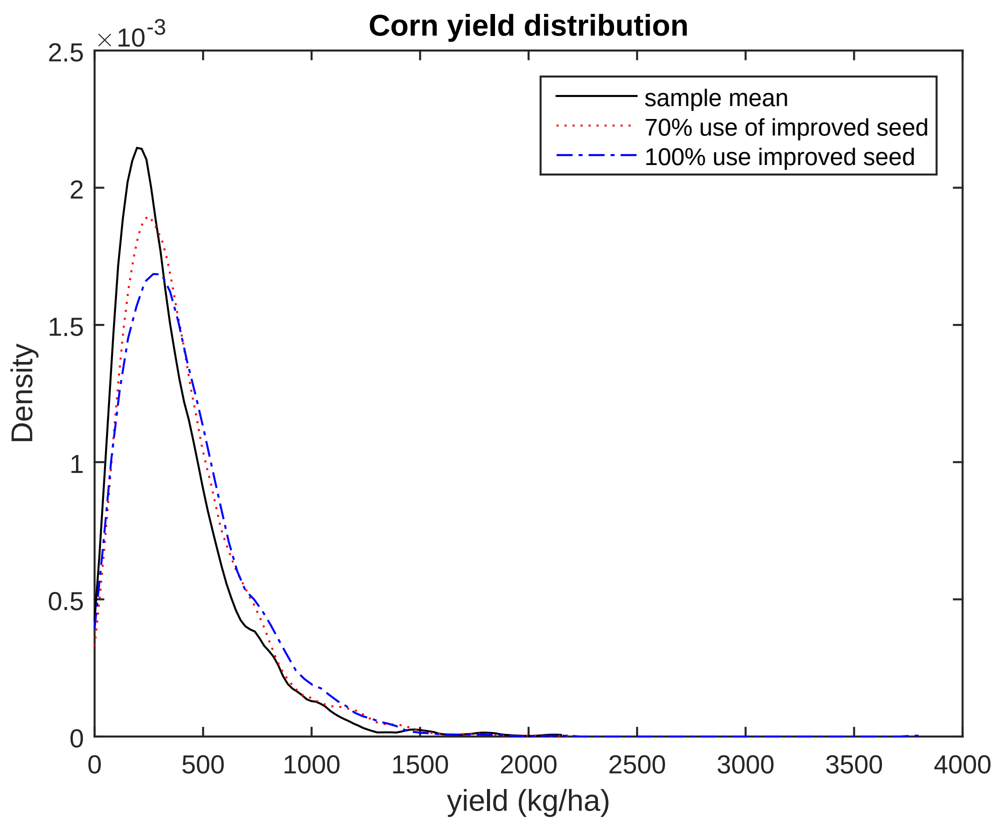
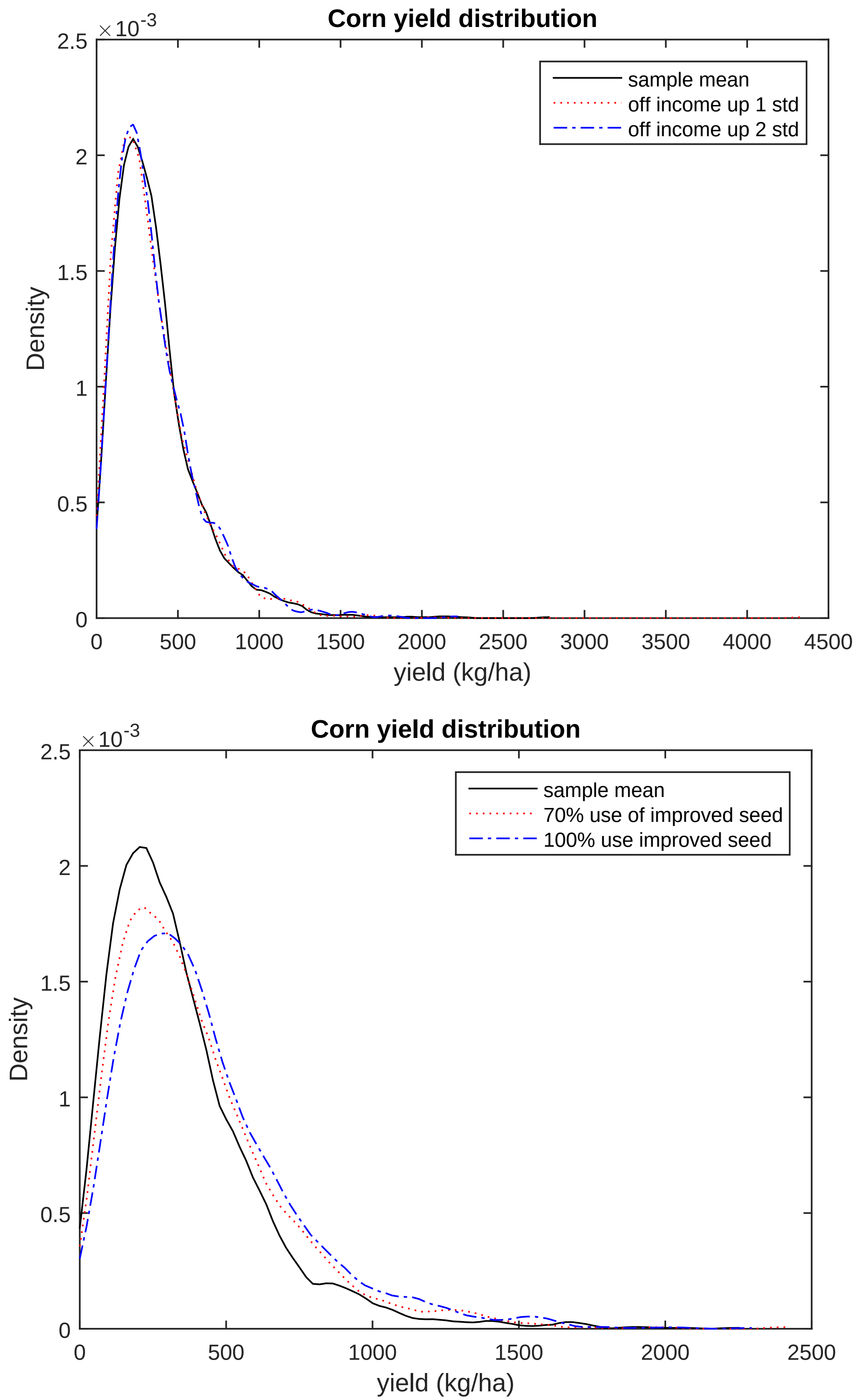



Figure 2: Kernel density of simulated corn yields for levels of off-farm income for Infertile-Flat-NoErosion soil

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## 5.1 *Impact of Improved Maize Varieties on Risk Premiums*

Figure 3 depicts simulation results to gauge the effect of using IMV on corn productivity and income from sale of corn, and the private cost of risk bearing, both at sample mean and under low (25% < sample mean) and high (25% > sample mean) use of inorganic fertilizer on Fertile-Flat-NoErosion plots. Figure 4 depicts similar results for a sample of Infertile-Flat-NoErosion plots.

The results in both figure 3 and 4 show that an increase in the use of IMV from 0% to 100% increases the variance of income from sale of corn but decreases skewness and kurtosis. The effect on kurtosis appears to be substantially higher than that on variance and skewness. Similarly, expected income and certainty equivalent steadily increase with an increase in the use of IMV. Overall, the risk premium decrease monotonically with an increase in the percentage of farmland planted with IMV. Figures 3.6, 3.7, 3.8, 4.6, 4.7 and 4.8 depict the decomposition of the risk premium into the variance, skewness and kurtosis components under the three fertilizer scenarios and the two soil profiles considered. With all variables held at the sample mean, the results reveal that while the cost of risk due to variance and kurtosis both decreases with an increase in the use of IMV, the variance component however accounts for the highest proportion of the risk. Conversely, the decrease in skewness following an increase in use of IMV tends to increase the risk premium. Note that while the change in risk premium associated to both skewness and kurtosis appears to be economically insignificant compared to the gross premium, it however reveals that failing to consider the reduction in risk associated with the decrease in kurtosis overstates the skewness component of risk cost (and thus the risk premiums) by about 1.21% and 1.54% for Infertile-Flat-NoErosion and Fertile-Flat-NoErosion plots respectively. Overall, the use of improved seeds on Fertile-Flat-NoErosion plots appears to have a slightly lower effect on the variance of income, expected income, risk premium components and a higher effect on the skewness and kurtosis of income, and mean risk premium compared to the results on Infertile-Flat-NoErosion plots.

Figure 3: Effect of IMV on variance, skewness, & kurtosis of on-farm income, risk premium, and individual components of risk premium for Fertile-Flat-NoErosion soil

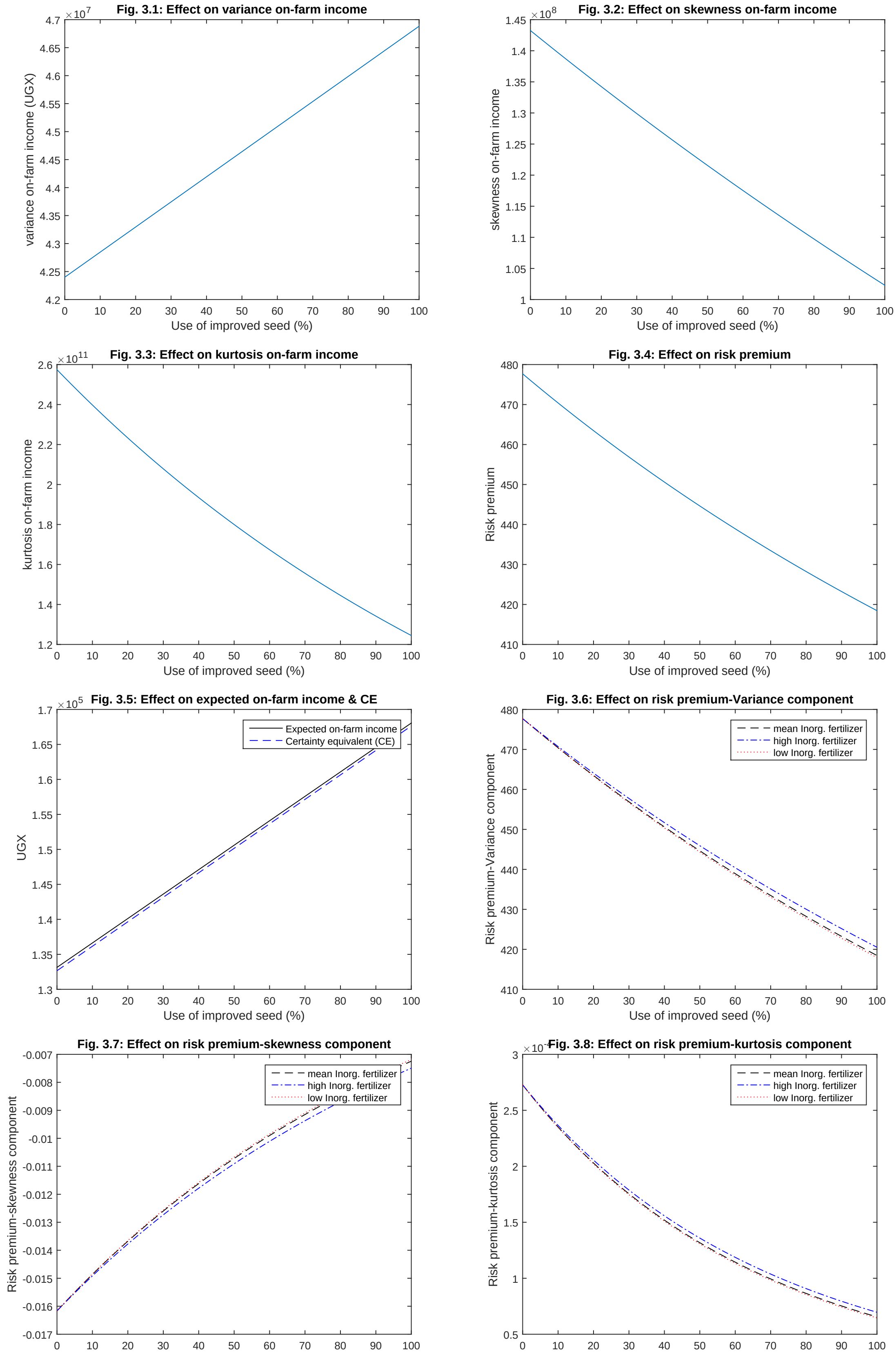
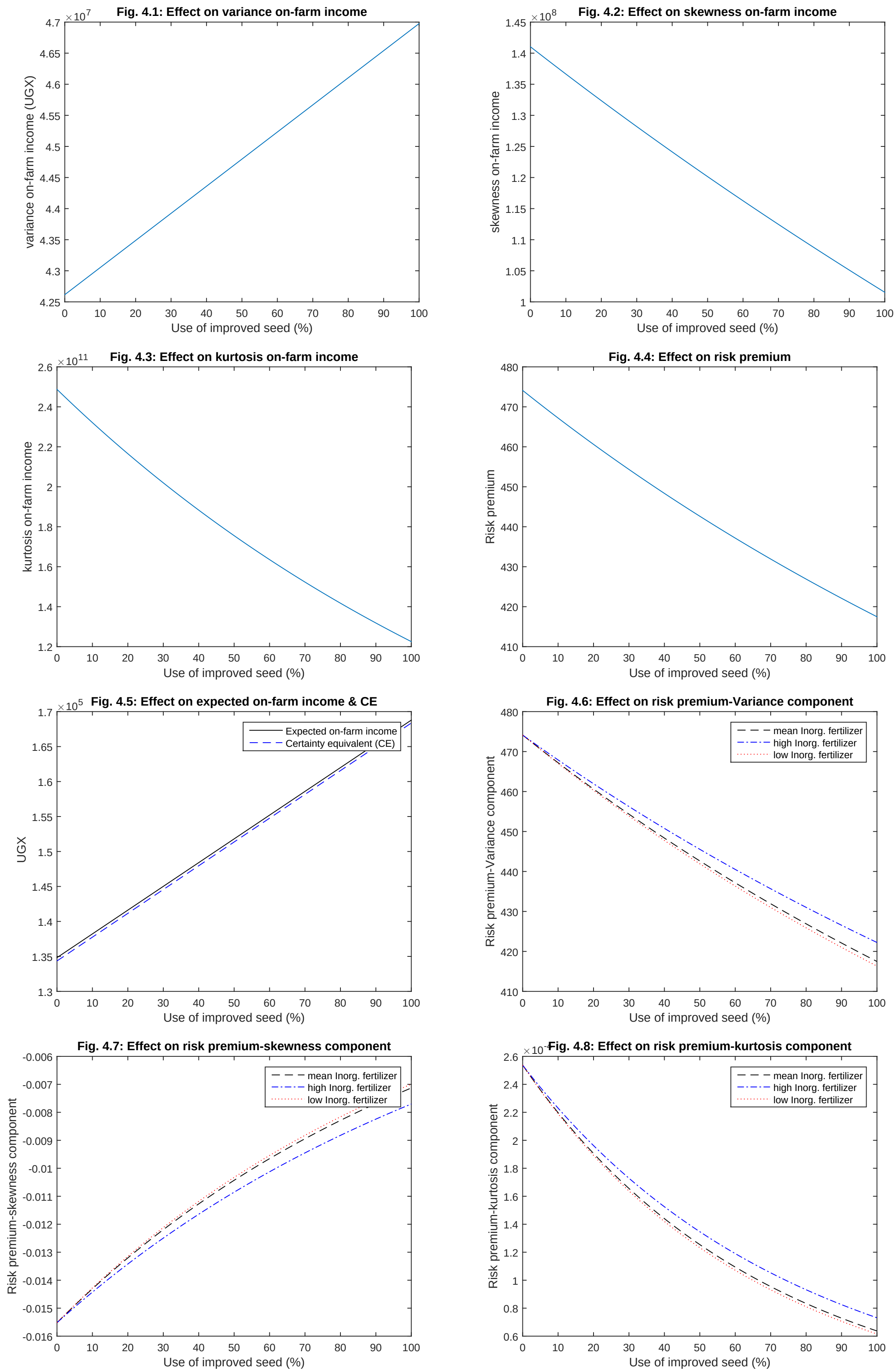


Figure 4: Effect of IMV on variance, skewness, & kurtosis of on-farm income, risk premium, and individual components of risk premium for Infertile-Flat-NoErosion soil



The trend in the results is maintained in the situations where the farmer plants IMV with low and high application of inorganic fertilizer. However, the risk premium reduction effect of IMV is much stronger when the use of IMV is accompanied with low application of inorganic fertilizer compared to high application. More interestingly, the risk reduction effect of IMV under scenarios of low application of inorganic fertilizer is stronger on Infertile-Flat-NoErosion plots than Fertile-Flat-NoErosion plots. To be more precise, the elasticity of risk premium with regards to IMV for Fertile-Flat-NoErosion plots was found to be -1.251 when all variables are held at the sample mean, -1.383 and -1.118 when use of IMV is accompanied with high and low application of inorganic fertilizer respectively. This implies that a 1% increase in the share of land under IMV will lead to a 1.383% (1.118%) reduction in risk premium when high (low) amounts of inorganic fertilizer is applied. On the other hand, the elasticity of the risk premium with regards to IMV for Infertile-Flat-NoErosion plots was found to be -1.312 and -1.678 and -1.122 when use of IMV is accompanied with high and low application of inorganic fertilizer, respectively. This implies that a 1% increase in the share of land under IMV will lead to a 1.678% (1.122%) reduction in risk premium when high (low) amounts of inorganic fertilizer is applied. Intuitively, these results make sense since the variance component of the risk premium dominates the other; IMV usually requires relatively high fertilizer application to produce optimal yields which occur with large variation. Whereas, using IMV with low fertilizer application gives low yields (and is tantamount to using low-yielding traditional maize varieties) which are more stable.

## 5.2 *Impact of Off-farm income on Risk Premiums*

Figure 5 presents simulation results to investigate the effect of off-farm income on corn productivity, income and the private cost of risk bearing. Three scenarios are investigated in which supply of farm labor is held at the sample mean, 25% below the sample mean (to simulate low supply) and 25% above the sample mean (to simulate high supply of farm labor). The simulations are separately conducted using a sample of Fertile-Flat-NoErosion and Infertile-Flat-NoErosion plots, and presented in figure 5 and 6 respectively.

In some parts, the results in figure 5 and 6 are similar to those revealed when examining the effect of IMV. Increasing off-farm income tends to increase the variance of farm revenues but decrease its skewness and kurtosis. Similarly, expected income and the certainty equivalent increases with an increase in the use of off-farm income, and the risk premium decreases monotonically with an increase in off-farm income. However, comparing the results under the two types of soil profiles overall reveals that on Fertile-Flat-NoErosion farm plots, off-farm income appears to have a slightly lower effect on the variance of income and expected income, and a higher effect on the skewness and kurtosis of income, and mean risk premium compared to the results on Infertile-Flat-NoErosion plots. More interestingly, the decomposition of risk premium presented in figures 5.6, 5.7, 5.8, 6.6, 6.7 and 6.8 show similarities amongst the two soil profiles in the presence of low supply of farm labor, but stark differences at both mean and high supply of labor. On a Fertile-Flat-NoErosion plot, the cost of risk due to variance and kurtosis steadily decreases with increase in off-farm income while the cost associated to skewness increases with increase in off-farm income at all levels of the labor supply. On the other hand, on Infertile-Flat-NoErosion plot, the decrease in the cost of risk only occurs when there is low supply of farm labor, and barely noticeable at the mean level of labor supply. Contrary to earlier results, increasing off-farm income while cultivating an Infertile-Flat-NoErosion plot in the presence of high labor supply tend to increase the private cost of risk associated with the variance and kurtosis, and decrease the cost of risk due to skewness of farm income. Even though the variance component accounts for the greatest percentage of the risk and the change in risk premium associated to both skewness and kurtosis appears to be economically insignificant compared to the gross premium, it reveals that failing to consider the reduction in premium attributable to the decrease in kurtosis also overstates the skewness component of risk by 1.50% and 2.42% for Infertile-Flat-NoErosion and Fertile-Flat-NoErosion plots respectively, and thus upwardly biases risk premiums.

The risk premium reduction effect of off-farm income is much stronger when there

Figure 5: Effect of off-farm income on variance, skewness, & kurtosis of on-farm income, risk premium, and individual components of risk premium for Fertile-Flat-NoErosion soil

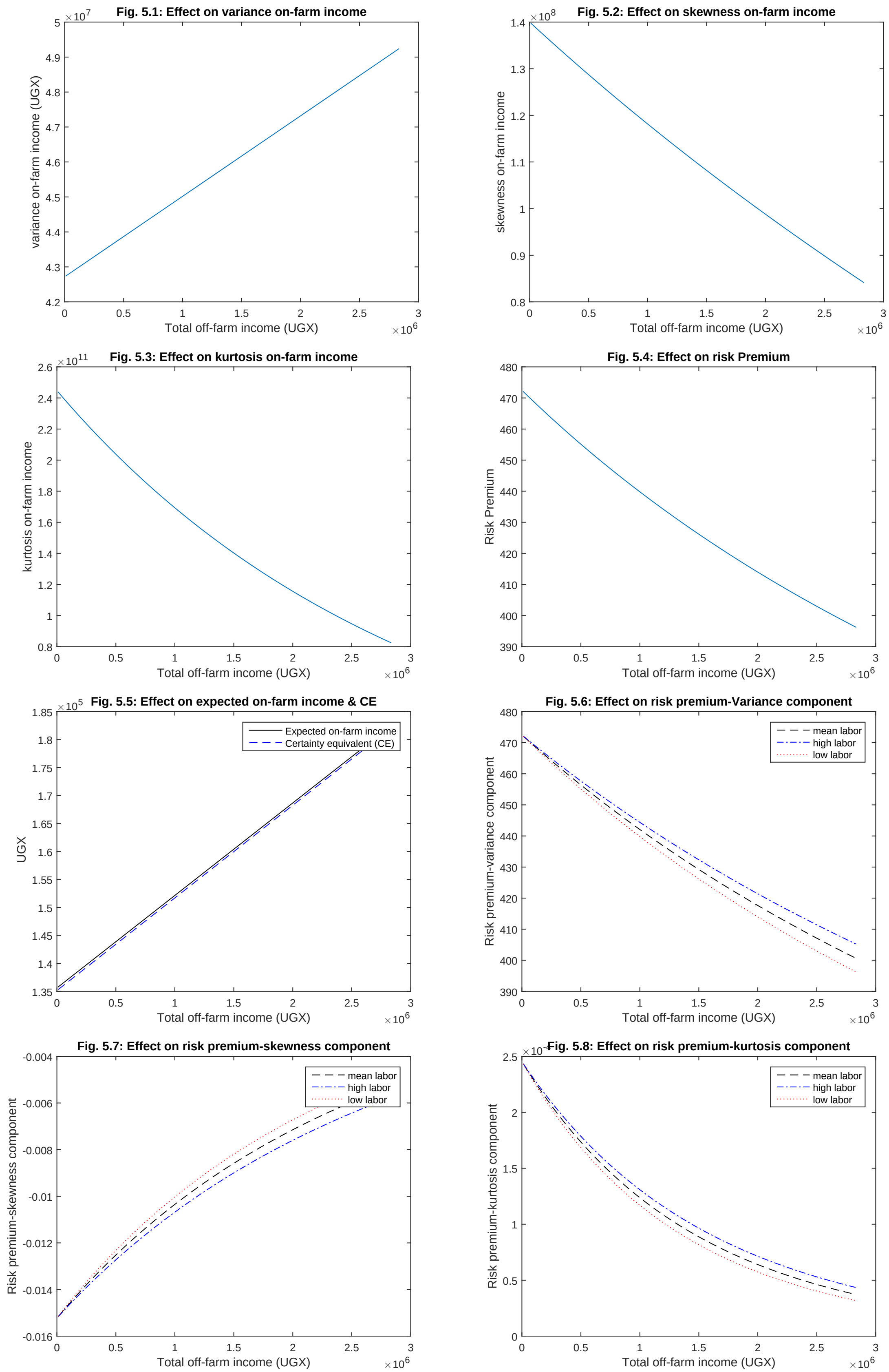
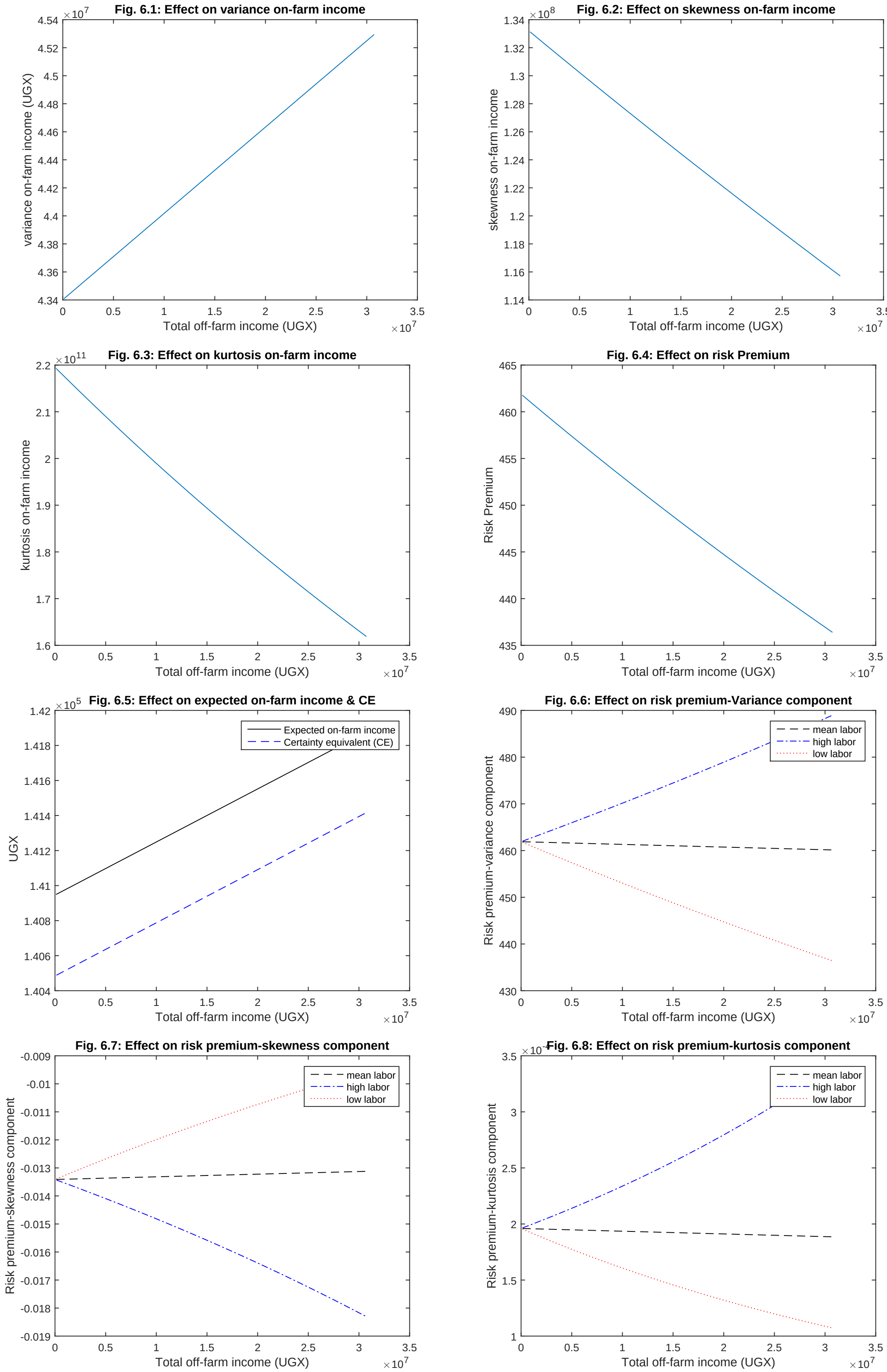


Figure 6: Effect of off-farm income on variance, skewness, & kurtosis of on-farm income, risk premium, and individual components of risk premium Infertile-Flat-NoErosion soil



is high supply of labor and even more so on an Infertile-Flat-NoErosion plot compared to Fertile-Flat-NoErosion plot. To be more precise, the elasticity of risk premium with regards to off-farm income for Fertile-Flat-NoErosion plots was found to be -1.470 when all variables are held at the sample mean, -1.684 and -1.068 when there is high and low supply of labor respectively. This implies that a 1% increase in off-farm income will lead to a 1.684% (1.068%) reduction in risk premium when there is high (low) supply of labor. On the other hand, the elasticity of risk premium with regards to off-farm income for Infertile-Flat-NoErosion plots was found to be -2.702 and -2.804 and -2.605 when there is high and low supply of farm labor respectively. This implies that a 1% increase in off-farm income will lead to a 2.804% (2.605%) reduction in risk premium when there is high (low) supply of farm labor. These results suggest that there is currently excess supply of farm labor, and rural development policies that spur off-farm employment opportunities will not compromise maize productivity. Rather it will be complementary and beneficial for smallholder farmers looking to move out of poverty.

# 6 Conclusion

Exceedingly low and puzzling patterns of demand for index based insurance in developing countries has raised several questions and explanations about its design and effectiveness, most of which remain open for discussion. In this light, we investigate the effect of using improved maize varieties and off-farm income (as self-protection) on the private cost of risk bearing for maize producers in Uganda using flexible production functions and a behavioral model for risk that explicitly captures risk components up to the fourth moment.

We find that IMV and off-farm income both increase corn revenues, its variance and certainty equivalent, but reduces its skewness and kurtosis. In addition, both IMV and off-farm income serve as self-protection reducing the cost of risk for producing maize in Uganda. However, the risk reduction effect was found to be higher on Infertile-Flat-NoErosion soils than Fertile-Flat-NoErosion soils. Moreover, the effect of IMV was found to be even higher when low amounts of inorganic fertilizer are use on the farm. Similarly, the risk premium reduction effect of off-farm income remain strong under low supply of farm labor, thus suggesting that improving off-farm income opportunities will not compromise maize productivity. Failing to consider kurtosis in the private cost of risk causes an overstatement of the cost of risk associated with skewness alone and thus the gross risk premium.

These results imply that self-protection practices on which smallholder farmers have relied on for decades may contribute to crowding out index based insurance if it is designed to insure risk layers already covered by these practices. This is possible because the premium charged to the farmers based on the weather index is most likely going to exceed their reservation cost and will be perceived as unfair, thus curtailing demand.

As a way forward, the index design process needs to properly consider and account for pre-existing sources of informal insurance and self-protection in order to produce contracts that are complementary, competitive and more efficient. This process will certainly be challenging especially given current data limitations, and thus makes a great area for future research. A possible approach will be to estimate a reservation premium from the farmer's point of view and use it as a constraint in searching for an actuarially fair premium. This will ensure contracts are based on complementary risk layers and fair premiums.

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