Efficient Estimation of Risk Attitude with Seminonparametric Risk Modeling

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Abstract

Recent development in production risk analyses has raised questions on the conventional approaches to estimating risk preferences. This study proposes to identify the risk separately from input equations with a seminonparametric estimator. The approach circumvents the issue of arbitrary risk specifications. Meanwhile, it facilitates analytical derivation of input equations. The GMM estimation method is then applied to input equations to estimate risk preferences. The procedure is validated by a Monte Carlo experiment. Simulation results show that the proposed method provides a consistent estimator and significantly improves estimation efficiency.

1. Introduction

A considerable literature has attempted to measure agents' risk preferences using information on observed production decisions. This literature directly estimates risk preference parameters from behavioral equations derived under the expected utility maximization framework (Saha et al. 1994). To elaborate, consider the following general risk decision problem:

(1) $\max_x \int u(\pi)h(\pi|x)\,d\pi,$

where x is a vector of choices; $u(\cdot)$ represents a general utility function of a random outcome π satisfying standard properties, $u' > 0$ and $u'' < 0$; $h(\cdot\,|x)$ is the probability density function of π conditional on x. Each function is assumed to depend on unknown parameters requiring estimation: $\pi = \pi(x, \alpha)$, where α is the parameter vector, e.g., of revenue; $h = h(\pi|x, \theta)$, where θ is the parameter vector of the probability distribution function; and $u = u(\pi, \gamma)$, where γ is the vector of risk preference parameters. The first order condition for utility maximization is

(2) $\int u'(\pi)\pi' h(\pi|x, \theta)d\pi = 0,$

which dictates optimal input choice decisions. The behavioral equations are determined by the interactions of $u(\cdot)$, $\pi(\cdot)$, and $h(\cdot)$ functions.[1] It means that the optimal input equations could confound producers' risk preferences, revenue structure and revenue risk. Since the information on individual response to risk is embodied in the behavioral equations, it is typical that these behavioral equations are derived and estimated to recover parameters of interest, in particular, risk preference parameters.

Recovering the unobservable risk preferences in (2) using production data has received much attention in the applied risk literature. This paper contributes to this body of research by proposing an innovative estimation method to generate an efficient estimator of risk preference

[1] Behavioral equations are defined by the first order condition, and both of them are used exchangeably throughout the paper.

parameters. This method is based on a separate estimation of parameters θ in the risk distribution h with a general approximation approach. Our method is validated by a Monte Carlo experiment with the risk calibrated to reflect realistic agricultural production. Results show that the estimator provides consistent estimates and increase estimation efficiency compared to existing methods.

2. Prior Works

Initial studies estimating risk preferences from actual production focused on estimating the level of risk aversion by imposing a restrictive utility structure while estimating behavioral equations alone (e.g. Brink and McCarl 1978). The subsequent development by Love and Buccola (1991) emphasized estimation efficiency with a joint estimation of behavioral equations and production technology. The joint estimation approach is now widely used in the literature. Starting with Saha, Shumway, and Talpaz (1994), more flexible utility functional forms were used to reveal not only the level of risk aversion, but also the structure of risk aversion (i.e.,, the changes in risk aversion relative to changes in wealth). However, increasing flexibility of utility function created a challenge for deriving a tractable system from behavioral equations that is estimable. To achieve tractability with a flexible utility specification, applied economists proposed various approaches. A standard practice was to place *a priori* restrictions on the risk distribution. Just and Just (2011) commented on several representative studies that used restrictive risk specifications.[2] We include four more recent studies which pose the similar restrictions on risk under a general assumption on risk preferences (Table 1). For instance, Kumbhakar (2002) and Kumbhakar and Tvetaras (2003) assumed non-stochastic prices and did not use any specific form of utility function. Isik and Khanna (2003) and Eggert and Tveterás (2004) accounted for different types of absolute and relative risk aversions and did not address price risk. In general,

[2] See table 1 in Just and Just paper (2011).

the flexibility in the utility specification always comes at the expense of flexibility in the risk specification.

The flexible utility function could improve model fit and allow the data to finely reveal the true relationship between wealth and risk aversion. However, some restrictive assumptions on risk imposed by researchers do not seem reasonable. As a result, the empirical findings in the literature show widely varying estimates that are theoretically implausible. Along with the erratic and contradictory results, many have casted serious doubt on whether flexible functional forms are desirable. One criticism concerns identification. Just and Just (2009) argued that since behavior equations (eq.2) confound risk preferences and risk through multiplication with common variables in each, there is an infinite set of paired specification of risk preferences and risk which will fit behavior. In other words, utility function with widely differing risk preferences accommodated with different risk specifications can imply the same behavior. Therefore, any incorrect or arbitrary risk specification would lead to inconsistent risk preference estimates. On the other hand, if both the risk preference and risk functions are general enough to admit all possible specifications, parameter identification would be difficult to attain from eq.2. To obtain risk preference estimates, one has to impose restrictions on the risk function which would indirectly determine risk aversion. Researchers have struggled to balance flexibility and identification.

Lence (2009) also raised the issue of parameter identification in a flexible utility functional form. The estimation is based on a system of unconditional moments implied by eq.2:

(3) $E(u'(\pi)\pi') = 0.$

No specific distribution was used in the estimation. He conducted a Monte Carlo experiment assuming the hyperbolic absolute risk aversion (HARA) utility function and concluded that the

structure of risk aversion cannot be estimated with reasonable precision at selected sample sizes. Wu and Guan (2013) replicated his experiment and found that consistent and unbiased estimation *is* possible but efficiency needs improvement for empirical application. As argued by Carrasco and Florens (2000), efficiency loss may be a result of employing a finite number of unconditional restrictions, since the conditional moment restrictions imply an infinite number of unconditional restrictions (Dominguez and Lobta, 2004). In the context of flexible specifications for risk preferences, restrictive risk specifications could result in inconsistent and biased estimates, while no restrictions on risk specification could generate consistent but inefficient estimates.

The purpose of this study is to propose a multistep estimation method to resolve the dilemma. The confounding effect in the first order conditions requires a method to identify the risk preferences and the risk separately. We will estimate risk with a seminonparametric (SNP) density estimator. The SNP approach approximates the conditional distribution of risk based on a series of expansion rather than attempting to establish a parametric model. Such a nonparametric approach can obtain very general approximations by increasing the number of terms in expansion. Good approximation can circumvent the influence of the arbitrary choice of risk specifications on risk preference estimates. Importantly, this approximation facilitates derivation of analytical expressions of the first order condition through advanced numerical integration methods. An estimable system of equations based on conditional moment restrictions instead of unconditional restrictions can be constructed, which will avoid potential efficiency loss. The generalized method of moments (GMM) is applied to the model consisting of the production function and the system of the first order conditions. A Monte Carlo experiment is conducted to

examine the performance of the method. The results suggest that the proposed method can achieve consistent and efficient estimation of risk preferences.

Current empirical practices in estimating risk preferences face various challenges,[3] which calls the entire scientific endeavor into question. The study contributes to the literature by addressing a major challenge — the failure of identification. We identify the risk distribution by estimating additional relationships that do not depend on the first order condition. Meanwhile, the SNP method does not impose any *a priori* restrictions on risk distributions. Improved efficiency ensures practical use of the approach for empirical production analysis. The proposed approach will hopefully help revalidate and revive production risk analysis.

3. A Multistep Estimator

Agricultural producers face risk from uncertain market prices and production fluctuation reflected in revenue:

(4) $\pi = p * y$,

where p is output prices, unknown when factor input choices are made, and y is production, affected by random production shocks such as weather, disease, or other events. The two risk components affect revenue risk independently or interactively. Revenue risk causes randomness in utility. Producers form expectations about the utility distribution and choose the optimal inputs accordingly. Rather than separately dealing with each risk source, we focus on the aggregate revenue risk. Since all probability information about any random process is completely characterized by its density, it is natural to estimate the density $h(\pi|\Omega)$, conditional on the information set Ω at the time of input choices. We consider a nonparametric method to

[3] Just et al. (2010) provides an overview of the production risk literature and discussed the recently discovered challenges, which include the failure of separately identifying risk and risk preferences through joint estimation, measuring the impact of wealth on risk behavior, unobservable producers' subjective perceptions, and so on.

approximate the risk distribution. Compared to the parametric approach, the SNP density estimator employs a Hermite series expansion to approximate the conditional density. The method is first proposed by Gallant and Tauchen (1989) in connection with an asset pricing application. The idea is that any smooth density function can be approximated arbitrarily close by a Hermite polynomial expansion. To describe the SNP, consider a scalar case of π. The SNP estimator is based on the class of densities:

$$(5)\ \mathcal{H}_K = \left\{h_K : h_K(\pi|\Omega,\theta) = \left[\sum_{i=0}^{K}\theta_i z^i\right]^2 \phi(\pi|\mu,\sigma^2), \theta \in \Theta_K\right\},$$

$$\Theta_K = \{\theta : \theta = (\theta_0, \theta_1, \dots, \theta_K), \int h_K(\pi|\Omega,\theta)d\pi = 1\},$$

where $\phi(\cdot)$ is a normal density with conditional mean μ and variance σ^2, and the formula in the parentheses is a Hermite polynomial with degree K in z, which is defined as $z = (\pi - \mu)/\sigma$. θ is the parameter vector to be estimated with θ_0 set at 1 for identification. In the approximation, the power function is to ensure that the density function is positive everywhere. In the homogeneous case, the distribution of *z* does not depend on the known information such as any variables in Ω.[4] This density will generate a Gaussian if *K* takes zero. When *K* is greater than zero, the shape of the Gaussian density will be modified by a polynomial in z. The shape characteristics of the standardized residual z will determine the distribution of π given Ω. Higher order terms in z accommodate deviations from Gaussianity such as skewness and kurtosis. The shape modifications thus achieved are rich enough to approximate densities from a large class that includes densities with fat, t-like tails, densities with tails that are thinner than Gaussian, and skewed densities (Gallant and Nychka 1987). By increasing K, an SNP model can achieve arbitrarily accurate approximation of any conditional density.

[4]In time series applications, data are always markedly conditionally heteroskedastic. The distribution *z* will depend on the past realizations (Gallant and Tauchen 1989; Gallant, Hsieh, and Tauchen 1997).

The model derived from nonparametric series expansions can be estimated by applying classical parametric estimation and inference procedures. Specifically, the parameters are estimated by a standard maximum likelihood procedure. We minimize the log-likelihood function:

(6) $s_N(\theta) = (-1/N)\sum_{i=1}^{N} log[h_K(\pi|\Omega,\theta)]$,

s. t. $\int h_K(\pi|\Omega,\theta)d\pi = 1.$

The integration in the constraint can be computed with a numerical method. The truncation point K is chosen with a model selection strategy such as the Bayesian information criterion (BIC). Under reasonable regularity conditions, the estimator is consistent and efficient (Gallant and Tauchen 1989). Note that the random process can be transformed to improve the stability of computations or approximation degree. It has been found that proper scaling is essential in computations to avoid cases where extremely large values of the polynomial part of the conditional density are required to accommodate deviations from Gaussianity. The consistency results are not affected by transformation (Gallant and Tauchen 1990). In applications, raw data are often centered and scaled or logarithmized. The location parameter μ can also depend on the known variables in Ω.

Let $\tilde{h}_K(\pi|\Omega,\tilde{\theta})$ denote the SNP estimator of the conditional density where $\tilde{\theta}$ are estimators of all parameters in eq. (5). Replacing the conditional density with the estimator, the first order condition (2) becomes:

(7) $\int u'(\pi)\pi'\tilde{h}_K(\pi|\Omega,\tilde{\theta})d\pi = 0,$

It is relatively easy to compute the expectation of a nonlinear function given the density function and density parameter values. We calculate the integral with the numerical integration method.[5] In the case of one dimension random process, the integral is a prescribed weighted sum of function values at the prescribed nodes. The choice of quadrature nodes and weights varies across different classes of numerical integration.[6] We adopt Gaussian quadrature method to choose the nodes and weights since this method is efficient when objective functions possess continuous derivatives. When the weight function is the probability function, Gaussian quadrature essentially "discretize" the random variable π by replacing it with a discrete random variable with mass points π_j and probability w_j that approximate π in the sense that both random variables have the same moments of order less than 2q:

(8) $\int \pi^k \, d\pi = \sum_{j=1}^{q} \pi_j^k w_j =$, for $k = 0,1, \dots, 2q-1$

where π_j and w_j are quadrature nodes and the respective quadrature weights, and q is the given order of approximation. As for our case, w_j is the probability associated with the normal distribution ϕ. Efficient and specialized numerical routines for computing these Gaussian quadrature nodes and weights are available in the CompEcon Toolbox developed by Miranda and Frackler (2002). Given the mass points and probabilities of the discrete approximant, the expectation of any function of π may be approximated using the expectation of the function of the discrete approximant, which requires only the computation of a weighted sum (Miranda and Fackler, 2002). Therefore, eq.7 can be approximated as:

(9) $\int u'(\pi)\pi' \tilde{h}_K(\pi|\Omega, \tilde{\theta}) d\pi \approx \sum_{j=1}^{q} u'(\pi_j)\pi_j' \left\{ \left[\sum_{i=0}^{K} \tilde{\theta}_i (z_j)^i \right]^2 w_j \right\} = 0,$

[5] In other applications, the SNP estimation requires high dimensional integration that cannot be computed accurately with analytical numerical methods. In those applications, we replace the analytical integration by simulated integration.

[6] There are three classes of numerical integration: Newton-Cotes methods, Gaussian quadrature methods, and Monte Carlo and quasi-Monte Carlo integration methods (Miranda and Fackler, 2002).

where $z_j = (\pi_j - \mu)/\sigma$. The approximation also analytically expresses the condition moment restrictions, which will facilitate to construct an estimable system of equations. The unknown parameters such as γ can be estimated by using the GMM estimator. Assume that production function is presented by

$$y = g(x, \alpha, e_y), \tag{10}$$

where y is output, x is the input amounts used, α are a vector of technology parameters, and e_y is a random error term representing production risk. In order to improve estimation efficiency, we adopt a joint estimation approach to estimate the production function (10) and the first order condition (9). Under fairly general conditions, the estimator $[\hat{\alpha}, \hat{\gamma}]$ is consistent and improves efficiency.

4. Monte Carlo Study

Given the methodology described in the previous section, we will investigate whether the method can identify risk preferences and achieve a reasonable performance compared to the Lence method in terms of estimation efficiency. The hypothesis is evaluated in Monte Carlo simulation. Data is generated according to the postulated decision-making model and is then used to estimate risk density and the underlying utility and technology parameters. We report Monte Carlo evidence on the finite-sample performance of our method based on the estimation procedure outlined above.

4.1 Data Generating Process

The data generating process is constructed to be consistent with a representative producer's production decision-making model. The experimental design largely follows Lence (2009)

unless otherwise stated. The producer is assumed to maximize his expected utility conditional on random, end-of-period wealth:

(11) $$W_1(x) \equiv \pi - r'x + W_0 = py - r'x + W_0,$$

where r is the vector of variable input prices, known at the time of decision making; and $W_0$is the agent's initial wealth. The production function (10) are explicitly specified as

(12) $$y = \alpha_0 x_A^{\alpha_A} x_B^{\alpha_B} e_y,$$

where α_0, α_A and $\alpha_B$are parameters with values of 3, 0.2, and 0.6, respectively. Unlike Lence (2009), e_y is assumed to follow a gamma distribution:

(13) $$e_y \sim \Gamma(k, \theta),$$

where k and θ are shape and scale parameters. Lence (2009) uses an empirical distribution derived from a set of Iowa corn yield data. The general gamma specification facilitates replication of results without relying on a specific dataset. It is also a reasonable choice for modeling random output (Saha 1993). Parameter values are set at $k = 0.0961$ and $\theta = 10.4058$ ensuring that output shocks have a mean of one and standard deviation of 0.310.

The end-of-period price is assumed to be generated from the following process:

(14) $$\ln(p) = -0.0659 + 0.5\ln(p_0) - 0.3\ln(e_y) + e_p\ ,$$

where p_0 is the initial price at the time of decision and known to the decision maker; e_p follows a zero-mean normal distribution with a standard deviation of 0.3. The level of price risk is associated with many agricultural products in the United States, such as edible beans, lettuce, and rice (Harwood et al. 1999). Since output shocks tend to have a negative impact on output prices, the $\ln(e_y)$ term is added into the equation. Moreover, output shocks e_y are independent of

e_p. The coefficients in eq. 14 are generated from regressions for historical corn price and yield data.[7]

The utility function $u(\cdot)$ takes the HARA form:

(15) $$u(W) = \frac{(\gamma_0 + W_1)^{1-\gamma_1}}{1-\gamma_1},$$

where γ_0 and γ_1 are risk preference parameters to be recovered in this study. This functional form is flexible enough to depict decreasing, constant, or increasing relative risk aversion (DRRA, CRRA, and IRRA) if parameter γ_0 is negative, zero, or positive, respectively. Producers are assumed to be maximizing their expected utility by choosing the optimal amounts of inputs (x):

(16) $$\max_{\boldsymbol{x}} E\{u[W_1(x)]\}.$$

$E\{\cdot\}$ is the expectation operator. With certain values for parameters in eq. (15), optimal input amounts can be derived by solving models (16), which in turn are used to generate yield from eq. (12). The computation of the maximization problem in (16) is performed using numerical integration methods. Writing the optimization problem (16) with respect to $x_{A,}$ and $x_{B,}$ as:

(17) $$E_{e_y,e_p}\left[u\left(x_A, x_B, e_y, e_p; W_{0,n}, p_{0,}, r_{A,}, r_B\right)\right]$$

$$= \iint u\left(x_A, x_B, e_y, e_p\right) f_p\left(e_p\right) f_y\left(e_y\right) de_y de_p,$$

$$= \frac{\sum_{q=1}^{Q} \sum_{s=1}^{10} u(x_A, x_B, e_{y,q}, e_{p,s}) w_{p,s}}{Q},$$

where $f_y(\cdot)$ and $f_p(\cdot)$ are the marginal probability density functions of output and price shocks. Since the price shock follows a lognormal distribution, we use Gaussian quadrature method to calculate the nodes $e_{p,s}$ and weights $w_{p,s}$ (Miranda and Fackler 2002). Nodes and weights are determined by a ten-point Gaussian quadrature, which suggests the first 19 moment matching

[7] Two regressions were run by Lence (2009). The dependent variable in the regressions is the national farm gate corn price deflated by CPI (1982-84=100). Variable $\ln(e_y)$ is the residual of the regression of $ln(yield_t)$on a constant and the time, where $yield_t$is the U.S. yield in the first regression, while it is the farm-level yield in the second regression. Details can be found in the appendix of Lence.

conditions are satisfied. Further, we use Monte Carlo integration method to calculate the integral with respect to e_y, for the routine for computing the Gaussian mass points and probabilities is not readily available for two-dimensional gamma distribution.10,000 random samples (Q=10,000) for $e_{y,q}$will be generated from the gamma distribution (13) and used in eq. 17 to calculate the expected utility. Finally, numerical optimization of the objective function (17) is solved to generate the optimal inputs x_A and x_B.

For each group of observed variables $[W_0, p_0, r_A, r_B]$, there will be a corresponding input set $[x_A, x_B]$. The initial wealth is simulated with $W_0 = 18.9 + 69.2\Gamma$, where the random variable Γ follows the standard $Beta$ (0.87, 1.27) distribution. All prices are scaled by setting their unconditional means equal to one. The prices known at the time of decision (i.e., p_0, r_A, r_B) are drawn from a log-normal distribution with unconditional mean of one; and the logarithms of prices have mean -0.03125 and variance 0.0625. For each group of simulated observed variables, we will calculate optimal inputs for three scenarios which correspond to three structures of risk aversion. Three sets of values ([-5, 2]; [0, 3]; and [43, 6]) are assigned to (γ_0, γ_1) to represent DRRA, CRRA, and IRRA, respectively.[8] The parameterizations are chosen so that they all yield an average value of relative risk aversion close to 3. In each scenario, the output, the end-of-period wealth, end-of-period price, and revenue are calculated from eqs. (4), (11), (12) and (14) with the randomly drawn values of e_y and e_p. The input and output quantities, together with their prices, provide a typical set of production data $[W_0, p_0, r_A, r_B, x_A, x_B, p_1, W_1, \pi]$, which are then used to recover risk preference parameters for each scenario.[9] The number of Monte Carlo

[8]Different from Lence (2009) setup, for the DRRA case, we assume $[\gamma_0, \gamma_1]$take [-5, 2] rather than [-18.4, 1]. We found that setting $[\gamma_0, \gamma_1]$as [-18.4, 1] would result in a large amount of corner solutions due to the binding constraint$(r_{A,n}x^*_{A,n} + r_{B,n}x^*_{B,n} \leq \gamma_0 + W_{0,n})$, which would bias the estimates of risk preferences.

[9]There is more detailed discussion on the experimental design in Lence (2009).

replications is 1000 for each scenario. Two sizes-500 and 2000 observations- are used for evaluating the finite sample performance and the asymptotic behavior of the estimator.

4.2 Estimation

To estimate the conditional density of revenue π, we use the nonparametric estimator with a Hermite series expansion. As discussed above, we take logarithms of the revenue to better approximate its distribution. Various descriptive statistics computed from π and $\ln(\pi)$ samples randomly drawn are displayed in Table 2. Statistics show that unconditional revenue distribution has a heavy tail and significant departures from a Gaussian specification as indicated by the Kolmogorov-Smirnov (KS) test. The logarithmic transformation substantially changes the original distribution and makes it more like a normal disribtuion, although KS test still rejects the null hypothesis of a normal distribution. To approximate the conditional revenue density, we assume location parameter μ is dependent on known variables. Specifically, we model the mean of $\ln(\pi)$ by taking a linear function of the price and inputs:[10]

$$\ln(\pi) = b_0 + b_1 \ln(p_0) + b_2 \ln(x_A) + b_3 \ln(x_B) + z. \quad (18)$$

In the first step, we will estimate the parameters in eq. (18) by an ordinal least square estimator, and estimates will be used to calculate the sample mean $\hat{\mu}$ of $\ln(\pi)$ and the residual $\hat{z}$. In the second step, the conditional density function of $\ln(\pi)$ is approximated by a Hermite expansion series as

$$\mathcal{H}_K = \left\{h_K : h_K(\ln(\pi)|\Omega,\theta) = \left[\sum_{i=0}^{K} \theta_i \, \hat{z}^i\right]^2 \phi(\ln(\pi)|\hat{\mu},\sigma^2), \theta \in \Theta_K\right\}, \quad (19)$$

$$\Theta_K = \{\theta : \theta = (\theta_0, \theta_1, \dots, \theta_K), \int h_K(\ln(\pi)|\Omega,\theta) d(ln\pi) = 1\},$$

[10] A more flexible model can be specified, such as the quadratic model, but the correct one can be discerned with nested test statistics.

Other parameters θ and σ can be estimated by the maximum likelihood estimation as shown in eq. 6. One advantage of two-step estimation for revenue density function is that the correct model for the conditional mean of $\ln(\pi)$ can be discerned. Eqs.(18) and (19) can also be simultaneously estimated to improve efficiency.

Now, we proceed to estimate parameters in the utility function by the GMM procedure. First, we discuss the model based on unconditional moments as our basis of comparison. The first order condition for optimization of (16) is:

(20) $$E_\pi[(\gamma_0 + W_0 + \pi - r_A x_A - r_B x_B)^{-\gamma_1} \times (\alpha_l x_l^{-1}\pi - r_l)|\Omega] = 0,\ l=A \text{ and } B,$$

Unconditional restrictions implied from eq. 20 are used to construct an estimable system of equations. In addition, a scaling factor in moment conditions is needed to address the degeneration problem, and the estimation is based on a system of regression equations corresponding to the production function and the first order condition:

(21) $$\begin{cases} \log(y_n) - \log(\alpha_0) - \alpha_A \log(x_A) - \alpha_B \log(x_B) = 0 \\ \left(1 + \frac{\pi - r_A x_A - r_B x_B}{\gamma_0 + W_0}\right)^{-\gamma_1} \times (\alpha_l x_l^{-1}\pi - r_l) = 0 \quad for\ \ l = A\ and\ B \end{cases}$$

The first equation is the logarithmic transformation of the production function (12).

In contrast, eq. 20 will be derived by numerical integration after the conditional density function of $\ln(\pi)$ is estimated. Therefore, our model is based on conditional moment restrictions. Likewise, we construct a model to jointly estimate production function and risk preference:

(22) $$\begin{cases} \log(y_n) - \log(\alpha_0) - \alpha_A \log(x_A) - \alpha_B \log(x_B) = 0 \\ \sum_{j=1}^{10} \left\{ \begin{array}{c} \left(1 + \frac{e^{\tilde{b}_0} p_0^{\tilde{b}_1} x_A^{\tilde{b}_2} x_B^{\tilde{b}_3} e^{z_j} - r_A x_A - r_B x_B}{\gamma_0 + W_0}\right)^{-\gamma_1} \\ \times \left(\alpha_l x_l^{-1} e^{\tilde{b}_0} p_0^{\tilde{b}_1} x_A^{\tilde{b}_2} x_B^{\tilde{b}_3} e^{z_j} - r_l\right) \left[\sum_{i=0}^{K} \tilde{\theta}_i (z_j)^i\right]^2 w_j \end{array} \right\} = 0, for\ \ l = A\ and\ B \end{cases}$$

where z_j and w_j are nodes and weights for the variate z with mean zero and variance $\tilde{\sigma}^2$. We use 10-degree Gaussian quadrature scheme to approximate it.

The risk preference parameters γ and the technology parameters α can be estimated by using a sample of N observations on $[W_0, p_0, r_A, r_B, x_A, x_B]$. We adopt the two-step GMM estimator. The set of instruments used for each of the equations above consists of the vector $Z = [1, W_0, p_0, r_A, r_B, x_A, x_B]$. In the first step the weighting matrix is derived directly from Z, while in the second step we set the weighting matrix as the estimate of covariance of the moment conditions.

5. Monte Carlo Results

5.1 Estimation of revenue risk density

The SNP procedure calculates the frequencies of all kinds of model choices based on BIC among 1000 replications. The frequency results show that, not surprisingly, the Gaussian specification dominates other choices. Figure 1 plots the mode of $h(z|\Omega)$; over plotted for comparison is SNP fits when K is set at 0 or 6. Figure 1 indicates that SNP(0) specification (K=0 in eq. (19)) can fit the risk distribution very well. The SNP(6) specification has a smaller location parameter in the sample size 500, while has a slightly greater location parameter in the sample size 2000. To choose the optimal dimension in the SNP, one can either let BIC automatically decide the SNP dimension in each replication, or, one can use a "posterior" fixed SNP specification. In views of the dominance of the Gaussian specification, we use the fixed SNP for all replications. That is, K is fixed at 0 to estimate other parameters using the maximum likelihood method.

Parameter estimation results are summarized in table 3. The table contains the median and the 2.5% and 97.5% quantiles (within parentheses) for parameter estimates in eqs. 18 and 19. In the following discussion, the 2.5-97.5% quantile intervals are referred to as the 95%

confidence intervals (CIs). To save space, outcomes for DRRA and CRRA are not reported, as they are similar to IRRA results. Table 3 shows that parameters in revenue mean and density functions can be accurately estimated, even with samples of 500 observations. Median estimates of b_1, b_2, b_3, and σ are nearly at the true values and the 95% CIs are narrow and very close to the true value. The estimate of b_0 is a little less precise and is slightly underestimated, but the gap between the true values and the bound of the 95% CI is very small. As expected, the precision of parameter estimates, as measures by the width of 95% CIs, increases with the sample size.

5.2 GMM Estimation

Tables 4 and 5 report summaries of measures of central tendency of the estimators of technology and risk preference parameters along with 2.5% and 97.5% quantiles using the GMM estimation method based on the unconditional moment model (eq.21) and our conditional moment model (eq.22). Comparing the two tables, we can see that technology parameter estimates are similar and accurate, because there is no identification issue for production function. Lence (2009) reported substantial bias for α_A estimates, and the 95% CIs often failed to contain its true value. Our simulation results show it is not the case and α_A and α_B can be estimated precisely even with samples size of 500. The results are consistent with Wu and Guan (2013). In addition, α_0 estimate shows downward bias because the mean of the logarithmic error is negative. Overall, technology parameters can be accurately estimated even under a flexible-utility specification and not affected by estimation models.

In regard to risk preferences, the GMM estimates based on unconditional moments perform poorly. The estimates for the DRRA and CRRA are upward biased, while those for the IRRA exhibit a downward bias. All biases are substantial reflected by the medians. In particular,

when the sample size is smaller , the results are disastrous. Although the bias declines along with the sample size, the width of 95% CIs is too large. The convergence speed is very slow, and an extremely large sample size is required to converge to true values. Wu and Guan (2013) found that most of the bias is gone at the sample size of 10,000. However, sample sizes typically used in the literature is far below that. Obviously, this method is not practical for empirical studies.

We turn to compare the convergence speeds of γ_0 and γ_1. γ_0 is clearly more difficult to pin down than γ_1. Although all the true values of γ_0 for the three scenarios lie inside the respective 95% CIs, the 95% CI are so large that estimates seem implausible. Even if there is an improvement as the sample size increases from 500 to 2000, the 95% CIs are still too wide. For instance, distribution of $\hat{\gamma}_0$ under DRRA and CRRA preferences are clearly skewed to the right. For the DRRA preferences, $\hat{\gamma}_0$is widely dispersed and the majority of estimates for γ_0 fall in the positive range in the 2000-observation-sample case. The pitfall stemming from a positive $\hat{\gamma}_0$ is that the econometrician would erroneously conclude that preferences are IRRA instead of DRRA. In contrast, the 95% CIs for γ_1 is narrower and the medians are closer to the respective true values. Its median estimates converge quickly toward the true values when increasing the sample size. Overall, the GMM estimation based on the unconditional moments cannot identify the structure of risk preferences with a reasonable sample size.

Table 5 exhibit substantial differences regarding the estimates of risk preference parameters when applying the proposed estimation method. The biases in risk preference parameters are sharply reduced. The potential gains that may be obtained are much more pronounced for the CRRA and IRRA. Their median estimates for γ_0 and γ_1 are typically close to the true values even in the small samples (N=500). Although the upward bias for γ_0 in the DRRA case for the small sample is still a little large, the bias has been almost eliminated for the

larger sample. Estimators for both parameters have distributions that are much more concentrated around the true parameter values than the prior estimator as evidenced by the 95% CIs. It is also clear from the comparison of tables 4 and 5 that the 95% CIs are closer to the true values of risk preference parameters and have no unreasonable large estimates. Moreover, the intervals can rapidly shrink with the number of observations in the sample. In sum, these results show that risk preference parameters can be accurately estimated with our method.

Among the three scenarios, DRRA case underperforms relative to other two cases in terms of the estimates of whether γ_0 or γ_1, because the constraint $\gamma_0 + W_0 > 0$ limits the movement of γ_0 to the direction of $-\infty$. A low γ_0 would result in the non-convergence problem. Our estimation shows that the DRRA case has the lowest frequency of convergences over all simulations. Those simulations that do not convergence are discarded. It is equivalent to eliminating samples that might produce low estimates of γ_0, and hence a significant upward bias in the median estimate may result. Similar biases will materialize for γ_1 estimates because they are correlated with the estimates of γ_0. In other two cases, the effect of this constraint is small.

In terms of relative efficiency, our estimates for the two risk preference parameters perform clearly better than the prior estimates. The latter one results in incredibly large root-mean-squared-errors (RMSEs) because of outlier estimates. In a sharp contrast, our method substantially declines the RMSE and improves the efficiency of GMM estimators as shown in table 6. The RMSE for parameters in all cases excluding γ_0 in the DRRA case declines roughly in line with $\sqrt{N}$ when the sample size goes from 500 to 2,000. For estimates of γ_0 in the DRRA case, the RMSE shrinks faster, which in part is due to rapidly shrinking biases in the parameter estimates. It implies that the bias can be corrected by increasing number of observations. The

results in this study suggest that our method can generate a great efficiency improvement that makes empirical studies practical.

5.3 Robustness Analysis

The efficiency and consistency of the estimator in our method hinge on the idea of approximating the risk distribution by using a nonparametric method. Different risk distributions will incur distinct magnitudes of approximation errors and in turn affect the first order condition and the estimates of risk preference. In order to investigate the robustness of our method to risk distributions, we perform extra simulations and estimations with a different assumption on output price shocks. In the baseline simulation, output price shocks are assumed to follow a lognormal distribution. Although the distribution is often employed in the agricultural economics literature, it may not reflect the random characteristics of actual prices (e.g., Chavas and Holt 1996). For instance, the specified logarithmic price shocks are symmetry rather than skewness. To gauge how much our estimates are affected by the price distribution, we re-estimate risk preference parameters assuming that prices are generated from a probability distribution whose shape mimics the empirical distribution of actual commodity prices. Specifically, we assume that end-of-period crop prices are still generated by the data generating process (14), but the price error e_p has a distribution shape similar to the US real seasonal–average corn price received by farmers. The deflated national corn price (logarithmic) is used in a regression on a constant, the marketing year *t*, the lagged price, and output shocks. The summary statistics of corn price (logarithmic) residuals over 1970-2012 show that their standard deviation is 0.18 and skewness is 0.8534. Figure 2 plots their histogram bars, the probability density estimated by kernel smoothing function, and a normal distribution density. Different from the normal distribution,

the empirical price distribution has a longer right tail. In the simulation, price shocks e_p will be randomly generated from the empirical distribution, and other simulated data are generated in a similar way to the baseline simulation.

SNP density estimation results show that the Gaussian specification still dominate other specifications for the revenue risk. Although more terms in polynomial can accommodate departures from Gaussian tails, the model is complicated by the number of parameters. When the minimal specification is used, the risk preference estimates are presented in table 7. In contrast with table 6, risk preference estimates in terms of both median and the 95% CIs are all largely unaffected. Overall the results clearly confirm the robustness of our previous findings with respect to price risk.

5.4. Approach to Inference

While our method can generate a consistent and efficiency estimator for utility parameters, we may have an inference problem due to the multistep nature of the estimation. In the density estimation, parameters in risk (θ) are consistently estimated and estimates ($\tilde{\theta}$) are used to construct variables contained in moment conditions. Therefore, the noise induced by $\tilde{\theta}$ is introduced into the moment conditions. In the GMM procedure, we apply an efficient GMM estimator which weighs the moment conditions by a consistent estimate of their covariance matrix which is constructed using $\tilde{\theta}$. Since these initial estimates contain estimation errors, the usual asymptotic variance formulae for the GMM estimators are not correct. Newey and McFadden (1994) determined the correct asymptotic covariance matrix of the two-step GMM estimators, and their correction to the estimate of the covariance formulae account for the variations in $\hat{\alpha}$ and $\hat{\gamma}$. But when additional estimation errors ($\tilde{\theta}$) are introduced, it is hard to

derive the correct formula for the covariance matrix. In this case, we can employ a bootstrap method, which is a method for estimating standard errors of an estimator or test statistic through repetitions using the same data. The method does not require theoretical calculation.

6. Conclusion

It is recognized in the literature that there is a fundamental trade-off in identification and flexibility of the functional forms of utility. To obtain parameter identification with a more flexible risk preference function, more restrictions have to be placed on the flexibility of risk. However, an arbitrary or inappropriately narrow specification of risk will bias risk preference estimates. In this paper we propose a new estimation method which estimates the risk independently from behavioral equations. The density function of the risk is estimated by a seminonparametric estimator, which circumvents the issue of arbitrary choice of inflexible specifications. Another appealing feature of this approach is that conditional moments can be analytically expressed, which facilitate GMM estimation. We conduct a Monte Carlo study to examine the properties of the proposed estimation procedure for estimating risk preference parameters. We found that our method can estimate risk preference parameters with reasonable precision. When the sample size increases, the estimates can quickly converge to their true values. In addition, our method significantly improves estimation efficiency. The efficiency improvement makes empirical risk analysis practical.

Table 1. Assumptions used for estimating risk preferences with flexible utility functions

Study [a]	Expected utility	Risk specifications
Saha et al. (1994)	$E(-exp\left(-\gamma_1 \pi^{\frac{1}{\gamma_2}}\right))$	Non-stochastic price; Weibull distributed production
Chavas and Holt (1996)	$E\left[\int \exp(\gamma_0 + \gamma_1 \pi + \gamma_2 \pi^2)\, d\pi\right]$	Truncated normal price; normally distributed production
Kumbhakar (2002)	No specific utility functional form	Non-stochastic price
Kumbhakar and Tveteras (2003)	No specific utility functional form	Non-stochastic price
Isik and Khanna (2003)	T-M model [b]	Non-stochastic price
Eggert and Tveteras (2004)	T-M model [b]	Non-stochastic price

[a] the first two studies have been commented in Just and Just (2011);

[b] M-V denotes the two-moment approach;

Table 2. Descriptive Statistics for Random Revenue and Logarithmic Revenue Samples of 2000 Observations

	π			$\ln(\pi)$		
	DRRA	CRRA	IRRA	DRRA	CRRA	IRRA
Skewness	2.962	2.557	2.369	-0.249	-0.191	-0.235
Kurtosis	18.477	12.576	12.120	3.018	3.091	2.989
KS statistic	0.888	0.872	0.878	0.678	0.691	0.670

Table 3. Estimates of Parameters in the Risk Structure and Density

	Parameter Estimates				
Sample Size	$b_0 = 1.03$	b_1=0.5	b_2=0.2	b_3=0.6	$\sigma = 0.37$
500	0.998	0.498	0.200	0.599	0.371
	(0.89,1.11)	(0.34,0.66)	(0.09,0.31)	(0.50,0.70)	(0.35,0.39)
2,000	0.998	0.502	0.199	0.600	0.373
	(0.94,1.05)	(0.42,0.58)	(0.14,0.26)	(0.55,0.65)	(0.36,0.38)

Note: For each parameter, the table reports the median and the 2.5% and 97.5% quantiles (within parentheses) from 1000 estimates for sample sizes of 500 and 2000. Here only present estimation results in the IRRA case. Results in the DRRA and CRRA cases are similar and available upon request.

Table 4. GMM Parameter Estimation Based on the Unconditional Moments

Risk Structure	Sample Size	Parameter Estimates				
		Utility		Technology		
		$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_A$	$\hat{\alpha}_B$
DRRA	500	-0.012	2.900	2.852	0.202	0.605
		(-16.70,138.33)	(0.85,14.06)	(2.72,2.98)	(0.19,0.21)	(0.58,0.63)
DRRA	2,000	-3.525	2.230	2.861	0.201	0.601
		(-14.20,36.54)	(1.08,5.04)	(2.80,2.92)	(0.20,0.20)	(0.59,0.61)
CRRA	500	4.106	4.063	2.853	0.201	0.604
		(-15.47,141.55)	(1.26,16.97)	(2.73,2.98)	(0.19,0.21)	(0.58,0.63)
CRRA	2,000	1.478	3.294	2.856	0.200	0.601
		(-11.73,39.94)	(1.78,6.89)	(2.79,2.92)	(0.20,0.20)	(0.59,0.61)
IRRA	500	27.211	5.907	2.857	0.201	0.603
		(-11.26,311.86)	(1.48,28.72)	(2.73,2.98)	(0.19,0.21)	(0.58,0.63)
IRRA	2,000	39.432	6.097	2.856	0.201	0.601
		(1.09,178.79)	(2.83,16.82)	(2.79,2.92)	(0.20,0.20)	(0.59,0.61)

Note: $[\gamma_0, \gamma_1]$ for DRRR, CRRA, and IRRA risk structures correspond to [-5 2], [0, 3], and [43, 6], respectively.

Table 5. GMM Parameter Estimation Based on the Conditional Moments

Risk Structure	Sample Size	Parameter Estimates				
		Utility		Technology		
		$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_A$	$\hat{\alpha}_B$
DRRA	500	-3.062	2.282	2.852	0.201	0.602
		(-8.80,3.48)	(1.44,3.61)	(2.68,3.01)	(0.19,0.21)	(0.58,0.63)
DRRA	2,000	-4.357	2.129	2.848	0.201	0.602
		(-8.26,0.35)	(1.57,2.88)	(2.78,2.94)	(0.20,0.20)	(0.59,0.61)
CRRA	500	0.686	3.136	2.858	0.201	0.601
		(-8.60,10.10)	(1.71,5.04)	(2.69,3.01)	(0.19,0.21)	(0.58,0.63)
CRRA	2,000	0.217	3.021	2.857	0.200	0.600
		(-5.65,5.92)	(2.19,4.08)	(2.78,2.92)	(0.20,0.20)	(0.59,0.61)
IRRA	500	43.570	5.931	2.855	0.201	0.601
		(23.99,62.09)	(3.22,10.06)	(2.70,3.02)	(0.19,0.21)	(0.58,0.63)
IRRA	2,000	42.970	5.980	2.856	0.200	0.600
		(33.49,53.69)	(4.38,7.76)	(2.76,2.95)	(0.20,0.21)	(0.59,0.62)

Note: $[\gamma_0, \gamma_1]$ for DRRR, CRRA, and IRRA risk structures correspond to [-5 2], [0, 3], and [43, 6], respectively.

Table 6. Finite Sample Bias and Efficiency Comparison

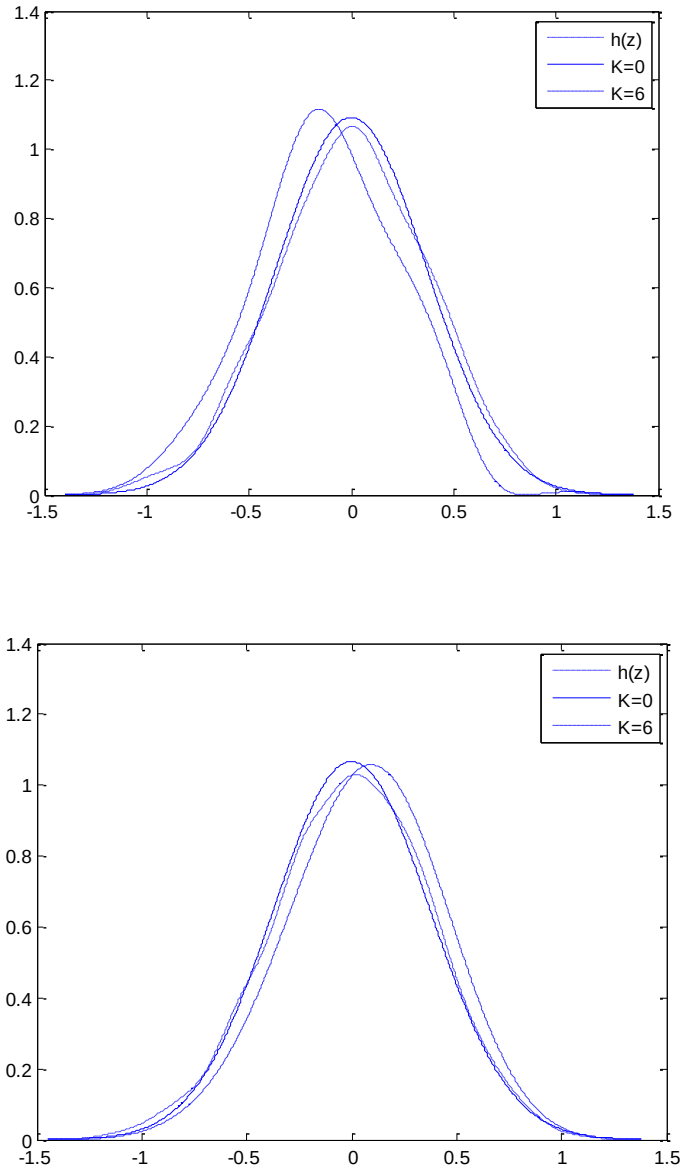
		Mean Bias		Median Bias		RMSE	
	True Value	T=500	T=2000	T=500	T=2000	T=500	T=2000
GMM based on the conditional moments							
DRRA	$\gamma_0 = -5$	2.033	0.829	1.938	0.643	8.747	2.622
	$\gamma_1 = 2$	0.364	0.147	0.282	0.129	0.694	0.388
CRRA	$\gamma_0 = 0$	0.733	0.188	0.686	0.217	5.273	3.232
	$\gamma_1 = 3$	0.206	0.055	0.136	0.021	0.955	0.533
IRRA	$\gamma_0 = 43$	0.435	0.110	0.570	-0.030	10.111	4.814
	$\gamma_1 = 6$	0.141	0.014	0.069	-0.020	1.763	0.890
GMM based on the unconditional moment							
DRRA	$\gamma_0 = -5$	15.001	5.384	4.988	1.475	50.799	16.900
	$\gamma_1 = 2$	1.961	0.445	0.900	0.230	4.353	1.164
CRRA	$\gamma_0 = 0$	19.939	5.211	4.106	1.063	54.984	16.483
	$\gamma_1 = 3$	2.012	0.559	1.478	0.294	6.361	1.497
IRRA	$\gamma_0 = 43$	10.366	9.536	-15.789	-3.568	79.230	48.154
	$\gamma_1 = 6$	1.957	0.981	-0.093	0.097	7.252	3.738

Table 7. GMM Parameter Estimation Based on the Conditional Moments under the Assumption of Empirical Price Risk Distribution

Risk Structure	Sample Size	Parameter Estimates				
		Utility		Technology		
		$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_A$	$\hat{\alpha}_B$
DRRA	500	-3.139	2.353	2.848	0.201	0.603
		(-10.05,3.04)	(1.35,3.89)	(2.69,3.01)	(0.19,0.21)	(0.58,0.63)
DRRA	2,000	-4.140	2.199	2.850	0.201	0.602
		(-9.39,2.70)	(1.41,3.33)	(2.73,2.94)	(0.20,0.21)	(0.58,0.62)
CRRA	500	0.975	3.201	2.853	0.201	0.602
		(-8.39,8.99)	(1.71,5.38)	(2.69,3.01)	(0.19,0.21)	(0.58,0.63)
CRRA	2,000	0.350	3.085	2.853	0.200	0.601
		(-6.53,8.94)	(1.99,4.67)	(2.74,2.95)	(0.19,0.21)	(0.58,0.62)
IRRA	500	42.514	5.936	2.854	0.200	0.601
		(15.51,71.83)	(2.08,12.25)	(2.69,3.02)	(0.19,0.21)	(0.58,0.63)
IRRA	2,000	42.855	6.031	2.853	0.200	0.601
		(32.47,52.14)	(4.01,8.02)	(2.75,2.93)	(0.19,0.21)	(0.58,0.62)

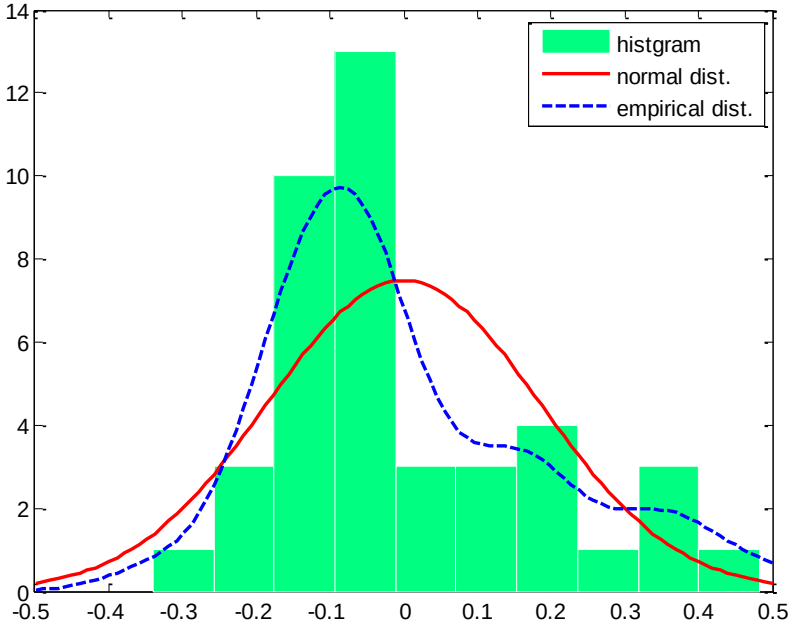
Note: $[\gamma_0, \gamma_1]$ for DRRR, CRRA, and IRRA risk structures correspond to [-5 2], [0, 3], and [43, 6], respectively.

Figure 1.The Risk Distribution and Simulation from SNP fits



Note: The upper panel contains plots for the distribution of *z* and simulations from SNP fits with *K*=0 and *K*=6 when the sample size is 500 in the IRRA case. The lower panel contains the same plots when the sample size is 2000.

Figure 2. Empirical Distribution of Corn Price Shocks over 1970-2012



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