Non-Optimal Behavior and Estimation of Risk Preferences

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Abstract

Non-optimal behavior due to budget constraint or credit availability is commonly observed in agricultural production. Not accounting for non-optimal behavior would result in biased estimates of risk preferences. A generalized model is developed in this article for estimating agents' risk attitude accommodating both optimal and non-optimal behaviors. Results from Monte Carlo simulations suggest that estimation based on the proposed model yields consistent and unbiased risk preference estimates, whereas estimation based on the conventional modeling procedure produces biased results.

Keywords: Corner Solution, Non-optimal Behavior, Risk Preferences, Budget Constraint, Monte Carlo Simulation, GMM Estimation.

Introduction

Farmers' risk attitudes have been a topic of interest for several decades in the literature. A significant amount of effort in this area has been devoted to estimating risk preferences from observed production decisions (see, e.g., Brink and McCarl 1978; Love and Buccola 1991; Saha, Shumway, and Talpaz 1994; Chavas and Holt 1996; Kumbhakar 2001, 2002a, 2002b). Early works tried to estimate risk preferences by assuming restrictive utility functions (e.g., mean-variance framework). Many of the later works relaxed the assumption and used more flexible utility functions (e.g., Saha, Shumway, and Talpaz 1994). In this extensive literature, the underlying logic is that farmers' production decisions (input use) reflect their risk preferences, which could be recovered from the observed production data. This literature usually assumes that farmers choose the optimal level of input use so as to maximize their expected utility and further assumes that farmers are not constrained in their ability to achieve optimality. This unconstrained, optimal behavior assumption is commonly made in the literature. In reality, however, farmers' behavior often systematically deviates from optimality due to the presence of various constraints, for example, budget constraints or credit availability, which in turn would result in corner solutions in the expected utility maximization problem when the constraint becomes binding. In such cases, models not accounting for the non-optimal behavior will mis-represent agents' decision process and mis-specify models in empirical analysis, thus resulting in biased estimates of risk preferences. Antle (1987) investigated the risk attitudes of farmers in south-central India and indicated that assuming optimal behavior in the use of both labor and fertilizer would produce conflicting results as farmers were actually constrained in the choice of fertilizer. When agents face binding constraints in the utility maximization problem, the marginal utility that has routinely been used as the first order conditions in the literature will be positive, instead of zero, which means an increase in production will further increase agents' utility; in other words, the current choice of the agent is not optimal.

In this article, we develop a model that accommodates both optimal and non-optimal behavior to address model misspecification and correct bias in risk preference estimates. We conduct Monte Carlo simulations to demonstrate the bias in risk preference estimates caused by corner solutions and further investigate the performance of bias correction of the proposed model. Simulation results show that not accounting for nonoptimal behavior results in significant biases, and the proposed model and estimation procedure can consistently estimate risk preference parameters and correct the bias arising from non-optimal, corner solutions.

The rest of the article is organized as follows. We first present the expected utility maximization framework and the Monte Carlo experiment design. Then we derive models to recover agents' risk preferences under both optimality and non-optimality assumptions, which will be followed by discussions of the simulation results. The final section summarizes the findings with some concluding remarks.

The Expected Utility Framework and Experiment Design

In the Monte Carlo experiment we assume producers maximize their expected utility of the end-of-period wealth, which is determined by initial wealth as well as profit made during the period. Profit is a random variable subject to the choice of production plan (levels of input and output), market prices, and risk associated with production and prices. The production plan can be defined with a production function, reflecting producers' choice of input level and the yield response to input choice. The production function is specified as:

$$(1)\ \tilde{y} = \alpha_0 x_A^{\alpha_A} x_B^{\alpha_B} \tilde{e}_y,$$

where α_0, α_A and α_B are parameters and are set as 3.8, 0.2, and 0.6, respectively; $\tilde{e}_y$ is an error term representing production risk and follows a log-normal distribution with mean 1 and stand deviation 0.2, which means $\ln(\tilde{e}_y)$ has mean -0.0196 and standard deviation 0.198;. The end-of-period output price is determined by the initial price, production shocks as well as a random component in the following process:

$$(2)\ \ln(\tilde{p}) = -0.07 + 0.6\ln(p_0) - 0.4\ln(\tilde{e}_y) + \tilde{e}_p\ ,$$

where p_0 is the initial price known to the decision maker at the time of decision and is drawn from a log-normal distribution with mean 1 and standard deviation 0.254, which means $\ln(p_0)$ has mean -0.03125 and standard deviation 0.25. $\tilde{e}_p$ follows a normal distribution with a zero mean and a standard deviation of 0.2. This specification and parameter values are in line with the price risk of many agricultural products in the United States (Harwood et al. 1999; Lence 2009). Once the production and price are determined, producers' end-of-period wealth could be written as:

$$(3)\ \widetilde{W}_1(x) = \tilde{p}\tilde{y} - \boldsymbol{r}'\boldsymbol{x} + W_0,$$

where $\boldsymbol{r}$ is the vector of input prices and $\boldsymbol{x}$ is the vector of inputs. W_0 is the initial wealth, which will be drawn from uniform distributions with different upper and lower bounds under different scenarios to be elaborated shortly. Like p_0, the input prices (r_A, r_B) are also drawn from a log-normal distribution with the same parameters.

The utility derived from the wealth takes the power functional form widely used in the literature:

$$(4)\ U(W_1) = \frac{{W_1}^{1-\gamma_1}}{1-\gamma_1},$$

where γ_1 is the risk preference parameter. γ_1 is the relative risk aversion coefficient and is the parameter of interest in this study. It takes the value of 2. The power utility function reflects decreasing absolute risk aversion (DARA) and constant relative risk aversion (CRRA). Producers maximize their expected utility by choosing the optimal amounts of inputs (x):

$$(5)\ \max_{\boldsymbol{x}} E\{U[\widetilde{W}(x)]\},$$

where $E\{\cdot\}$ is the expectation operator; and the end-of-period wealth is a random variable. As parameters in the production function Eq. (1) and the utility function Eq. (4) are known, optimal choice of input level that would maximize producers' utility can be solved from the optimization model in (5). The optimal input solution and the corresponding output amount, together with their prices, provide a typical set of production data, which will be used in econometric estimation to recover the risk preference parameter γ_1.

Scenarios of Initial Wealth

The level of initial wealth constitutes a budget constraint for producers. When the constraint is binding, the producer does not have enough financial resources to purchase inputs needed to maximize his expected utility, resulting in corner solutions. We assume four different scenarios for initial wealth distribution to generate samples with different levels of corner solutions in order to evaluate estimation performance:

(6) W_0= 5+20z,

(7) W_0= 10+40z,

(8) W_0= 20+70z,

(9) W_0= 80+100z,

where z follows the standard uniform distribution [0,1]. In the four scenarios, the initial wealth steadily shifts to the right with increasingly wider intervals. Higher levels of initial wealth will generate less corner solutions. Once the initial wealth is determined, the computation of the maximization problem in (5) is performed using the numerical quadrature method (Miranda and Fackler 2002, chap. 4; Lence 2009).

We generated two million observations for each scenario; a total of eight million observations were generated in the simulation. Examination of generated data shows that the percentages of corner solutions under the four scenarios (Eqs. (6) through (9)) are 45.29%, 20.42%, 7%, and 0.46%, respectively.

Models for Estimation

Estimation of the risk preference parameter relies on the first order conditions (FOCs) of the expected utility maximization problem in Eq. (5). In unconstrained optimization, the first order conditions of the problem are:

(10) $\frac{\partial}{\partial x} E\{U[\widetilde{W}_1(x)]\} = 0,$

which means:

$$\text{(11) } E_{\tilde{e}_y,\tilde{e}_p}\{\widetilde{W}_1{}^{-\gamma_1}(\tilde{p}\alpha_j x_j^{*-1}\tilde{y}-r_j)\}=0, j\text{=A, B},$$

where $x_{A,}^*, x_B^*$ are the amounts of inputs generated from the expected utility maximization problem in (5), and $\widetilde{W}_1$is defined in Eq. (3). Because of the highly nonlinear form of Eq. (11) and its complex distribution, we will use the Generalized Method of Moments (GMM) to estimate the first order conditions. By the law of iterated expectations, Eq. (11) can be rewritten in the following form for empirical estimation:

$$\text{(12) } \delta_{j,n}=(W_{1,n})^{-\gamma_1}(p_n\alpha_j x_{j,n}^{*-1}y_n-r_{j.n}),$$

where $E(\delta_{j,n}|Z_n)=0$, Z_n is the information set known at the time of producers' decision; n = 1, …, N indexes observations. In order to exclude the solution of +∞ for γ_1, we append a scaling factor $W_{0,n}^{\gamma_1}$ to Eq. (12) and rewrite it as follows:

$$\text{(13) } \varepsilon_{j,n}=(W_{1,n}/W_{0,n})^{-\gamma_1}(p_n\alpha_j x_{j,n}^{*-1}y_n-r_{j.n}).$$

Note that the scaling treatment is customary in GMM estimations. The treatment helps alleviate singularity problems in the computation of the weighting matrix in GMM estimations when original moment conditions are badly scaled.

To increase estimation efficiency, the FOCs in Eq. (13) can be jointly estimated with the production technology:

$$\text{(14) } \varepsilon_{y,n}=[\log(y_n)-\log(\alpha_0)-\alpha_A\log(x_{A,n}^*)-\alpha_B\log(x_{B,n}^*)],$$

We have derived the equations (13) and (14) for estimation to recover the risk preference parameter γ_1 based on the assumption that producers face no constraints in the expected utility maximization, which is routinely practiced in the literature. The producer's input decisions $x_{A,n}^*, x_{B,n}^*$ should be optimal solutions to the maximization problem. However, in the real world, agents' decisions may not be optimal due to various constraints. In this

Monte Carlo experiment, producers' optimization process was subject to the budget constraint:

(15) $r_{A,n}x_{A,n}^{*} + r_{B,n}x_{B,n}^{*} \leq W_{0,n}$.

When the budget constraint becomes binding in solving the maximization problem, the solutions derived are corner solutions. In this case, $x_{A,n}^{*}, x_{B,n}^{*}$ are not truly optimal; it is only "optimal" under the constrained optimization. Producers would have used more inputs that would further increase their expected utility; the marginal utility in the first order conditions in Eq. (10) would be positive instead of zero. The resulting equations (11) – (13) will systematically deviate from zero, and the parameter estimates based on the unconstrained first order conditions will be biased. The data generated from our Monte Carlo experiments under different scenarios of initial wealth have varying degrees of corner solutions. To address this nonoptimal behavior, we define a Lagrangian function for the maximization problem that incorporates the budget constraint (15):

(16) $L = E\{U[\widetilde{W}_1(x)]\} + \rho(W_0 - \boldsymbol{r'x})$,

Maximizing the expected utility requires that:

(17) $\frac{\partial L}{\partial x_j} = \frac{\partial}{\partial x_j}E\{U[\widetilde{W}_1(x)]\} - \rho r_j = 0$, j = A, B.

(18) $\rho\left(W_0 - r^{\prime}\ x\right) = 0$.

Eq. (18) is the complementary slackness condition of the Lagrangian; ρ is the Lagrange multiplier and $\rho \geq 0$. Eq. (17) can be rewritten as:

(19) $\rho = \frac{1}{r_j}\frac{\partial}{\partial x_j}E\{U[\widetilde{W}_1(\boldsymbol{x})]\}$.

ρ could be interpreted as marginal utility. Substitute (19) into (18), we have:

$$(20)\ \frac{1}{r_j}\frac{\partial}{\partial x_j}E\{U[\widetilde{W}_1(x)]\} * (W_0 - \boldsymbol{r}'\boldsymbol{x}) = 0.$$

Eq. (20) can be used as moment conditions for estimation to recover the parameters of interest. It can be rewritten as:

$$(21)\ E_{\tilde{e}_y,\tilde{e}_p}\{\widetilde{W}_1{}^{-\gamma_1}(\tilde{p}\alpha_j x_j^{*-1}\tilde{y} - r_j)\} * (W_{0,n} - \boldsymbol{r}'\boldsymbol{x}) \ = 0.$$

Eq. (21) means that, when the marginal utility is positive, the budget constraint must be zero ($W_0 - \boldsymbol{r}'\boldsymbol{x} = 0$), i.e., the budget constraint is binding, and corner solution occurs. When the budget constraint is not binding ($W_0 - \boldsymbol{r}'\boldsymbol{x} > 0$), Eq. (21) suggests that the marginal utility is zero, in which case interior solution results and optimality is achieved. For estimation purpose, Eq. (21) can be rewritten as:

$$(22)\ v_{j,n} = (W_{1,n})^{-\gamma_1}(p_n\alpha_j x_{j,n}^{*-1}y_n - r_{j.n})\,(W_{0,n} - r'x)\ ,\ j\text{=}A,B.$$

$v_{j,n}$ is the random error with mean zero. Again, we include a scaling factor $W_{0,n}^{\gamma_1}$ as in (13) to facilitate estimation:

$$(23)\ \epsilon_{j,n} = (W_{1,n}/W_{0,n})^{-\gamma_1}(p_n\alpha_j x_{j,n}^{*-1}y_n - r_{j.n})\,(W_{0,n} - r'x)\ ,\ j\text{=}A,B.$$

This equation captures both binding and non-binding budget constraints and provides a unified framework for estimation of agents' risk attitude. It can be estimated jointly with the production technology in Eq. (14).

For GMM estimation, we define the conditional moment restrictions as follows:

$$(24)\ E[\phi(Q_n,\theta)|Z_n] = 0,$$

where $\phi(Q_n,\theta) = [\varepsilon_{y,n}\ \ \varepsilon_{A,n}\ \ \varepsilon_{B,n}]'$ or $\phi(Q_n,\theta) = [\varepsilon_{y,n}\ \ \epsilon_{A,n}\ \epsilon_{B,n}]'$, Q_n is a 7-dimensional vector $[y_n, W_{0,n}, p_n, r_{A,n}, r_{B,n}, x_{A,n}^*, x_{B,n}^*]'$, and θ is a 4-dimensional parameter vector $[\alpha_0, \alpha_A, \alpha_B, \gamma_1]'$ to be estimated. The GMM estimation is implemented based on a set of unconditional moment restrictions implied by (24):

$$(25)\ E[\phi(Q_n,\theta)\otimes Z_n] = 0,$$

Variables in the information set Z_n known at the time of decision are used as instruments. The parameters estimates $\hat{\theta}$ are derived by minimizing a quadratic form with respect to the unknown parameters (Hansen, 1982):

$$(26)\ \hat{\theta} = argmin_{\theta}[g(Q_n,Z_n,\theta)'V_N g(Q_n,Z_n,\theta)],$$

where $g(Q_n,Z_n,\theta) = 1/N\sum_{n=1}^{N}\phi(Q_n,\theta)\otimes Z_n$ and V_N is a positive definite weighting matrix.

Results and Discussions

We first estimated the conventional first order conditions in Eq. (13) jointly with Eq. (14) under four scenarios with varying corner solutions. For each scenario, four sample sizes (100, 500, 1,000 and 10,000) are used. The sample size of 10,000 is used to examine how well the estimates converge to the true values in the large sample. The estimation results are presented in Table 1.

Table 1: Estimation Results Using Conventional Approach

		Parameter Estimates			
Initial Wealth	Sample Size	Utility	Technology		
		$\hat{\gamma}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_A$	$\hat{\alpha}_B$
Scenario 1	100	5.512	3.592	0.207	0.621
Corner:45.29%		(3.14,10.21)	(3.12,4.03)	(0.19,0.22)	(0.58,0.67)
	500	4.583	3.596	0.206	0.619

		(3.65,5.74)	(3.42,3.77)	(0.20,0.21)	(0.60,0.64)
	1,000	4.417	3.595	0.206	0.618
		(3.75,5.22)	(3.47,3.72)	(0.20,0.21)	(0.61,0.63)
	10,000	4.243	3.597	0.206	0.618
		(3.98,4.47)	(3.56,3.64)	(0.20,0.21)	(0.61,0.62)
Scenario 2	100	4.479	3.626	0.205	0.613
		(1.88,9.46)	(3.20,4.10)	(0.19,0.22)	(0.58,0.66)
Corner:20.42%	500	3.351	3.657	0.203	0.608
		(2.34,4.59)	(3.48,3.85)	(0.20,0.21)	(0.59,0.63)
	1,000	3.201	3.663	0.20	0.608
		(2.50,3.97)	(3.53,3.80)	(0.20,0.21)	(0.60,0.62)
	10,000	3.047	3.667	0.202	0.607
		(2.84,3.29)	(3.62,3.71)	(0.20,0.20)	(0.60,0.61)
Scenario 3	100	4.233	3.642	0.204	0.610
		(0.92,10.52)	(3.22,4.09)	(0.19,0.22)	(0.58,0.65)
Corner: 7%	500	2.811	3.691	0.201	0.604
		(1.56,4.39)	(3.51,3.89)	(0.20,0.21)	(0.59,0.62)
	1,000	2.615	3.699	0.201	0.603
		(1.75,3.61)	(3.57,	(0.20,0.20)	(0.59,0.61)
	10,000	2.407	3.710	0.201	0.602
		(2.14,2.69)	(3.67,3.76)	(0.20,0.20)	(0.60,0.61)
Scenario 4	100	5.091	3.637	0.203	0.610

		(-0.77,15.73)	(3.23,4.07)	(0.19,0.22)	(0.58,0.64)
0.46%	500	2.701	3.701	0.201	0.603
		(0.61,5.40)	(3.52,3.88)	(0.20,0.21)	(0.59,0.62)
	1,000	2.372	3.714	0.201	0.601
		(0.92,4.10)	(3.59,3.84)	(0.20,0.20)	(0.59,0.61)
	10,000	2.099	3.721	0.200	0.600
		(1.68,2.47)	(3.69,3.76)	(0.20,0.20)	(0.60,0.60)

Note: The table reports the median and the 2.5% and 97.5% quantiles (within parentheses) for sample sizes of 100, 500, 1,000, and 10,000, respectively. True values of the parameters are $\gamma_1 = 2$, $\alpha_0 = 3.8$, $\alpha_A = 0.2$, $\alpha_B = 0.6$.

The results suggest that production function parameters, especially the slope parameters, can be relatively well recovered even in small samples, and in scenario 1 that has the most corner solutions. This is because the moment conditions for the technology parameters are linear, and the parameters do not directly depend on behavioral assumptions. However, comparisons across scenarios do show that estimates in scenarios that have more corner solutions are less precise because of the spillover effects from the estimation of the first order conditions which include α_A and α_B.

The risk preference parameter estimates for γ_1 are clearly biased in the first two scenarios where the values of the 2.5% and 97.5% quantiles of the simulation results in parentheses show that the 95% confidence intervals do not cover the true value of 2. In scenario 3 that has 7% corner solutions, the 95% confidence interval in the large sample does not contain the true value, either. But in scenario 4 which has only 0.5% corner solutions, the 95% confidence intervals contain the true value under each sample size. In this scenario, the spread narrows down substantially from (-0.77, 15.73) in the sample size of 100 to (0.61, 5.40) in the sample size of 500. The median value approaches the true value of 2 in the large sample, which suggests that consistent and unbiased estimation could be achieved when there are no corner solutions.

Table 2: Estimation Results Using the New Model

Initial Wealth	Sample Size	Parameter Estimates			
		Utility	Technology		
		$\hat{\gamma}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_A$	$\hat{\alpha}_B$
Scenario 1	100	6.406	3.486	0.211	0.631
		(0.87,32.53)	(2.34,4.13)	(0.19,0.27)	(0.56,0.80)
	500	2.813	3.68	0.202	0.606
		(1.11,5.51)	(3.46,3.91)	(0.19,0.21)	(0.58,0.63)
	1,000	2.350	3.707	0.201	0.603
		(1.27,3.69)	(3.56,3.86)	(0.20,0.21)	(0.59,0.62)
	10,000	2.001	3.725	0.200	0.600
		(1.71,2.36)	(3.68,3.78)	(0.20,0.20)	(0.60,0.61)
Scenario 2	100	5.546	3.535	0.207	0.621
		(0.55,26.53)	(2.45,4.11)	(0.19,0.25)	(0.57,0.75)
	500	2.642	3.688	0.202	0.604
		(0.97,4.74)	(3.48,3.90)	(0.20,0.21)	(0.59,0.62)
	1,000	2.294	3.709	0.201	0.602

		(1.18,3.54)	(3.57,3.86)	(0.20,0.21)	(0.59,0.62)
	10,000	2.024	3.724	0.200	0.600
		(1.17,2.42)	(3.68,3.77)	(0.20,0.20)	(0.60,0.60)
Scenario 3	100	5.347	3.575	0.205	0.616
		(0.02,21.70)	(2.81,4.10)	(0.19,0.23)	(0.57,0.69)
	500	2.601	3.694	0.201	0.604
		(10.69,4.78)	(3.51,3.90)	(0.20,0.21)	(0.59,0.62)
	1,000	2.286	3.707	0.201	0.602
		(1.08,3.71)	(3.57,3.85)	(0.20,0.20)	(0.59,0.61)
	10,000	2.032	3.723	0.200	0.600
		(1.61,2.46)	(3.68,3.72)	(0.20,0.20)	(0.60,0.60)
Scenario 4	100	5.900	3.601	0.204	0.613
		(-1.34,23.59)	(3.03,4.09)	(0.19,0.22)	(0.58,0.66)
	500	2.733	3.699	0.501	0.603
		(0.23,5.66)	(3.52,3.88)	(0.20,0.21)	(0.59,0.62)
	1,000	2.331	3.715	0.200	0.601
		(0.62,4.29)	(3.59,3.84)	(0.20,0.20)	(0.59,0.61)
	10,000	2.037	3.723	0.200	0.600
		(1.58,2.55)	(3.69,3.77)	(0.20,0.20)	(0.60,0.60)

Note: The table reports the median and the 2.5% and 97.5% quantiles (within parentheses) for sample sizes of 100, 500, 1,000, and 10,000, respectively. True values of the parameters are $\gamma_1 = 2$, $\alpha_0 = 3.8$, $\alpha_A = 0.2$, $\alpha_B = 0.6$.

Table 2 presents the results from estimations using the unified model proposed in this article. The results show that, in all scenarios and sample sizes, the 95% confidence intervals for the risk preference parameter cover the true value, and the parameter could be accurately estimated in large samples. The estimation performances are significantly improved, especially in the first two scenarios where numbers of corner solutions are large. In scenario 1 where corner solutions account for 45% of the total observations, the new model fully corrects the bias due to nonoptimal behaviors and achieves a narrow 95% confidence interval (1.71, 2.36) in the large sample. Compared to the accurate estimate, the uncorrected model produces an estimate of 4.243 in the large sample (table 1), two times higher than the true value. Notice that other scenarios in table 2 have slightly lower performances in terms of convergence speed and 95% confidence intervals. This is likely due to the increasing values of the budget constraint multiplier $\left(W_{0,n} - \boldsymbol{r}'\boldsymbol{x}\right)$. The increasing initial wealth in these scenarios increases the variances of the moment conditions estimated. However, the impact is minimal and the estimators are consistent and unbiased. Estimation efficiency could be further improved by first estimating risk separately using a seminonparametric approach (Wu and Guan, 2014).

The technology parameters can be estimated with very high performances. The slope parameters converge quickly to the true value with no exceptions in all scenarios. The estimations are highly efficient. The intercept α_0 is slightly biased downward, which was actually expected. The bias results from the logarithmic transformation of the error term $\tilde{e}_y$ of the Cobb-Douglas function. The bias due to the logarithmic transformation could be analytically calculated using moment generating functions. The corrected α_0 converges to the true value 3.8.

Conclusions

Agents often face constraints when making economic decisions. As a result, non-optimal economic behavior may result. Non-optimal behavior could exist for various reasons, and is commonly observed in real farm production. Not accounting for the presence of non-optimal behavior in economic analysis could produce biased results. In this article, we relaxed the assumption of optimal behavior in economic decisions and developed a general, unified model for estimating agents' risk preferences, accommodating both optimal and non-optimal behaviors due to budget constraints. We conducted Monte Carlo simulations to evaluate the performance of the proposed approach and compared the results with those using the conventional approach that does not account for the systematic deviation from optimality. The new approach yielded consistent and unbiased risk preference estimates under both binding and nonbinding scenarios, whereas the conventional approach produced biased results when binding constraints cause non-optimal behavior. The biases were successfully corrected using the unified modeling framework proposed in this study.

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