

Applied Sabbatical: A Discussion of Crop Insurance: Lecture IX

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Reading Question

- Derive the general form of the normal from the standard normal distribution

$$f(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right). \quad (1)$$

- 1 State Dependent Production Function
- 2 Consequences of Crop Insurance
- 3 The Actual Crop Insurance Contract

State Dependent Production Functions

- As a starting point, we must consider how randomness is “built into” most production function estimations. As I will discuss in Production Economics, this typically involves an error of convenience. For example, modeling production using a Cobb-Douglas production

$$f(x_1, x_2) = Ax_1^\alpha x_2^\beta \quad (2)$$

- The typical approach is to estimate this by taking the logarithms of both sides

$$\ln(y) = \ln(A) + \alpha \ln(x_1) + \beta \ln(x_2) + \epsilon. \quad (3)$$

A basic question is what do we assume about ϵ ? We can make several assumptions that make estimation easier – we can assume that $\epsilon \sim N[0, \sigma^2]$.

- Another approach is model production as state-dependent following the general derivation of Chambers. and Quiggin (2000).
- As a simplified version of this concept, assume that production is a function of two “inputs” – $f(x, \omega)$.

$$\begin{aligned}
 f(x, \omega) &= f(x_0, \omega) + \left. \frac{\partial f(x, \omega)}{\partial x} \right|_{x=x_0} (x - x_0) + \\
 &\quad \left. \frac{\partial^2 f(x, \omega)}{\partial x^2} \right|_{x=x_0} (x - x_0)^2 + \epsilon(x, \omega) \\
 &= a(\omega) + b(\omega)x + c(\omega)x^2 \\
 a(\omega) &= f(x_0, \omega) - \left. \frac{\partial f(x, \omega)}{\partial x} \right|_{x=x_0} x_0 + \frac{1}{2} \left. \frac{\partial^2 f(x, \omega)}{\partial x^2} \right|_{x=x_0} x_0^2 \quad (4) \\
 b(\omega) &= \left. \frac{\partial f(x, \omega)}{\partial x} \right|_{x=x_0} - \left. \frac{\partial^2 f(x, \omega)}{\partial x^2} \right|_{x=x_0} x_0 \\
 c(\omega) &= \frac{1}{2} \left. \frac{\partial^2 f(x, \omega)}{\partial x^2} \right|_{x=x_0}
 \end{aligned}$$

- Next, if we restrict the random variable to a Bernoulli distribution $a(\omega) \rightarrow \{a(\omega_1), a(\omega_2)\}$,
 $b(\omega) \rightarrow \{b(\omega_1), b(\omega_2)\}$, $c(\omega) \rightarrow \{c(\omega_1), c(\omega_2)\}$,
 $P[\omega_1] = \theta$, and $P[\omega_2] = 1 - \theta$, we derive a stochastic (state-dependent) production function for two specific outcomes

$$f(x, \omega) = \begin{cases} a(\omega_1) + b(\omega_1)x + c(\omega_1)x^2 \\ a(\omega_2) + b(\omega_2)x + c(\omega_2)x^2 \end{cases} \quad (5)$$

- For those in Research Methodology, remember the production function from Bareille and Chakir

$$y_{i,j,t} = \alpha_j (w_{i,t}) - \frac{1}{2} \sum_{k=1}^2 \sum_{l=1}^2 \gamma_{j,k,l} (w_{i,t}) [\beta_{j,k} (w_{i,t}) - x_{i,j,k,t}] [\beta_{j,l} (w_{i,t}) - x_{i,j,l,t}] \quad (6)$$

- In a two-input model

$$g(x_1, x_2, \omega) = a_0(\omega) + \begin{bmatrix} a_1(\omega) \\ a_2(\omega) \end{bmatrix}' \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}' \begin{bmatrix} A_{11}(\omega) & A_{12}(\omega) \\ A_{12}(\omega) & A_{22}(\omega) \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad (7)$$

- Suppose that the choice of x_2 (fertilizer) (i.e., $x_2 = \tilde{x}_2$) is fixed, the production function would then be written as

$$\begin{aligned}
 g(x_1, \tilde{x}_2, \omega) &= \left[a_0(\omega) + a_2(\omega) \tilde{x}_2 + \frac{1}{2} A_{22}(\omega) \tilde{x}_2^2 \right] + \\
 &\quad a_1(\omega) x_1 + \frac{1}{2} A_{11}(\omega) x_1^2 + A_{12}(\omega) x_1 \tilde{x}_2 \\
 &= (a_1(\omega) + A_{12}(\omega) \tilde{x}_2) x_1 + A_{11}(\omega) x_1^2 + \epsilon(\omega) \\
 \epsilon(\omega) &= a_0(\omega) + a_2(\omega) \tilde{x}_2 + \frac{1}{2} A_{22}(\omega) \tilde{x}_2^2
 \end{aligned} \tag{8}$$

- I will solve for an approximation of the production function using the profit maximization conditions under certainty. Specifically, I will assume that

$$\begin{aligned}
 a(\omega) &= 0 \\
 b(\omega), c(\omega) &\Leftarrow \begin{cases} x(\omega) = \left[\frac{p_x}{p_y} - b(\omega) \right] \frac{1}{2c(\omega)} \\ y(\omega) = b(\omega)x(\omega) + c(\omega)x(\omega)^2 \end{cases} \quad (9) \\
 \exists: \omega \in \{\omega_1, \omega_2\} \quad x(\omega) &= \{x_1^*, x_2^*\}, \quad y(\omega) = \{y_1^*, y_2^*\}
 \end{aligned}$$

If we set $p_y = 3.50$, $p_x = 250$, and in state 1 $x_1^* = 55$ and $y_1^* = 125$ Equation 9 implies that $b(\omega) = 4.6097$ and $c(\omega) = -0.0407$. Similarly, if $x_2^* = 65$ in state 2 and $y_2 = 145$, Equation 5 implies that $b(\omega_1) = 4.4258$ and $c(\omega_2) = -0.0338$.

- The expected value of the production function then becomes

$$\begin{aligned} E[f(x, \omega)] &= 0.5 [4.5097x - 0.0407x^2] + \\ &\quad (1 - 0.5) [4.4258x - 0.0338x^2] \\ &= 4.4678x - 0.0372x^2 \end{aligned} \tag{10}$$

Consequences of Crop Insurance

- As a starting point, assume that the farmer simply maximizes expected profit

$$\max_x [4.4678x - 0.0372x^2] 3.50 - 0.125x \quad (11)$$

where we assume that the price of output is \$ 3.50 per bushel and the cost of fertilizer is \$ 0.125 per pound. The result is $\pi^* = 461.41$ and $x^* = 59.4904$.

- Next, we define an insurance contract

$$\phi(x, p_y) = \text{Max}(y^* - f(x), 0) p_y = \begin{cases} (y^* - f(x)) p_y, & \text{if } f(x) < y^* \\ 0 & \text{if } f(x) \geq y^* \end{cases} \quad (12)$$

where $\phi()$ defines the indemnity payment in dollars.

- If we set $y^* = 125$ and assume that the farmer still uses $x^* = 59.4904$, the yield in state 1 is 124.2422 bushels and in state 2 is 143.6708 bushels. Therefore, the insurance policy pays \$ 2.364 per acre in state 1.
- From a slightly different perspective, the farmer receives

$$R(y^*, x, p_y) = \text{Max} f(y^*, f(x)) p_y = \begin{cases} y^* p_y & \text{if } f(x) \leq y^* \\ f(x) p_y & \text{if } f(x) \geq y^* \end{cases} \quad (13)$$

where $R()$ is the revenue function.

- The revenue function can be rewritten slightly as

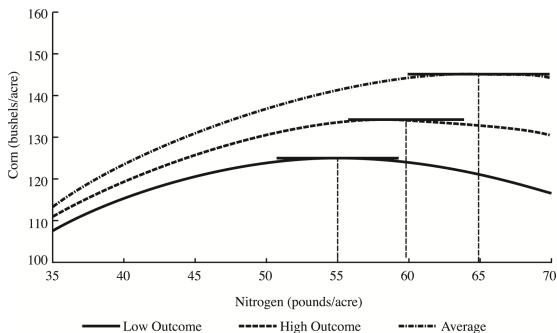
$$f(x)p_y + \phi(x, p_y) = \begin{cases} f(x)p_y + (y^* - f(x))p_y = y^*p_y & \text{if } f(x) < y^* \\ f(x)p_y + 0 & \text{if } f(x) \geq y^* \end{cases} \quad (14)$$

Based on this formulation, the firm's maximization problem becomes

$$\pi = \max_x 0.5 [\text{Max}(4.5097x - 0.0407x^2, 125) 3.50 - 0.125x] + 0.5 [\text{Max}(4.4258x - 0.0338x^2, 125) 3.50 - 0.125x] - \phi \quad (15)$$

where ϕ is the cost of the insurance policy.

- Note that even if we make the insurance policy actually sound (i.e., $0.5 \times 2.364 = 1.326$), the existence of the insurance payoff distorts the optimum level of fertilizer which becomes $x^* = 64.414$.



The Actual Crop Insurance Contract

- The implementation of the current crop insurance program is based on an expected or average level of payment.
 - To start our discussion, we will assume that the proven average yield for soybeans in Alachua county Florida is 45 bushels per acre.
 - My previous results indicate that soybean yield tend to be normally distributed Ramirez et al. (1994).
 - So let's assume that $y_S \sim N(45, 100)$. Following the notions in Equation 14, we want to set the insured level of yield.

- Under the current program, this is typically expressed as a percentage of the average yield. Also in the program, the USDA will pay 80 % of the cost of insurance for 50 % coverage. Let us begin by asking a simple question – what is the likelihood that this instrument will pay?

$$P[y_S \leq 0.50 \times 45] = \int_{-\infty}^{0.50 \times 45} f(z|\mu = 45, \sigma^2 = 100) dz = 0.0122 \quad (16)$$

so the probability that this insurance policy pays off is relatively small.

- To make this problem more interesting, let us consider a payoff trigger of 80 % which payoff with probability 0.1841.
- Given this payoff limit – what does the insurance product pay?

$$\phi = 3.50 \int_{-\infty}^{0.80 \times 45} (0.80 \times 45 - z) f(z|\mu = 45, \sigma^2 = 100) dz = 3.51464 \quad (17)$$

- Most of my research in this area has dealt with the non-normality of yield distributions. Specifically, I have been interested in deviations in the third and fourth moments of the yield distribution.
- Moss and Shonkwiler (1993) use a transformation to normality referred to as the Inverse Hyperbolic Sine Transformation

$$\epsilon = \frac{\ln \left(\theta z + \sqrt{1 + \theta^2 z^2} \right)}{\theta} \quad (18)$$
$$\nu \sim N [\delta, \sigma^2] .$$

- This transformation introduces the potential for skewness and leptokurtosis (fat tails).

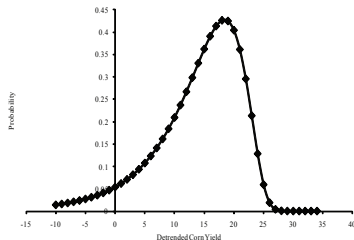


Figure: Inverse Hyperbolic Sine Distribution

References

- Chambers., R. G. and Quiggin, J. (2000). *Uncertainty, Production, Choice, and Agency*. Cambridge University Press.
- Moss, C. B. and Shonkwiler, J. (1993). Estimating yield distributions using a stochastic trend model and nonnormal errors. *American Journal of Agricultural Economics*, 75(5):1056–1062.
- Ramirez, O. A., Moss, C. B., and Boggess, W. G. (1994). Estimation and use of the inverse hyperbolic sine transformation to model nonnormal correlated random variables. *Journal of Applied Statistics*, 21:289–304.