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Human Capital, Complex Technologies, Firm size and Wages: A Test of the O-Ring Production Hypotheses

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HUMAN CAPITAL, COMPLEX TECHNOLOGIES, FIRM SIZE AND WAGES:

A TEST OF THE O-RING PRODUCTION HYPOTHESES

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Abstract

Kremer's O-Ring production theory (QJE, 1993) describes a process in which a single mistake in any one of several tasks in firm's production process can lead to catastrophic failure of the product's value. This paper tests the predictions of the O-Ring theory in the context of a single market for a relatively homogeneous product: hog production. Consistent with the theory, the most skilled workers concentrate in the largest and most technologically advanced farms and are paid more. As with observed skills, workers with the greatest endowments of unobserved skills also sort themselves into the largest and most technology intensive farms.

JEL: L11; O33; J43

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I. INTRODUCTION

Kremer's O-Ring production theory (QJE, 1993) describes a process in which a single mistake in any one of several tasks in the firm's production process can lead to catastrophic failure of the product.[1] When an error in any one task causes the entire product to fail, workers or skills in any one task become natural complements to workers or skills in the other tasks. The amount workers can earn in performing any one task will depend on the quality of the workers in the other tasks. As a result, employees will seek to work with others of similar skill, as working with lesser skilled workers risks loss of income from greater likelihood of production errors. The number of tasks in the production process can be regarded as a measure of technological complexity. Because the cost of mistakes increases in the number of tasks, workers with higher skills will be used more intensively in more complex and technologically advanced production processes. In sum, the O-ring production theory predicts that firms hiring more skilled workers will tend to be larger, more technologically complex and pay higher wages.

The O-Ring theory seems to fit recent incidences of massive recalls of agricultural commodities. E. coli tainted lettuce was recalled in 2006. Later that year, E-coli contaminated spinach sickened consumers in 25 states, and another spinach recall occurred from salmonella contamination a year later. In 2007, tainted wheat gluten used in cat food and chicken feed led to massive recalls of poultry and pet food and the curtailment of food ingredient imports from China. The slaughter of sick or crippled cattle led to the recall of 145 million pounds of beef in 2008.[2] These cases show that with agricultural production, mistakes in hygiene, diagnosis, segregation, quality control, or any number of other tasks can lead to the loss of an entire crop.

Given the importance of the O-Ring production process as a conceptual tool in economics,[3] the theory has not previously been subjected to a comprehensive test. Instead, individual predictions from the theory have been shown to be consistent with various regularities seen in data from labor or product markets. For example, several papers have found evidence supporting the complementarity between human capital and technology adoption. In agriculture, evidence takes the form of more educated farmers being the first to attempt new tillage practices, plant new varieties, or implement new technological advances.[4] In manufacturing, the complementarity has been supported by the positive correlation between average wages and information technology investments at the firm or individual levels.[5]

Another set of papers has shown that larger firms will pay higher wages than smaller firms. The size-wage premium was first documented by Henry Moore (1911), and corroborated by others, among them, Brown and Medoff (1989) and Oi and Idson(1999). Because they are complements in production, skilled workers are more productive when they work together in larger firms than when they work alone or in small firms, and so the O-Ring theory offers an explanation for the size-wage premium.

There is substantial evidence that larger firms adopt more advanced technologies (Stoneman and Kwon, 1994; Colombo and Mosconi, 1995; Idson and Oi, 1999; McBride and Key, 2003), consistent with a third of the O-Ring predictions. There are alternative explanations for the positive correlation, including that larger firms face fewer liquidity constraints to investments or that large firms are better able to diversify the risk of innovation, but the O-Ring explanation that firms are larger because more complex production processes attracts both more workers generally and more skilled workers in particular seems compelling.

None of these papers provides a comprehensive test of all the predictions of the O-Ring hypothesis in the context of a single market. The reason is that the data requirements are significant and the estimation requirements are nontrivial. We undertake such a test using three surveys of employees on hog farms in the United States conducted in 1995, 2000 and 2005. The hog market seems to be an appropriate one to test the O-Ring theory. First, a large number of hog farms compete in a relatively homogeneous product market. Though the hog market has experienced a large decline in farm numbers since 1995, there were still sixty nine thousand farms producing hogs as of 2004 (USDA, 2005), and so there is a strong presumption that the output is priced competitively.[6] Farms enter, remain in, or exit the market without considering the actions of rival farms. At the same time, technological advances have occurred rapidly, and so farms vary dramatically in the number and the variety of technologies used as well. Farms also vary in the skills of their employees, from laborers to veterinary doctors. Finally, hog farm production is subject to the sort of catastrophic failures represented by the O-Ring process: lapses in sanitation, litter segregation, feed, or swine health maintenance can lead to substantial output losses including the potential destruction of the entire herd.

Our empirical methodology allows us to test whether workers with more skills, measured by observable attributes such as education and sector specific experience or by unobserved attributes, congregate on farms that are simultaneously larger, use more complex technologies, and pay higher wages. These hypotheses cannot be rejected, providing strong support that the O-Ring production theory can characterize production on the U.S. hog farms.

II. IMPLICATION FROM THE O-RING THEORY: COMPLEMENTARITY BETWEEN TECHNOLOGY ADOPTION, FIRM SIZE AND WAGES

Kremer (1993) defines the O-Ring production function as a series of indivisible tasks. Let the number of tasks t represent the complexity of the technology employed. Each of the tasks requires the same amount of labor whose performance levels q are exogenously determined and crucial to the output level y.[7] We subdivide q into two parts: human capital we can observe, h, which includes education and work experience; and abilities the farmer can observe but we cannot, e. The worker's productivity in the i^{th} task is assumed to be the weighted sum of these two skill sets: $q_i = \alpha h_i + (1-\alpha)e_i$, $0 < \alpha < 1$.

We consider the problem faced by a competitive firm that maximizes profit by choosing the degree of technology complexity, *t*, and the task specific skill level of workers, q_i:

$$(1) \qquad \underset{t,\{q_i\}}{Max} \quad (\prod_{i=1}^{t} q_i)\, tB(t) - \sum_{i=1}^{t} w(q_i) .$$

$B(t)$ is the value of output per task with $B'(t) > 0$ and $B''(t) < 0$. Output price is normalized to be one, consistent with a market where firms are price takers, and so the variation in output per task is due entirely to firm productivity differences and not to market power over price. The first term in (1) is the firm's output level, $y = (\prod_{i=1}^{t} q_i) tB(t)$, which we will use as a measure of firm size.

An implication of the O-Ring production function is that the complementarity between tasks leads to a process of positive assortative matching among workers. The marginal product of workers in task i positively depends on the level of output of workers in any other task, as shown by $\frac{d^2 y}{dq_i d(\prod_{j \neq i} q_j)} = tB(t) > 0$. As a result, workers will have an incentive to match with others whose skills are no worse than theirs. If workers are freely mobile, all workers in a firm will end up with the same level of skill in equilibrium, and so $q_i = q_j = q, \ i, j = 1, 2, ..., t, \quad i \neq j$. These preliminaries can be shown to imply regularities that we should be able to confirm or reject in the data. We summarize these regularities in the form of three hypotheses that we then demonstrate as implications of the theory.

Hypothesis 1: The most skilled workers are employed on the largest farms, will use the most complex technologies, and will be paid the highest wages.

While all workers in a firm will be homogeneous in skill at level q, the level of skills will differ across firms of differential size and technological complexity. To show this, we simplify the firm's optimization problem in (1) as

(1) $$\underset{t,q}{Max} \quad q^t \, tB(t) - tw(q).$$

The first order conditions with respect to skills, q and tasks, t are

(2) $$tq^{t-1} B(t) - w'(q) = 0$$

(3) $$q^t \ln q \ \ tB(t) + q^t B(t) + q^t tB'(t) - w(q) = 0$$

The zero profit condition implies

(4) $$q^t\ B(t) - w(q) = 0\,.$$

Inserting condition (4) into (4) implies that

(5) $$\ln q = -\frac{B'(t)}{B(t)} \quad .$$

Equation (6) shows that technological complexity t is an implicit function of skill level q. Because $B'(t) > 0$ and $B''(t) < 0$, $\frac{\partial t}{\partial q} > 0$, and so more skilled workers will be allocated to more complex production processes.

Given that all the workers will have the same level of skill, q, the firm's production function is $y = q^t tB(t) \equiv f(q^*, t^*(q^*))$. The total derivative with respect to skill is

(7) $$\frac{\partial y}{\partial q} = f_1 + f_2 \frac{\partial t}{\partial q} = tq^{t-1}B(t) + \{q^t tB(t)\ln q + q^t B(t) + q^t tB'(t)\}\frac{\partial t}{\partial q} > 0$$

That in turn implies that $\frac{\partial y}{\partial q} > 0$ and so more skilled workers will be allocated to larger firms. Additionally, the first order condition (3) implies that $\frac{\partial w}{\partial q} > 0$, and so more skilled workers will be paid higher wages.

Hypothesis 2: Technology complexity, firm size and wages are all positively correlated.

These relationships are not causally related but represent expected bilateral correlations among the three variables. It is straightforward to show that larger firms have more complex production processes. $\frac{\partial y}{\partial t} = q^t tB(t)\ln q + q^t B(t) + q^t tB'(t) = w(q) > 0$, which follows from first order condition (3), regardless of skill levels. To show that firms using technologies more intensively will pay workers higher wages, take the natural log on both sides of the zero profit condition (4),

$$\ln w(g(t)) = t \ln q + \ln B(t) = -t\frac{B'(t)}{B(t)} + \ln B(t), \qquad (8)$$

where $q = g(t)$ and $g(t)$ is the inverse function of $t(q)$ which is increasing in t according to (5). Taking derivatives with respect to w on (8), we obtain

$$\frac{\partial w}{\partial t} = w\left(-t\frac{B''}{B} + \left(\frac{B'}{B}\right)^2\right) > 0 .$$

In order to show $\frac{\partial y}{\partial w} > 0$, define an inverse function v: $q = v(w)$, evaluated where profit is maximized. $v(w)$ is increasing in w. The zero profit condition can be rewritten as $y(v(w), t(v(w))) = t(v(w))w$. Taking derivatives on both sides of this equation with respect to w,

$\frac{\partial y}{\partial w} = \frac{\partial y}{\partial v}\frac{\partial v}{\partial w} + \frac{\partial y}{\partial t}\frac{\partial t}{\partial v}\frac{\partial v}{\partial w} = t + w\frac{\partial t}{\partial v}\frac{\partial v}{\partial w} > 0$. Larger firms pay workers higher wages.

Hypothesis 3: At least two and perhaps all three of the distributions of technological complexity, firm size and wages will be similar, given the distribution of worker skills.

The size distribution of hog farms is heavily skewed to the right with a few very large firms and many small firms, given the symmetric distribution of worker skills. However, $y = tw(q)$ implies that the distribution of y is linearly related to the distributions of t and w. We would therefore expect that at least one and possibly both of the distributions of technological complexity and of wages would be similarly skewed to the right. Specifically, holding technology usage constant, output is homogeneous of degree t in q. As long as t is greater than one, output y and wage w will be convex in q. Whenever skills of worker are distributed symmetrically or skewed to the right, output y and w will also be skewed to the right. However, whether the distribution of technological complexity is also right skewed relative to the distribution of worker skills q is conditional on the functional form of B[8].

III. DATA

We test these hypotheses using survey data from employees on U.S. hog farms in 1995, 2000, and 2005 collected from a random sample of subscribers to *National Hog Farmer Magazine*. Because the subscribers are not a representative sample of all hog farm employees and because the propensity to respond to surveys may also differ by farm size, the survey data are weighted to conform to the size distribution of employees on U.S. hog farms as reported in the Agricultural Census Data (ACD) of the US Department of Agricultural (USDA). [9]

Distribution of Technology Complexity, Farm Size and Wages

Larger farms tend to adopt technologies more heavily and pay their workers higher wages. As can be seen in Table I, there were eight technologies included on the surveys that were available to hog farmers between 1995 and 2005. Two new technologies Auto Sorting System (AS) and Parity Based Management (PBM) were only included in the 2005 questionnaire, and so we constrain the available technology set to the first eight options. Of those eight, the average number of adopted technologies used on hog farms increased from 3.2 in 1995 to 4.2 in 2005. Over that same time frame, the distribution of employees has shifted toward farms using more technologies. Figure I shows the distribution of employment in farms by number of adopted technologies. The distribution is right skewed with more than half of hog farm employees working for farms using no more than four technologies.

The employment share by farm size category is presented in Table II. The size categories varied across surveys, reflecting shifts in market share away from the smallest farms toward much larger operations (McBride and Key, 2003). The smallest farm size category was fewer than 500 pigs in the 1995 and 2000 surveys and less than 1,000 pigs in 2005. The largest farm was defined as producing more than 25,000 pigs in 1995 and 2000 and producing 50,000 or more in 2005. The distribution of employment across farm sizes is shown in Figure II. The distribution is skewed to the right, similar to the distribution of technology usage except that there is a mass in the upper tail. Furthermore, larger farms tend to adopt more technologies as shown in the last column of Table II. The smallest farms use an average of three technologies while the largest farms use an average of 5.6.

Average annual salary categories range from less than $10,000 to more than $50,000, as shown in Table III. The distribution of employees earning different levels of salaries is shown in Figure III. The distribution is also right skewed and has similar distributional statistics with those of the farm size distribution. Moreover, Table III shows an apparent positive relationship between salary level and either farms size or technology complexity. For example, employees who earn less than $15,000 work on farms using less than three technologies and producing less than 2,000 pigs annually.

Employees paid more than $30,000 per year work on farms using at least four technologies and producing more than 3,000 pigs annually.

Table IV summarizes the other variables included in our analysis. Only 8.8% of hog farm employees are *Female*. *Education* is measured by years of schooling completed. The average worker has completed at least a junior college program. Work experience is indicated by three measures. *Tenure* and *PrevExp* indicate the working time on the current farm and previous experience on other hog farms respectively. Average tenure is nearly nine years with 41 percent of employees having had prior hog farm work experience. *Raise* indicates being raised on a hog farm. Over half the workers were raised on a hog farm. Farm location is categorized by four regions: Midwest, Northeast, Southeast and West[10]. These are captured by three dummy variables with the base being the Midwest region where 63 percent of employees are found.

Among these characteristics, education level of workers is positively related with the technology complexity, farm size and wages. Figure IV clearly shows that the distributions of wages, technology adoptions, and farm sizes by worker education level are all skewed to the right. Workers with a bachelor's degree are more likely to work on larger and more technologically advanced farms and are paid more than those who did not complete high school. Though there is no satisfied statistics to show the matching of similar workers skills, Figure IV graphically shows that workers skills tend to be matched to farms with different sizes and technology complexity, otherwise, the worker skills should not be biased toward large farms and technologically advanced farms.

IV. ECONOMETRIC TESTING OF THE O-RING PRODUCTION FUNCTION

In this section, we propose an estimable model which involves the simultaneous choices of technological complexity, farm size and wages, given the human capital attributes of the workers and other observed characteristics on the farm. In another context, Abowd, Kramarz and Margolis (1999) found that individual heterogeneity explains a large proportion of the wage variation between different firm size categories. Consequently, a test of the mutual complementarity among workers, as the O-Ring production theory predicts, requires that the three choices be simultaneously determined given heterogeneity of both observed and unobserved worker skills.

An Empirical Model to Test O-Ring Hypotheses

We consider three latent dependent variables: t_i^* is the number of technologies used by the farm employing individual i; s_i^* is the size of individual i's farm; and w_i^* is the salary paid to individual i. We posit that the joint choices of t_i^*, s_i^* and w_i^* take the form

$$
\begin{aligned}
t_i^* &= x_i\beta_t - u_{ti} \\
s_i^* &= x_i\beta_s - u_{si} \\
w_i^* &= x_i\beta_w - u_{si}
\end{aligned}
$$

$$
\begin{pmatrix} u_{ti} \\ u_{si} \\ u_{wi} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1+\lambda_t^2\sigma^2 & \lambda_t\lambda_s\sigma^2 & \lambda_t\lambda_w\sigma^2 \\ \lambda_t\lambda_s\sigma^2 & 1+\lambda_s^2\sigma^2 & \lambda_w\lambda_s\sigma^2 \\ \lambda_t\lambda_w\sigma^2 & \lambda_w\lambda_s\sigma^2 & 1+\lambda_w^2\sigma^2 \end{pmatrix} \right). \tag{9}
$$

where x_i is a vector of person attributes and farm characteristics specified in Table IV with coefficient vectors β_t, β_s, and β_w to be estimated in technology adoption, farm size and wage rate equations respectively. The random disturbance terms of the form

$u_{ji} = \lambda_j e_i + \mu_{ji}$, $j = t, s, w$ are composed of two parts: the unobserved ability component of skill, $e_i \sim N(0, \sigma^2)$, and a pure random factor μ_{ji} that varies across choices and is assumed to be an independent draw from a standard normal distribution. The observed worker skills h_i are included in the vector x_i. *Hypothesis 1* can be tested based on the signs of the parameters attached to observable skills. A finding of positive signs in all of the equations can be viewed as evidence that productive skills (i.e. skills that raise wages) are complementary with both farm size and technology.

The signs and magnitudes of the parameters λ_t, λ_s and λ_w will show how and to what extent the unmeasured talents of workers affect the technological intensity, farm size and wages on their farms respectively. Assuming that these unobserved abilities are productive, they should positively influence all three dependent variables, and so they should be positively inter-correlated. The correlation coefficient between any two random errors out of the three equations is

$$\text{(10)} \qquad \rho_{kl} = \frac{\lambda_k \lambda_l \sigma^2}{\sqrt{1+\lambda_k^2\sigma^2}\sqrt{1+\lambda_l^2\sigma^2}}, \quad k, l = t, s, w, k \neq l .$$

A finding that $\rho_{ts} > 0$, $\rho_{sw} > 0$, and $\rho_{tw} > 0$ is consistent with *Hypothesis 2* that unobserved skill positively affects the number of technologies adopted, the size of farm and the wage level paid to workers after controlling the observed characteristics. The implied variance covariance matrix of the error term in equation (9) will reflect the underlying correlation between the unobserved λ_t, λ_s and λ_w.

Estimation

Our measures of technical complexity, farm size and wages are categorical. For example, the latent continuous variable t_i^* is not directly observable, but the number of technologies used on the farm is observed as a discrete category, t_i. We define it as:

$$
\begin{aligned}
(11) \qquad t_i &= 0 \quad if \quad t_i^* < a_0 \\
&= 1 \quad if \quad a_0 \le t_i^* < a_1 \\
&\cdots \\
&= 8 \quad if \quad a_7 \le t_i^* \quad , a_c > a_{c-1}, \forall c = \{1,2,...,7\}
\end{aligned}
$$

The a_c are unknown cut-points parameters to be estimated. The unconditional probability that individual *i* works on a farm adopting *k* technologies is

$$
\begin{aligned}
(12) \qquad & \Pr(t_i = k) = \Phi\left(\frac{x_i\beta_t - a_{k-1}}{\sqrt{1+\lambda_t^2\sigma^2}}\right) - \Phi\left(\frac{x_i\beta_t - a_k}{\sqrt{1+\lambda_t^2\sigma^2}}\right), \\
& \forall k = \{0, 1, 2, ..., 8\}, \quad a_{-1} = -\infty, \quad a_8 = +\infty,
\end{aligned}
$$

$\Phi(\cdot)$ denotes the cumulative density function of the standard normal distribution.

Farm size and wages are also divided into categories from zero to eight. The corresponding probability for farm size and wages in a specific category can be written according to (12). The joint estimation can be treated as a trivariate ordered probit model based on equations (9) to (12). The log likelihood function is

$$LL = \prod_{i=1}^{n} \omega_i \ln \Pr(t_i = k, s_i = m, w_i = l), \quad k = 0, 1, ..., 8, m = 0, 1, ..., 8, l = 0, 1, ..., 8$$

where

$$
\begin{aligned}
&\Pr(t_i = k, s_i = m, w_i = l) \\
&= \Pr(a_{k-1} \le t_i < a_k, a_{m-1} \le s_i < a_m, a_{l-1} \le w_i < a_l\ ) \\
&= \Pr(t_i < a_k, s_i < a_m, w_i < a_l) \\
&- \Pr(t_i < a_{k-1}, s_i < a_m, w_i < a_l) \\
&- \Pr(t_i < a_k, s_i < a_{m-1}, w_i < a_l) \\
&- \Pr(t_i < a_k, s_i < a_m, w_i < a_{l-1}) \\
&+ \Pr(t_i < a_{k-1}, s_i < a_{m-1}, w_i < a_l) \\
&+ \Pr(t_i < a_{k-1}, s_i < a_m, w_i < a_{l-1}) \\
&+ \Pr(t_i < a_k, s_i < a_{m-1}, w_i < a_{l-1}) \\
&- \Pr(t_i < a_{k-1}, s_i < a_{m-1}, w_i < a_{l-1}) \\
&k = 0, 1, ..., 8,\ \ m = 0, 1, ..., 8,\ \ l = 0, 1, ..., 8.
\end{aligned} \tag{13}
$$

and $\Pr(t_i = k, s_i = m, w_i = l)$ is the cumulative density function evaluated at an individual worker i's realizations of x_i, who is employed on a hog farm using k technologies and producing in size category m and is paid at the wage level l. ω_i is the sampling weight assigned to individual i. When the normal distribution is assumed, the corresponding probability density function is

$$
\begin{aligned}
&f_Y(k, m, l) = \frac{1}{(2\pi)^{2/n}\sqrt{\det \Sigma}}\, e^{-\frac{1}{2}(Y-\bar{y})^T \Sigma^{-1}(Y-\bar{y})}, \\
&Y = (t_i^*, s_i^*, w_i^*)^T, \\
&\bar{y} = (x\beta_t, x\beta_s, x\beta_w)^T, \\
&\Sigma = \begin{pmatrix} 1+\lambda_t^2\sigma^2 & \lambda_t\lambda_s\sigma^2 & \lambda_t\lambda_w\sigma^2 \\ \lambda_t\lambda_s\sigma^2 & 1+\lambda_s^2\sigma^2 & \lambda_w\lambda_s\sigma^2 \\ \lambda_t\lambda_w\sigma^2 & \lambda_w\lambda_s\sigma^2 & 1+\lambda_w^2\sigma^2 \end{pmatrix}
\end{aligned} \tag{14}
$$

Y is the vector of latent dependent variables representing technological complexity, farm size and wages. $\bar{y}$ is the corresponding mean vector of Y. T denotes the transpose of the matrix. Σ is the variance – covariance matrix of Y defined by equation (9). We use the

Generalized Linear Latent and Mixed Models (GLLAMM) procedure in STATA 9.1 to estimate the model[11].

Some Issues in Estimation

Several additional assumptions are necessary to make the estimation tractable. First, λ_t is normalized to be one in order to identify the model. The remaining parameters $\beta_t, \beta_s, \beta_w, \sigma^2, a_c, \lambda_s$ and $\lambda_w, c = 0, 1, ..., 7$ are estimated subject to that normalization.

The GLLAMM procedure is flexible in estimating models with multivariate categorical dependent variables, but the time required for convergence increases rapidly with the complexity of the model (Grilli and Rampichini, 2003). In practice, we found that the model had convergence problems when we tried to allow all 24 separate cut points across the 3 equations. Conceptually, the distributions of the three dependent variables should be similar, and Figures 1-3 indicate that the observed distributions are indeed similar. Therefore, we imposed the simplification that the threshold parameters were the same across the technology adoption, farm size and earnings equations. We added some additional flexibility by allowing different variances across three equations while assuming that the errors are jointly normally distributed.

Because this assumption could potentially influence our hypothesis tests, we tried alternative specifications that allowed alternative thresholds across equations. We obtained similar qualitative results when we transformed the estimating equations into a trivariate probit with less informative dependent variables: More (>5) versus Fewer technologies; Larger (>10,000 head) versus Smaller farms; and Higher (>$34,999) versus

Lower pay. The results shown in Table B.1 are broadly consistent with the one we report from out trivariate ordered probit.[12] We also tested the model assuming a trivariate extreme value distribution that has a relatively heavy tailed distribution. The estimated results are very consistent with those obtained under our specification.

Farms specializing in farrow-to-feeder or feeder-to-finish operations would be expected to have fewer technology options than would farms that take pigs all the way from farrow to finish pigs. This is not a major issue if farms make the choice of type of operation contemporaneously with the choice of technology mix. Nevertheless, it is plausible that type of farm operation is correlated with the unobservable employee attributes that also affect farm size or wages. We replicated our analysis of model (9) using a restricted sample that included only farrow-to-finish farms. The results of the trivariate ordered probit and trivariate probit specifications are shown in Tables B.2 and B.3 in the Appendix. Again, qualitative results and conclusions are consistent with those obtained with the full sample, and so our results are not driven by type of operation.

V. EMPIRICAL FINDINGS

Coefficient estimates from the trivariate ordered probit are shown in Table V. We first assess whether the results are consistent with *Hypothesis 1* that human capital will simultaneously raise technical complexity, firm size and wages. Coefficients on observed years of schooling are positive in all three equations, indicating that schooling raises wages, farm size and the number of technologies used on farms. A similar result holds for prior experience on hog farms—more sector-specific experience increases all three dependent variables. Our other two human capital measures perform in ways generally consistent with the theoretical proposition that skills should raise all three dependent variables but with some notable exceptions. Tenure on the current farm significantly raises farm size but has no significant impact on the other two dependent variables. Having been raised on a farm increases farm size and technical complexity, but it lowers wages. It is possible that farm raised workers have another source of returns on the farm, namely that they are atypically working on a farm of a parent or relatives in anticipation of eventually taking over the operation. In fact, farm-raised workers are more likely to say that they plan to have their own operations in the future.

As with observed measures of human capital, unobserved human capital also positively influences all three dependent variables. The estimated variance of unobserved individual ability σ^2 is statistically significant. With λ_t restricted to be one, the finding that λ_s and λ_w are both positive and significant means that unmeasured individual abilities affect the technology adoption, farm size and wage rates in the same direction. The largest impact is on farm size ($\lambda_s = 1.92$), more than twice the size of the effects on technological intensity ($\lambda_t = 1$) and the wage rate ($\lambda_w = 0.96$). That implies that holding worker skills fixed, there is a greater dispersion of farm sizes than of technologies or wages, consistent with the patterns in Figures I-III.

Taken together, the evidence on both observed and unobserved skills are broadly supportive of *Hypothesis 1.* Both observed and unobserved measures of human capital simultaneously increase wages, technologies and farm size.

Hypothesis 2 is concerned with the correlations among the three dependent variables. The O-Ring theory predicts that more skilled workers will congregate in more technologically complex firms and larger firms and evidence that they will be rewarded with higher wages. The implied pair-wise correlation coefficients among the errors in the technology adoption, farm size and wage rate equations computed using equation (10) are reported at the bottom of Table V. The standard errors are calculated using the delta method. All three correlations are positive and statistically significant, consistent with *Hypothesis 2.*

There are two other interesting results. First, women are paid less than observationally equivalent men. However, women are also significantly less likely to work in the larger and more technologically complex operations that also pay more. Second, hog farms have become larger and increasingly more technology intensive since 1995, coincident with the large increases in real earnings paid in the pork sector over the last ten years. In O-Ring terms, women are less likely to be found on the operations that are atypically productive due to the complementarities between skills, size and technologies, operations that have become increasingly more important in market share over time.

VI. Conclusion and Discussion

Kremer's (1993) O-Ring production theory describes a process in which a single mistake in any one of several tasks in the firm's production process can lead to catastrophic failure of the product's value. The theory implies that that there is a natural complementarity between worker skills and the size and complexity of the production process. Workers of like skill are sorted into individual firms with the more skilled labor allocated to larger and higher paying firms with more complex production processes. These hypotheses are tested and confirmed in the context of farm production of hogs in the United States from 1995 to 2005. We find evidence that technology adoption and farm size are complements with both observed and unobservable components of worker human capital and evidence that workers on larger and more technologically advanced farms are paid more than otherwise comparably skilled workers on smaller and less technology intensive farms.

A recent study by Iranzo, Schivardi and Tosetti (2008), using a matched employer-employee data set from the Italian manufacturing sector, found that dispersion of worker skills within occupational groups is positively related to firm productivity. Because the O-Ring theory predicts that workers of like skills should sort together within a firm, their finding is at odds with the O-ring hypothesis. We cannot replicate their tests with our data because we cannot match employees to firms. On the other hand, they did not test the O-ring predictions we focus on: that the most skilled workers went to the largest firms with the most complex technologies and the highest pay.

While there is no reason to suspect that the O-Ring production process will be appropriate for all industries, there are important differences between our setting and theirs that are worth emphasizing. First, whereas hog farms are dedicated to a single product, manufacturing firms are more likely to have multiple product lines. Second, variation in output across manufacturing firms will reflect differential market power as well as differential productivity, and that market power may be correlated with variation in worker skills within firms. Third, manufacturing firms produce very different products with different production processes and different labor productivities. Finally, the O-Ring specification allows firms with multiple production stages to use workers of different skills in different stages even if they do not use the same skills in a given stage.

It is possible that the Iranzo et al finding of a positive correlation between within firm skill variation and output across the Italian manufacturing firms is actually due to differences across firms in the number of product lines, market power, product attributes or stages of production that are also correlated with the variation in worker skills within firms. A definitive test in their context would be to examine the relationship between within firm skill variation and productivity using firms producing the same manufactured product.

In our setting, we found evidence supporting the other O-ring predictions: that the most skilled workers went to the largest firms with the most complex technologies and the highest pay. It may be that these predictions hold in other settings such as agricultural sector or a manufacturing subsector, even if the sorting by skill proves inconsistent with the data.

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ENDNOTE

[1] The name recalls how a failed O-ring led to the destruction of the Space Shuttle Challenger.

[2] USDA food recalls are reported at http://www.usrecallnews.com/section/recalled-food.

[3] As of February 19, 2008, there are 483 citations to the original paper on Google Scholar.

[4] See Griliches, 1957; Wozniak, 1987, 1993; Huffman and Mercier, 1991; Dorfman, 1996; Foster and Rosenzweig, 1995; Khanna, *et al*, 1999; and Abdulai and Huffman, 2005. Huffman (1999) presented a comprehensive review.

[5] Examples include Krueger, 1993; Reily, 1995; Caselli and Coleman II, 2001 and Dunne, *et al*, 2004. Acemoglu (2002) reviews the literature.

[6] Forward and futures markets help even isolated producers to expand the pool of buyers, reach new markets and expand sales opportunities where buyers bid against each other for hogs, equipment and materials. This financial channel makes the hog market more competitive because sellers need not have fixed buyers in order to market their hogs.

[7] According to Kremer, $q \in (0,1)$ represents the expected percentage of maximum value the product retains if the worker performs the task.

[8] The sufficient conditions are specifically derived in the appendix. In the appendix, two simulation examples show the predicted distributions.

[9] Consistent with the USDA classifications, each employee in our survey is placed into one of eight regions and one of the three farm size categories. The number of employees who have either full time or part time jobs on hog farms is taken as the population

universe. The weights are computed as follows: there are N employees in total in the US and n_j of them in region-size cell j. The proportion of employees on hog farms which have region and size attributes in the j^{th} cell is then $\frac{n_j}{N}$. The comparable number of employees in the same region-size cell j in our sample is s_j. Each worker in the sample is then assigned a probability weight $\frac{n_j}{s_j}$. The USDA cells originally included eighteen regions and four size classifications. However, some of the region-size cells contained only a small number of sampled employees, and so we aggregated some of the region-size cells. Our eight regions are categorized as follows: 1. IL 2. IN 3. IA 4. MN 5. MO, TX, OK and AR 6. OH, WI and MI 7. NE 8 all other states. Farm size was divided into three levels in 1995, small: less than 3,000 pigs per year; medium: 3,000 to 9,999 pigs per year; and large: more than 10,000 pigs per year. For the 2000 and 2005 year surveys, farm size is divided into two levels, small: less than 10,000 pigs per year; and large: more than 10,000 pigs per year. Weights based on the 1992 Census were used for the 1995 survey responses, and the 1997 Census was used to weight the 2000 and 2005 survey responses.

[10] States included in the mid-west: IA, IL, IN, MN, MO, ND, NE, OH, SD, WI; in the northeast: CT,DC, DE, MA, MD, ME, MI, NH, NJ, NY, PA, RI, VT; in southeast: AL,FL, GA, KY, LA, MS, NC, SC, TN, VA, WV; and in the west: AK, AR, AZ, CA,CO, HI, ID, KS, MT, NM, NV, OK, OR, TX, UT, WA, WY.

[11] The method uses the Newton–Raphson method and adaptive quadrature to approximate the likelihood function by numerical integration (Rabe-Hesketh *et al*. 2004). Sample

weights are assigned to each individual employee to obtain the robust standard errors (Rabe-Hesketh *et al*. 2006).

[12] The only substantive difference is that employee schooling is positively related to wages and number of technologies but is not significantly correlated with farm size. Schooling has a positive and significant effect in all three equations in the ordered probit specification.

TABLE I

FRACTION OF EMPLOYEES ON HOG FARMS USING VARIOUS TECHNOLOGIES

Number	Name	Notation	1995		2000		2005	
			Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
1	Artificial Insemination	AI	0.41	0.49	0.61	0.49	0.69	0.46
2	Split Sex Feeding	SSF	0.32	0.47	0.45	0.50	0.35	0.48
3	Phase Feeding	PF	0.48	0.50	0.54	0.50	0.49	0.50
4	Multiple Site Production	MSP	0.22	0.41	0.33	0.47	0.29	0.45
5	Early Weaning	EW	0.09	0.29	0.22	0.42	0.23	0.42
6	All in / All out	AIAO	0.57	0.50	0.64	0.48	0.57	0.50
7	Formal Management	FM	0.48	0.50	0.58	0.49	0.69	0.46
8	Computer Usage	CU	0.59	0.49	0.69	0.46	0.72	0.45
9	Auto Sorting Systems	AS	.	.	.	.	0.03	0.16
10	Parity Based Management	PBM	.	.	.	.	0.19	0.39
-	Total Number of Technologies	-	3.21	1.84	4.07	1.98	4.21	2.03

Note: Statistics are weighted. "." represents that the category is not asked in the survey. The estimates of the adoption rates of individual technologies are weighted using sampling weights.

TABLE II

SIZE CLASS AND FREQUENCIES

Code	Size Class (number of pigs producer in 1995 and 2000)	Size Class (number of pigs producer in 2005)	Average Number of Used Technologies
0	Less than 500	less than 1000	2.99
1	500 to 999	1,000 to 1,999	3.04
2	1,000 to 1,999	2,000 to 2,999	2.81
3	2,000 to 2,999	3,000 to 4,999	3.52
4	3,000 to 4,999	5,000 to 9,999	4.04
5	5,000 to 9,999	10,000 to 14,999	3.78
6	10,000 to 14,999	15,000 to 24,999	4.83
7	15,000 to 24,999	25,000 to 49,999	4.72
8	25,000 or more	50,000 or more	5.55

Note: The estimates of technology complexity are weighted using sampling weights.

TABLE III

POSITIVE RELATIONSHIPS BETWEEN FIRM SIZE, TECHNOLOGY COMPLEXITY AND WAGES

		Farm Size		Technology Complexity	
Code	Wage Level	Mean	Std dev	Mean	Std dev
0	$10,000 Or Less	2.39	1.79	2.51	1.52
1	$10,000 To $15,000	2.78	1.63	2.97	1.72
2	$15,000 To $20,000	3.21	1.68	2.94	1.68
3	$20,000 To $25,000	3.67	2.01	3.64	1.85
4	$25,000 To $30,000	4.15	2.27	4.16	1.87
5	$30,000 To $35,000	4.37	2.59	4.21	1.98
6	$35,000 To $40,000	4.55	2.53	4.73	1.86
7	$40,000 To $50,000	4.00	2.96	4.78	2.09
8	$50,000 Or more	3.60	3.03	5.28	1.98

Note: The estimates of farm size and technology complexity are weighted using sampling weights.

TABLE IV

CHARACTERISTICS OF EMPLOYEES IN THE U.S. HOG INDUSTRY, 1995-2005

Variables	Description	Mean	Std Dev
Technology	Number of technologies used	2.54	1.65
Size	Farm size category	3.61	2.30
Wage	Salary range	3.12	2.21
Female	Gender of workers, equal to 1 if the worker is a female	0.09	0.28
Education	Years of schooling	14.16	2.81
Tenure	Working experience in the current farm	8.94	8.18
PrevExp	Dummy variable, equal to 1 if previously working in a hog farm	0.41	0.49
Raise	Dummy variable, equal to 1 if raised in a hog farm	0.53	0.50
Northeast	Dummy variable, equal to 1 if located in the northeast	0.09	0.28
Southeast	Dummy variable, equal to 1 if located in the southeast	0.14	0.35
West	Dummy variable, equal to 1 if located in the west	0.14	0.35

Note: The numbers are the weighted mean and the standard deviation. The statistics of the variables are weighted and are based on the surveys in 1995, 2000 and 2005. The education level reflected in the survey is categorical. The continuous schooling years (SY) of a worker is defined in the following way. SY = 9 if she is a high school drop out. SY = 12 if she is a high school graduate. SY = 14 if she attended the four year college but did not complete or had other equivalent diploma, such as completing vocational technical /school program or junior college program. SY = 16 if she is has a bachelor’s degree. SY = 19 if she has master degree. SY = 23 if she is a Ph.D. degree holder or a Doctor of Veterinary Medicine.

TABLE V

WEIGHTED TRI-VARIATE ORDERED PROBIT MODEL RESULTS

	Technology		Farm Size		Wage	
Variables	β_t	t-value	β_s	t-value	β_w	t-value
(a) Regression parameters						
Female	-0.355	-3.13**	-0.214	-1.18	-0.476	-3.37**
Education	0.111	7.19**	0.057	3.46**	0.099	5.64**
Tenure	-0.012	-1.06	0.035	2.05*	0.011	0.76
Tenure^2	-0.0003	-0.75	-0.002	-3.34**	-0.0003	-0.60
PrevExp	0.274	3.72**	0.456	4.46**	0.393	4.26**
Raise	0.078	1.06	0.276	2.92**	-0.356	-4.02**
Northeast	-0.047	-0.38	-0.123	-0.71	0.005	0.02
Southeast	0.143	1.41	0.298	1.88	0.170	1.39
West	0.382	4.01**	0.393	2.69**	-0.198	-1.27
Year 2000	0.451	5.58**	1.166	11.68**	0.492	5.00**
Year 2005	0.517	5.91**	0.520	4.41**	0.771	6.78**
(b) Thresholds						
α_0	-0.012	-0.05				
α_1	0.567	2.34*				
α_2	1.223	4.99**				
α_3	1.867	7.49**				
α_4	2.453	9.61**				
α_5	2.959	11.34**				
α_6	3.345	12.59**				
α_7	3.781	13.84**				
(c) Variance parameters						
σ^2	0.257	0.037 [a]**				
λ_s	1.917	0.191[a]**				
λ_w	0.958	0.151[a]**				
(d) Correlation Coefficients						
ρ_{ts}	0.315	0.041 [a]**				
ρ_{sw}	0.305	0.043 [a]**				
ρ_{tw}	0.198	0.037 [a]**				

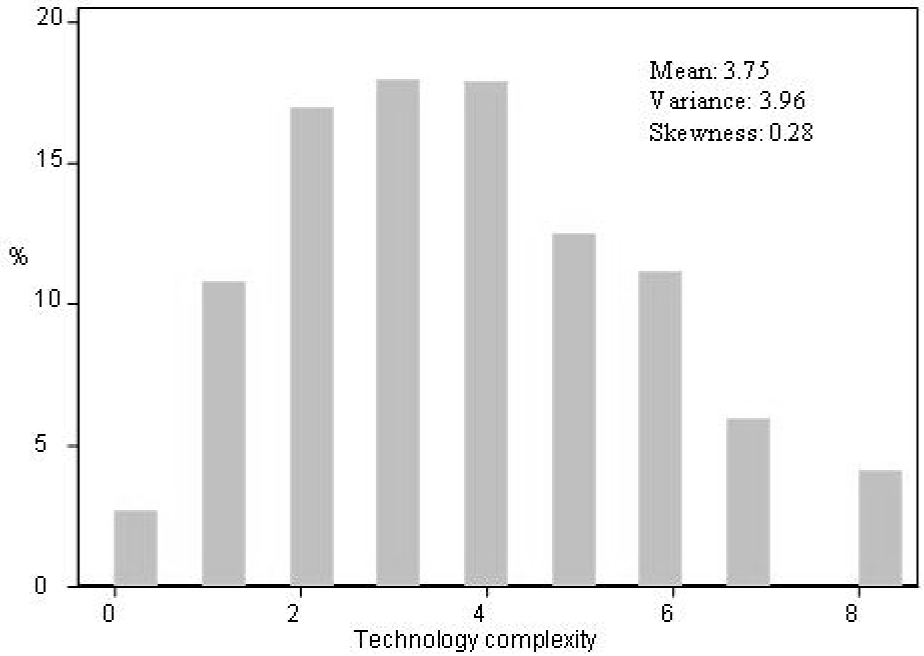
Note: * Statistic significant at 5%; ** Statistic significant at 1%.

ρ_{kl}, $k,l = t,s,w,\ k \neq l$ are calculated according to formula (10) with estimated standard errors obtained using delta method.

a. the number is the standard error of the corresponding estimate.

FIGURE I

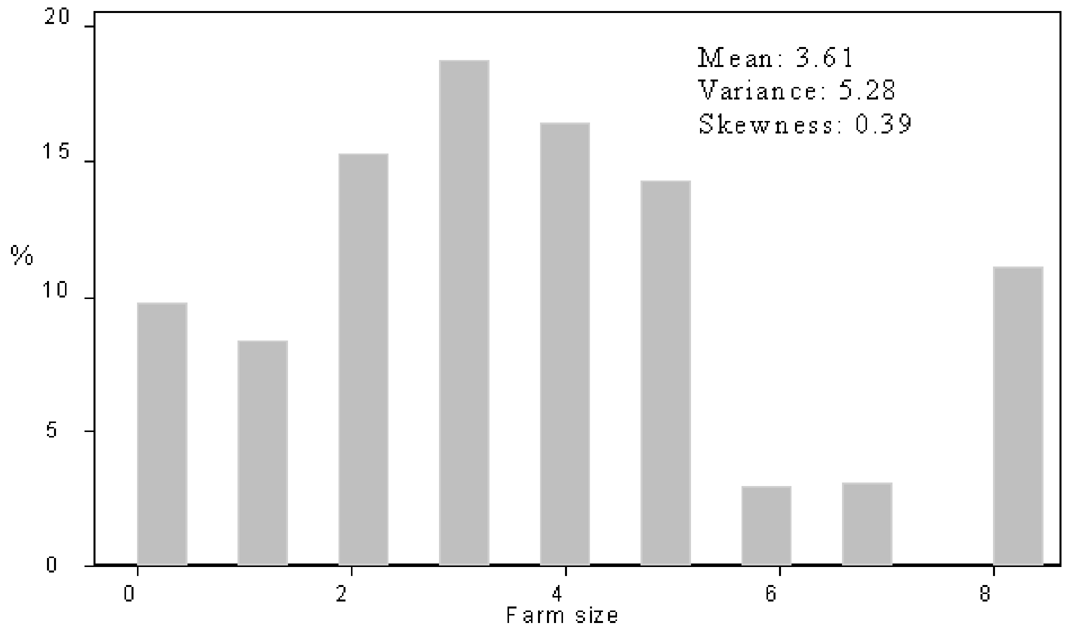
DISTRIBUTION OF TECHNOLOGY COMPLEXITY



Note: Technology complexity is represented by the number of technologies adopted on hog farms. The distribution is weighted by sampling weights such that it reflects the population distribution of hog farms. Auto Sorting system technology (AS) and Parity Based Management (PBM) in 2005 are censored in the variable of technology complexity. Technology complexity ranges from zero to eight in each of the survey years.

FIGURE II

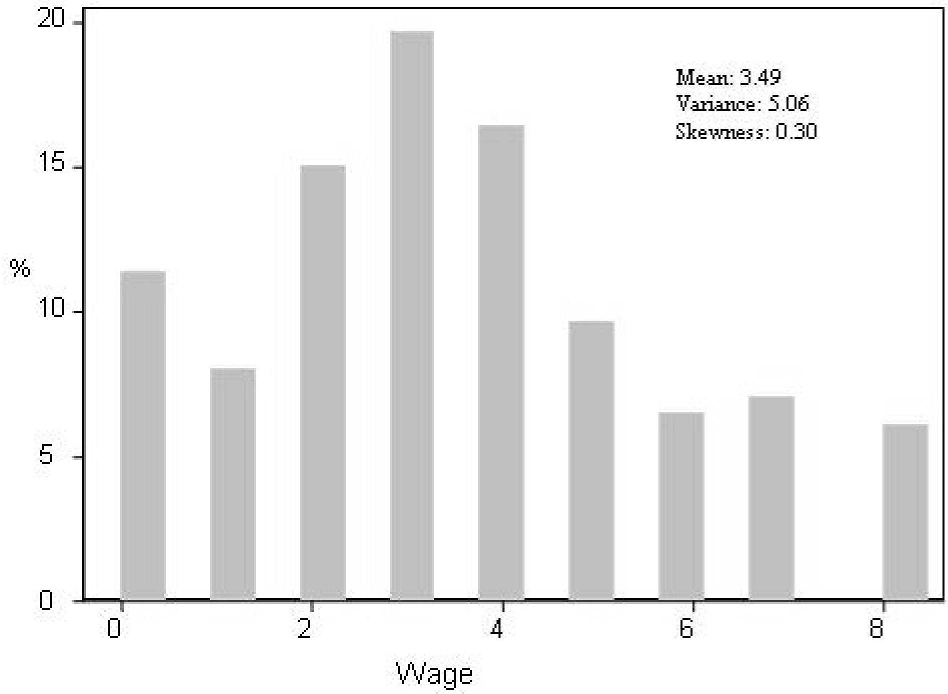
DISTRIBUTION OF FARM SIZE



Note: The size class is defined in the Table II. The size distribution is weighted by sampling weights farms.

FIGURE III

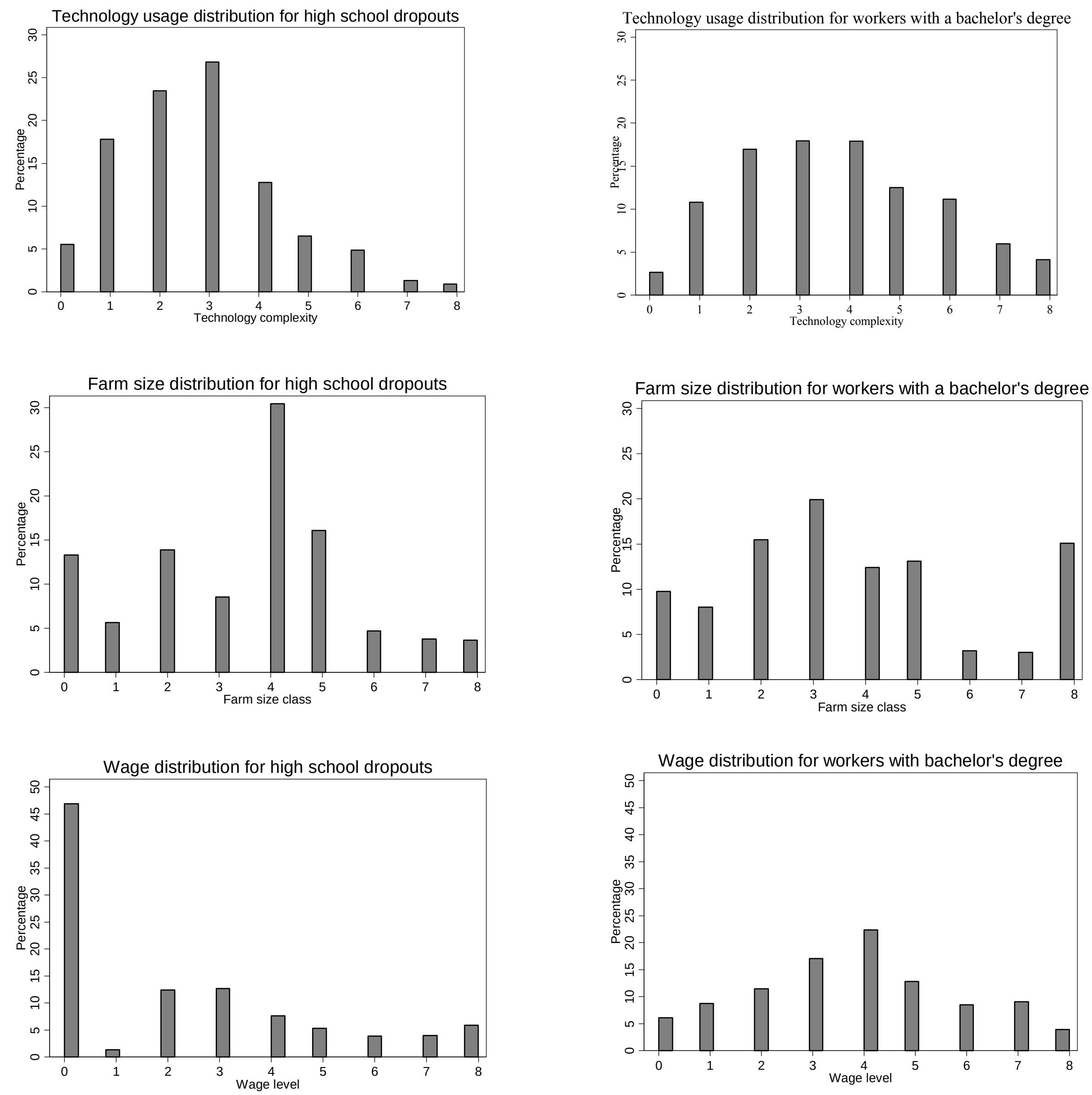
DISTRIBUTION OF WAGES



Note: The corresponding wage range is defined in the Table III**Error! Reference source not found.**. The wage distribution is weighted by sampling weights farms.

FIGURE IV

RELATIONSHIPS OF WORKER SKILLS AND TECHNOLOGY COMPLEXITY, FARM SIZE AND WAGES



APPENDIX A

Expected distribution shape for technology complexity, firm size and wages

As far as the distribution of technology complexity is concerned, the sufficient condition for the right skewness of its distribution is $\frac{\partial^2 t}{\partial q^2} > 0$. Denote

$A = -\frac{B''(t)}{B(t)} + \frac{[B'(t)]^2}{B^2(t)}$, then $\frac{\partial t}{\partial q} = \frac{1}{qA} > 0$ because $A > 0$.

→ $\frac{\partial^2 t}{\partial q^2} = -\frac{1}{q^2 A^2}(A + q\frac{\partial A}{\partial q})$ where $\frac{\partial A}{\partial q} = (\underset{?}{-\frac{B'''}{B}} + \underset{<0}{\frac{3B'B''}{B^2}} - \underset{<0}{\frac{(B')^3}{B^3}})\frac{\partial t}{\partial q}$ where t is omitted for simplicity. Denote $E = -\frac{B'''}{B} + \frac{3B'B''}{B^2} - \frac{(B')^3}{B^3}$, $\frac{\partial A}{\partial q} = E\frac{\partial t}{\partial q} = E\frac{1}{qA}$.

$$\frac{\partial^2 t}{\partial q^2} = -\frac{1}{q^2 A^2}(A + q\frac{\partial A}{\partial q}) = -\frac{1}{q^2 A^2}(A + \frac{E}{A})$$

Technology complexity t is convex in q if $\frac{\partial^2 t}{\partial q^2} > 0 \Leftrightarrow A + \frac{E}{A} < 0 \Leftrightarrow E < -A^2$.

When $E < -A^2$, technology complexity will have a right skewed distribution given normally/symmetrically distributed (or even right skewed distributed) skills of workers.

Below are two simulation examples with functional forms satisfying the condition above, showing the shape of the three distributions. It is assumed that skill level q is assumed to be normal with mean 0.5 and standard deviation 0.1. Technologies are from 1.05 to 8.

EXAMPLE A.1 $B(t) = -0.2t^2 + 4t$

FIGURE A.1

SIMULATED HISTOGRAMS OF PRODUCTION PROCESS COMPLEXITY AND OUTPUT

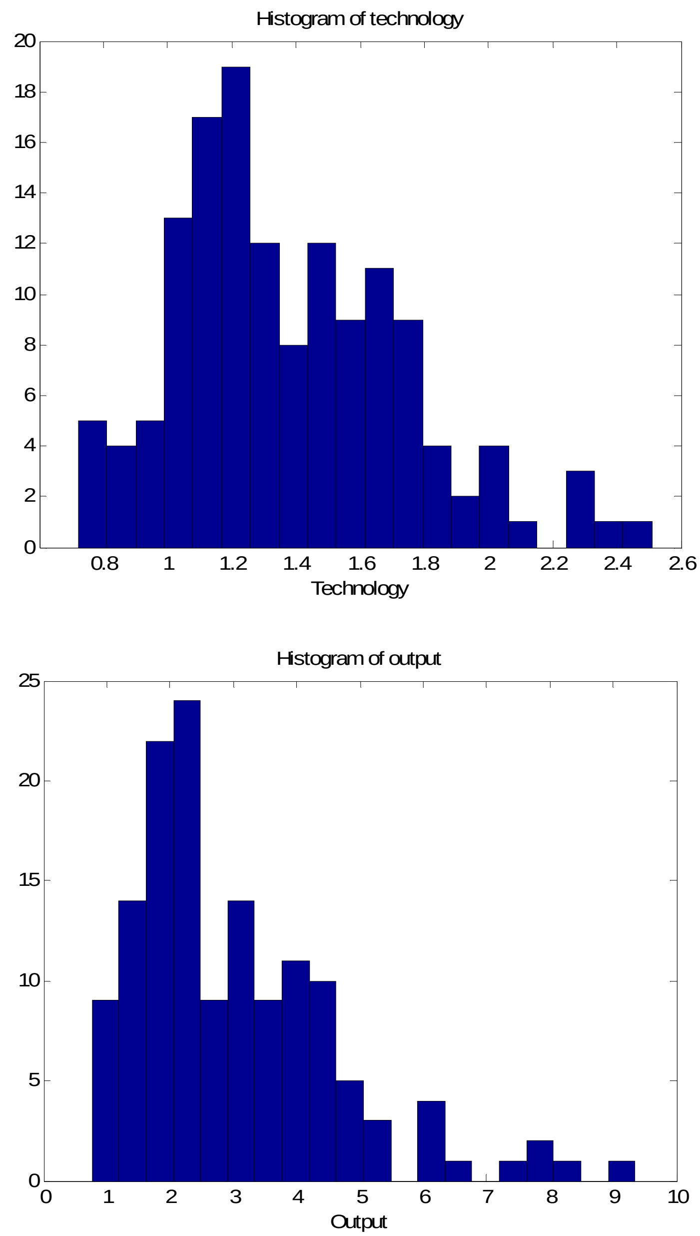
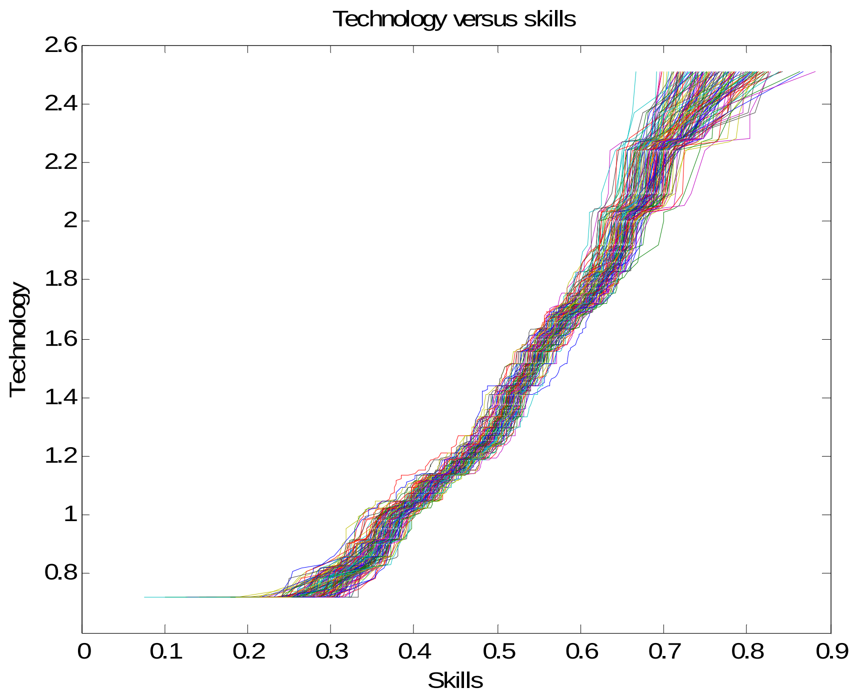


FIGURE A.2

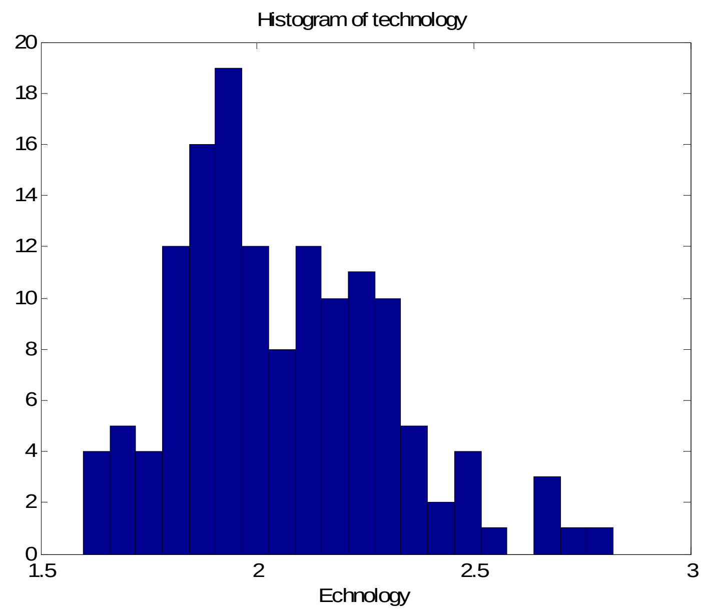
SIMULATED RELATIONSHIP BETWEEN PRODUCTION PROCESS COMPLEXITY AND SKILLS



EXAMPLE A.2 $B(t) = \log(t)$

FIGURE A.3

SIMULATED HISTOGRAMS OF PRODUCTION PROCESS COMPLEXITY AND OUTPUT



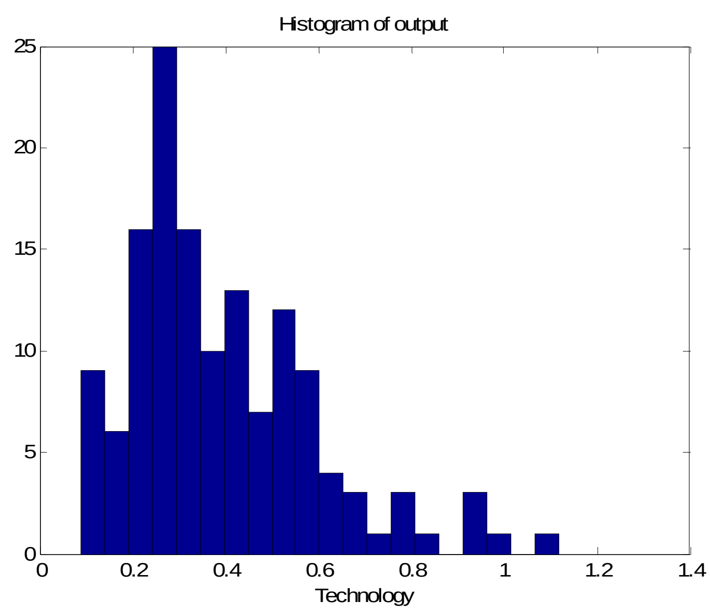
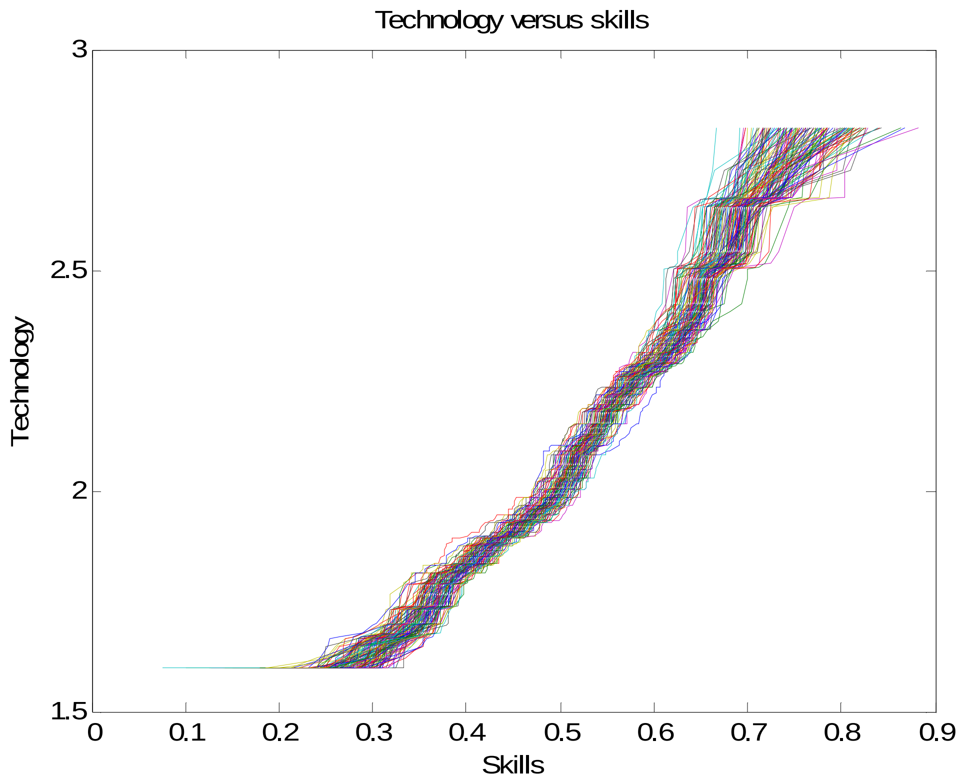


FIGURE A.4

SIMULATED RELATIONSHIP BETWEEN PRODUCTION PROCESS COMPLEXITY AND SKILLS



APPENDIX B

TABLE B.1
TRIVARIATE PROBIT MODEL OF TECHNOLOGY ADOPTION, FARM SIZE AND WAGES

Variable	Equation 1: Technology Adoption	Equation 2: Farm Size	Equation 3: Wage
Female	-0.264	-0.059	-0.544
	(1.83)	(0.48)	(2.58)**
Education	0.105	-0.015	0.156
	(5.85)**	(1.13)	(7.44)**
Tenure	0.001	-0.053	0.030
	(0.08)	(4.27)**	(1.72)
Tenure^2	-0.000	0.001	-0.000
	(0.91)	(1.53)	(0.73)
PrevExp	0.259	0.204	0.235
	(2.74)**	(2.92)**	(2.19)*
Raise	0.184	-0.083	-0.008
	(1.95)	(1.16)	(0.08)
Northeast	-0.431	-0.262	0.437
	(2.40)*	(1.95)	(2.02)*
Southeast	0.028	0.461	0.107
	(0.18)	(4.11)**	(0.74)
West	0.343	0.246	0.195
	(2.56)*	(2.29)*	(1.25)
Year 2000	0.478	0.797	0.592
	(4.61)**	(10.55)**	(4.72)**
Year 2005	0.570	0.923	0.865
	(4.96)**	(10.74)**	(6.75)**
Constant	-2.845	-1.076	-3.996
	(10.04)**	(5.48)**	(11.10)**
Correlation Coefficients			
ρ_{12}	0.460		
	(9.30)**		
ρ_{13}	0.318		
	(4.71)**		
ρ_{23}	0.366		
	(6.42)**		

Note: The estimation is based on the total sample and is not specific to farm operation specializations. Dependant variables are binary choices. Technologies are intensively adopted if more than five technologies are used. Farms are large is more than 10,000 pigs produced per year on the farms. Wages are high if annual income is at least $35,000. * denotes the estimated parameters are significant at 5% and ** denote the significance at 1%. Absolute value of *t* statistics is in parentheses and standard error in square bracket. Probability weights are considered in the model and the standard errors are therefore robust. ρ_{ij} is a series of the correlation coefficients between equation i and equation j.

TABLE B.2

TRIVARIATE ORDERD PROBIT MODEL FOR EMPLOYEES WORKING ON FARMS WHICH HAVE FARROW-TO-FINISH OPERATIONS

	Technology		Farm Size		Wage	
Variables	β_t	t-value	β_s	t-value	β_w	t-value
(a) Regression parameters						
Female	-0.468	-2.8**	-0.036	-0.15	-0.975	-5.3**
Education	0.114	5.63**	0.059	2.83**	0.115	5.35**
Tenure	-0.033	-2.31*	0.030	1.65	-0.022	-0.83
Tenure^2	0.000	1.19	-0.002	-2.82**	0.001	0.99
PrevExp	0.401	4.02**	0.399	3.29**	0.319	2.72**
Raise	0.021	0.21	0.240	1.96*	-0.513	-4.42**
Northeast	0.070	0.46	-0.057	-0.27	0.003	0.01
Southeast	0.157	1.10	0.190	0.99	-0.014	-0.08
West	0.275	2.22*	0.287	1.68	-0.406	-2.11*
Year 2000	0.571	4.68**	1.000	7.87**	0.476	3.41**
Year 2005	0.770	6.46**	0.520	3.52**	0.849	5.41**
(b) Thresholds						
α_0	-0.200	-0.65				
α_1	0.407	1.30				
α_2	1.110	3.52**				
α_3	1.788	5.62**				
α_4	2.415	7.41**				
α_5	2.923	8.76**				
α_6	3.355	9.95**				
α_7	3.809	10.99**				
(c) Variance parameters						
σ^2	0.364	0.063 [a]**				
λ_s	1.400	0.175[a]**				
λ_w	0.826	0.170[a]**				
(d) Correlation Coefficients						
ρ_{ts}	0.333	0.049 [a]**				
ρ_{sw}	0.288	0.044 [a]**				
ρ_{tw}	0.230	0.046 [a]**				

Note: * Statistic significant at 5%; ** Statistic significant at 1%.

ρ_{kl}, $k, l = t, s, w,\ k \neq l$ are calculated according to formula (8) with estimated standard errors obtained using delta method.

a. the number is the standard error of the corresponding estimate.

TABLE B.3

TRIVARIATE PROBIT MODEL FOR EMPLOYEES WORKING ON FARMS WHICH HAVE FARROW-TO-FINISH OPERATIONS

Variable	Equation 1: Technology Adoption	Equation 2: Farm Size	Equation 3: Wage
Female	-0.319	0.064	-1.734
	(1.74)	(0.40)	(6.38)**
Education	0.102	-0.008	0.177
	(4.34)**	(0.51)	(6.48)**
Tenure	-0.030	-0.057	0.006
	(1.50)	(3.34)**	(0.27)
Tenure^2	0.000	0.001	0.001
	(0.76)	(1.38)	(1.13)
PrevExp	0.268	0.179	0.248
	(2.24)*	(2.01)*	(1.62)
Raise	0.064	-0.251	0.020
	(0.52)	(2.72)**	(0.14)
Northeast	-0.542	-0.373	0.414
	(2.46)*	(2.15)*	(1.34)
Southeast	0.016	0.156	-0.038
	(0.07)	(1.06)	(0.20)
West	0.179	0.145	0.202
	(1.08)	(1.19)	(1.01)
Year 2000	0.599	0.697	0.417
	(4.41)**	(7.04)**	(2.47)*
Year 2005	0.724	0.858	0.957
	(4.69)**	(7.59)**	(5.30)**
Constant	-2.482	-1.044	-4.252
	(6.95)**	(4.05)**	(8.99)**
Correlation Coefficients			
ρ_{12}	0.545		
	(8.87)**		
ρ_{13}	0.448		
	(4.51)**		
ρ_{23}	0.421		
	(6.13)**		

Note: The estimation is based on responses from employees who work for farms which have comprehensive operations from farrowing to finishing hogs. Dependant variables are binary choices. Technologies are intensively adopted if more than five technologies are used. Farms are large is more than 10,000 pigs produced per year on the farms. Wages are high is at least $35,000. * denotes the estimated parameters are significant at 5% and ** denote the significance at 1%. Absolute value of *t* statistics is shown in parentheses and standard error in square bracket. Probability weights are considered in the model and the standard errors are therefore robust. ρ_{ij} is a series of the correlation coefficients between equation i and equation j.