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Three essays on technology adoption, firm size, wages and human capital

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Abstract

This dissertation consists of three essays on the interrelationships between multiple technology adoptions, firm size, wages and human capital. The application is to four surveys of producers and employees in the US hog industry in the last two decades.

The first chapter investigates the size-wage premium in the competitive hog market. Particular attention is paid to the matching process by which workers are linked to farms of differing size and technology mix, and to whether the matching process can explain differences in wages across farms. The sector is characterized by large wage premia paid to workers on larger and more technologically advanced farms that persist over time. These wage premia are found for workers of all skills and are not reduced when methods are employed to control for nonrandom sorting across farms.

The second chapter shows that current methods to test for the complementarity or substitutability between technologies have been subject to the curse of dimensionality. Efforts to deal with more than a few technologies have had to impose that the technologies are independent or substitutes for tractability. The chapter presents a strategy to identify complementarity or substitutability that can be easily applied to any number of technologies. The method is applied to choices of eight technologies commonly used on U.S. hog farms. Technologies are increasingly likely to be complementary with one another as the number of bundled technologies increases, even if subsets are substitutes when viewed in isolation. As a result, farmers have an incentive to adopt many technologies at once, contributing to the trend toward larger farms over the sample period. It is the most educated producers that tend to adopt more technologies and to have larger farms.

The third chapter tests whether production on U.S. hog farms can be characterized as an O-Ring production process (Kremer, QJE, 1993), 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. Consistent with the theory, distributions of wages, technology adoptions, and farm size are all skewed to the right. The most skilled workers concentrate in the largest and most technologically advanced farms and paid highest. As with observed skills, workers with the greatest endowments of

unobserved skills also sort themselves into the largest and most technology intensive farms.

General Introduction

The last two decades have been characterized by dramatic changes in the U.S. hog industry. Hog farms have grown larger and have experienced rapid advancement in available technologies. They have increasingly employed more educated workers and have experienced rapid wage growth. The trends appear to be related in that it is the largest farms that use more complex technologies, use the most educated workers and pay their workers the highest wage rates. Similar tendencies have been observed in other sectors as well. This dissertation explores the magnitude and underlying causes of these trends.

Economists have long puzzled over the fact that large firms pay higher wages than small firms, even after controlling for worker's observed productive characteristics. One possible explanation has been that firm size is correlated with unobserved productive attributes which confound firm size with other productive characteristics. One of these possibilities is that farms differ in technologies. Rapid technological innovation over the last two decades occurs in the areas of nutrition, health, breeding and genetics, reproductive management, and environmental management. These technologies have been associated with improved feed efficiency, lower death loss, higher quality meat, more rapid weight gain, and other improved outcomes that raise farmer profits. Another possibility is that some farms can disproportionately attract workers with skills that are not easily measured by traditional measures such as education or experience. In this dissertation, we can directly test whether wage differences by farm size can be explained by these differences in worker skills or farm technologies

In the economics literature, numerous studies have explored the process of technology adoption. Most of studies focus on the decision to adopt a specific technology without explicitly considering other technologies. An aspect of technology adoption that has received less attention is the extent to which different technologies work well together and are adopted collectively or do not work well together and are adopted separately; or, in economic parlance, the extent to which combinations of technology are complementary or substitutable. Testing the relationship among multiple adopted technologies is frustrating mainly because of computational complexity. A tractable methodology is developed to identify the complementarity or substitutability among technologies, which is also critical to understanding the effect of technical innovation on industry growth and structure.

Though producing a homogenous product, hog farms differ in size, technology intensity and composition of worker skills. It is important to understand how such differences can result in a competitive market. One possibility follows from one feature of hog production: that mistakes in hygiene, diagnosis, segregation, quality control, or any number of other tasks can lead to the loss of an entire herd. Such a production process corresponds closely to Kremer's O-Ring production theory (QJE, 1993). The theory has relevance in agricultural settings where mistakes have led to large recalls of organic spinach, pet food, chicken, beef and other products. Given the importance of the O-Ring production process as a conceptual tool in economics, the theory has not previously been subjected to a comprehensive test. A direct test on the implications of O-Ring production theory is conducted in the dissertation in order to understand the type of hog production, the interrelationship among human capital, technology complexity, farm size and wages.

The empirical work in this dissertation relies on four surveys of employers and employees on hog farms collected in 1990, 1995, 2000, and 2005. There is a potential sample selection bias because responses from people in larger farms are expected to be more than those in smaller farms. Sample weights corresponding to national distributions of hog farms by size and region are used in all of the analysis and estimation such that the empirical results consistently reflect the universe of U.S. hog farms and of hog farm employees.

Dissertation organization

The dissertation is composed of five chapters. This chapter is a general introduction motivating the research in the US hog industries and illustrating the related aspects I will deal with. The second chapter investigates the size – wage premium issues by paying particular attention to a matching process and premium among differential groups of workers. The next chapter provides a testing method to identify complementarity and substitutability among multiple technologies and applies this method to technology adoption in the US hog farms. Choices on size and technology adoption intensity are simultaneously determined and shown to be positively correlated. The fourth chapter combines all of factors above to test if the hog production process is of the O-Ring type. The final chapter concludes the dissertation.

Chapter 2 opens by showing that a standard Mincerian wage equation yields large and persistent returns to working on larger farms and on farms that use technologies more intensively. It is possible that these apparent returns are due to more skilled workers sorting into larger or more technologically advanced operations. To correct for that possibility, alternative propensity score matching methods are investigated to correct for sorting across farm sizes or technologies based on observable factors. Although more educated and experienced workers are more likely to work on larger and more technologically advanced hog farms, the positive relationships between wages and both farm size and technology adoption remain large and statistically significant even after controlling for differences in observable worker attributes and in the observed sorting process of workers across farms.

Chapter three proposes a strategy to identify the complementarity or substitutability among technology bundles which are not restricted by the dimension of technologies. Under the assumption that alternative technologies are independent, a hypothetical distribution of multiple technology adoptions is developed. Differences between the observed distribution of technology choices and the hypothetical distribution can be subjected to statistical tests. Combinations of technologies that occur with greater frequency than would occur under independence are complementary technologies. Combinations that occur with less frequency are substitute technologies. The method is applied to test the relationship of technologies adopted in the US hog industry. It is found that some technologies used in pork production are substitutable for one another while others are complementary. However, as the number of bundled technologies increases, they are increasingly likely to be complementary with one another, even if subsets are substitutes when viewed in isolation. This finding suggests that farmers have an incentive to adopt many technologies at once. Larger farms and farms run by more educated operators are the most likely to adopt multiple technologies. The complementarity among technologies in large bundles is contributing to a form of returns to scale that contributes to growth in average farm size.

The fourth chapter tests the predictions of the O-Ring theory in the context of hog production in the United States. Empirical results show that, consistent with the theory, distributions of wages, technology adoptions, and farm size are all skewed to the right. The most skilled workers concentrate in the largest and most technologically advanced farms. Workers on the larger and more technologically advanced farms are paid more than comparably skilled workers on smaller and less technology intensive farms. Positive correlations among the unmeasured factors that lead to higher wages, more complex technologies and larger farms suggest that, as with observed skills, workers with the greatest endowments of unobserved skills also sort themselves into the largest and most technology intensive farms.

Chapter five provides a general conclusion for the dissertation.

Firm Size, Technical Change and Wages in the Pork Sector: 1990 -2005

Li Yu, Terry M. Hurley, James B. Kliebenstein and Peter F. Orazem

Abstract

Economists have long puzzled over the fact that large firms pay higher wages than small firms, even after controlling for worker's observed productive characteristics. One possible explanation has been that firm size is correlated with unobserved productive attributes which confound firm size with other productive characteristics. This study investigates the size-wage premium in the context of firms competing within a single market for a relatively homogeneous product: hogs. We pay particular attention to the matching process by which workers are linked to farms of different size and technology use, and whether the matching process may explain differences in wages across farms. The study relies on four surveys of employees on hog farms collected in 1990, 1995, 2000, and 2005. We find that there are large wage premia paid to workers on larger farms that persist over time. Although more educated and experienced workers are more likely to work on larger and more technologically advanced hog farms, the positive relationships between wages and both farm size and technology adoption remain large and statistically significant even after controlling for differences in observable worker attributes and in the observed sorting process of workers across farms.

Introduction

A long-standing puzzle in labor economics has been the positive relationship between wages and firm size first discovered by Moore (1911). Large firms pay 15 % more than small firms for observationally equivalent workers in the United States (Lluis 2003). Even after controlling for worker's observed characteristics such as education, work experience, gender, and geographic location and further correcting for wage differences due to unobserved abilities, a significant size-wage effect remains. Having exhausted supply-side explanations, various labor demand-side explanations have been advanced to explain the size-wage premium (Brown and

Medoff 1989; Troske 1999). These include that larger firms use more capital-intensive technologies, more skilled managers, more skilled workers, and more sophisticated technologies. Larger firms may also pay efficiency wages to limit monitoring costs or to share rents from returns to scale. All of these demand-side explanations have been found to hold in cross-sectional studies, but none alone or in aggregate have been able to fully explain why larger firms pay more than smaller firms.

One concern has been that firm size may itself be correlated with differences across firms in the nature of the products produced. If, for example, larger firms have more power to set price, firm size may be positively correlated with worker marginal products for reasons that are not controlled in the analyses. We believe that the size-wage premium would be more convincingly supported if the pattern were found within a single competitive product market.

Of other explanations for the size-wage premium, three involve the interaction between technology and workers' skills. Evidence from manufacturing firms shows that workers in plants that used more capital per worker, used research and development more intensively, and that adopted more information technologies were paid more than comparable workers in firms lacking those investments (Krueger 1993; Reily 1995; Dunne and Schmitz 1995; Troske 1999; Dunne et al 2004). Such evidence would be even stronger if the variation in technologies occurs within a single product market, eliminating the chance that variation in capital is correlated with different input, product or regional markets.

We examine evidence of the size-wage premium in the context of the US hog industry. The industry is characterized by a large number of producers selling a virtually homogeneous output. Farms vary dramatically in size and in technology adoption intensity with the heaviest technology adopters being the largest farms (McBride and Key 2003). The largest farms also use more educated labor. Hurley, Kliebenstein and Orazem (1999) found evidence of a substantial size-wage premium in a single cross section of hog farms. This paper explores whether that size-wage premium persists over time and whether it can be explained by the observed differences in skill levels and technology usage between large and small farms. We also investigate whether the pay differential can be explained by the matching process which sorts employees into farms of different size and technology use.

The study relies on four surveys of employees on hog farms conducted in 1990, 1995, 2000, and 2005. Regardless of the methodology employed, we find large and persistent effects of farm size and technology adoption on worker's wages. The farm size effect remains large, even after controlling for differential technology adoption across all types of farms, suggesting that workers on large hog farms are earning rents from returns to scale. Workers of all types on large hog farms receive the wage premia, regardless of education level, related experience or region of the country.

The paper is organized as follows. Section two reviews the stylized facts regarding hog farm size and wages. Section three reviews the baseline empirical strategy and describes the data while section four provides traditional least-squares estimates of the size-wage premium. Section five reviews an alternative statistical matching method to correct for selection bias due to observable differences across farm sizes. Section six presents results from application of the same strategy applied to differences in intensity of technology adoption. Both sets of estimates suggest that the wage premia paid by large and more technologically advanced farms are due to the technologies adopted and not to unmeasured worker productivity.

Trends in Farm Size, Technology, and Wages on U.S. Hog Farms

The U.S. hog industry has a large range of farm sizes, from farms producing fewer than 500 hogs to farms producing more than 100,000 hogs per year. The employment share by farm size category is presented in Table 1.1. The size categories varied across surveys, but it is nevertheless apparent that the employment share of the largest farms is rising dramatically. The employment share on farms producing more than 10,000 hogs rose from 8% in 1990 to 23% in 2005. In contrast, the employment share on farms producing fewer than 5,000 pigs fell from 79% in 1990 to 47% in 2005.[2]

A size-wage pattern similar to that found in other labor markets is apparent in the relationship between salaries and size of operation on hog farms. Figure 1. 1 shows the log salary distribution on small, medium and large hog farms. The log salary is skewed to the right for farms producing fewer than 3,000 pigs per year. In contrast, the wage profile for farms producing more than 10,000 pigs a year is heavily weighted toward the upper tail of the distribution. As the size categories rise, the median log salary moves to the right while wages disappear from the lower tail of the salary distribution.

The rapid change in employment share on large farms since 1990 corresponds to a period of rapid technology adoption in the industry. The technology adoption measures summarized in table 2 are only available for three years, 1995, 2000, 2005. Questions regarding Auto Sorting Systems and Parity Based Management were only reported for 2005 and so we do not incorporate them in our statistical analysis.[3] Of the other technologies, the strongest growth is in Artificial Insemination, Formal Management Practices and Computer Usage. Phase Feeding or Split-Sex Feeding, Multiple Site Production and All In All Out methods have been utilized by a nearly constant proportion of employees in the industry.

From the last two columns of Table 1.1, we find that farms with fewer than 500 hogs use an average of 2.8 technologies while those producing over 10,000 hogs use 4.6 technologies. Farms over 25,000 head use an even larger numbers of technologies. The average number of technologies used has increased over time, as shown in Table 1.2; from 3.2 technologies in 1995 to 4.2 technologies in 2005. Farm wages are correlated with the number of technologies employed on the farm. As shown in Figure 1. 2, farms using at most five of the technologies listed in Table 1. 2 have log salary distributions weighted toward the lower tail of the observed range. Farms using six or more technologies had salary distribution heavily weighted in the upper-half of the observed wage range. The pattern suggests that the size-wage premium may be due to differences in technologies used in smaller and larger firms.

Empirical Strategy and Data

To examine the role of changing farm size and technology utilization on the distribution of wages for hog farm employees, we augment the standard Mincerian earnings function as

(1) $$\ln W = \beta_x X + \beta_z Z + \beta_t T + \beta_s S + \varepsilon$$

where lnW is the natural log of the worker's annual salary; X is a vector of individual productive and demographic attributes including gender, education, tenure, prior farm experience, and having been raised on a farm; and ε is a disturbance term.

We augment the earnings function by adding aspects of the farm. Technology T is measured alternatively as a vector of dummy variables indicating the use of specific technologies or else indicating the number of technologies used. Farm size S is measured alternatively by the number of pigs produced or by a dummy variable indicating production exceeding 10,000 pigs per year. The vector Z includes remaining farm characteristics including location and year of interview.

This study uses survey data from a random sample of subscribers to National Hog Farmer Magazine. The surveys were conducted in years 1990, 1995, 2000 and 2005. Because subscribers to National Hog Farmer Magazine are not a representative sample of all hog farm employees and because 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. We base our sample weights on the Agricultural Census Data of the US Department of Agriculture (USDA). To be consistent with USDA classifications, each hog farms in our survey samples is categorized into one of eight regions and one of the three size levels. The number of employees who have either full time or part time jobs on hog farms is taken as the population universe.[4]

The weights are computed as follows: Let N be the total number of employees on U.S. hog farms and let n_j of them be in region-size cell j . The proportion of employees in the j^{th} cell is n_j /N. The corresponding number of employees in the j^{th} cell in our sample is s_j . Each worker in our sample is then assigned a probability weight $\frac{n_j}{s_j}$.[5]

Characteristics of workers and farms are shown in Table 1. 3. Hog farm workers are more educated than average for the U.S. labor market as a whole: 93% have completed at least high school and 43% have at least a 4 year university degree. It is likely that we under-sample the lower tail of the skill distribution, particularly workers who do not read, write or speak English and would therefore be unlikely to subscribe to National Hog Farmer Magazine.

Workers' average age is 36.6 years. Tenure on the current hog farm averages 8.9 years with 41 % of the workers having experience working on other hog farms.

In addition, 53% of workers were raised on a hog farm. Farm location is categorized by four regions in the survey: Midwest, Northeast, Southeast and West[6]. These are captured by three dummy variables with the Midwest region serving as the base.

Some notable differences between large and small farms are apparent in addition to the wage and technology differences already discussed. Large farms in the sample pay workers 38 %(or 0.32 log points)[7]more than the average farms in the US. Small farms employ a relatively higher proportion of high school graduates while large farms employ relatively more workers with at least a four-year college degree. Workers on large farms have three fewer years of job tenure but are more likely to have prior experience on other hog farms. Employees on small farms are more likely to have been raised on a farm. Small farms are atypically located in the Midwest while large farms are more likely to be in the Southeast and the West.

Earnings Functions

Least-squares regression results from various specifications of the augmented earnings function are presented in Table 1. 4. Model (1), the standard Mincerian earnings function which excludes farm size and technology serves as our base of comparison. It produces expected results. Earnings increase steadily in years of schooling so that high school graduates earn a 23% premium and university graduates earn a 55% premium over high school dropouts. Female workers are paid 18% less than males. Earnings increase in age though at a decreasing rate. Workers are not rewarded for tenure on the farm, but they do earn a premium for prior work experience before coming to the current farm. The latter effect is moderated somewhat for those who were raised on a farm. There are no significant wage differences between workers in the Midwest, the Northeast, or the West. The pattern of coefficients on the year dummies suggest that real wages rose in hog production from 1990 to 2000, though the rate of increase declined modestly after 2000.

Model (2) presents the size augmented earnings function. It is apparent that some worker attributes are correlated with farm size. With farm size held constant, the implied wage advantage decreases for males, for high school and college graduates, and for those with prior work experience. Instead, workers benefit from employment on larger farms. Although the marginal gains decrease with farm size, the effect is always positive across the range of farm sizes in the data. Evaluated at sample means, the wage elasticity with respect to farm size is 0.11.

The increase in the importance of large hog farms masks the trend in real wages in the industry. Once farm size is controlled, it is apparent that real wages in the sector are stable. The gains in average pay over time are attributable to workers receiving a share of the gains from the rising average scale of operations over the period.

Model (3) replaces the continuous measure of farm size with a dummy variable indicating whether the farm has annual production exceeding 10,000 hogs per year. Coefficients are similar to those in the first two models. Workers on farms producing more that 10,000 pigs earn 39% more than those working on farms producing 10,000 or fewer pigs.

Model (4) adds the effect of technology adoption. Returns to males, college graduates and workers with prior hog farm experience are moderated further when we add a dummy variable which indicates farms using at least six technologies, although the differences are modest. The biggest change is that returns to working on large farms falls by nearly one-quarter, suggesting that part but not all of the farm-size effect is due to the technologies used on those farms. Other things equal, workers on farms using at least six technologies earn 27% more than those in farms using fewer technologies.

In Table 1.5, we replicate the earnings function allowing for separate wage effects for individual technologies listed in Table 1. 2. We estimate the equation separately by year and then pool the data across years. Although most technologies have positive estimated effects on wages, only Artificial Insemination (AI); Phase Feeding (PF); and Formal Management (FM) have significant positive effects on wages. The only significant outlier is a negative estimated effect from computer usage in 2005. Joint tests of the equality of the coefficients across survey years reject the null hypothesis for many of the coefficients including several of the technologies, but the signs rarely change. The parsimonious pooled regression seems to yield adequate inferences about the effects of farm size and technology over the sample period. Farmers using more advanced technologies and larger operations pay a premium for their workers above that paid to similarly educated and experienced workers on small farms and farms not using those technologies.

These results suggest that the pooled regressions reported in columns five and six are the most relevant for making conclusions regarding the impacts of technology adoption on earnings. Estimated returns to gender, current working experience, previous related working experience, and most of individual technology adoption are remarkably stable. Nevertheless, some of the changes in returns over time are worth noting. Returns to college and post graduate training appear to have increased over the sample period. Wage returns to farm size have declined, although the size-wage effect remains positive and significant in each period.

Worker Returns Measured Using Propensity Score Matching

The inference from Figure 1.1 and Table 1.4 and 1.5 is that workers on larger farms are paid higher wages. However, that analysis treats farm size as exogenous. Those inferences may be misleading if workers sort non-randomly across firms based on unobserved worker attributes that are correlated with farm size. For example, if more ambitious workers are attracted to larger farms, the wage premium on large farms may reflect this differential ambition and not farm size *per se*.

In this section, we quantify the size-wage premium using Propensity Score Matching (PSM) to see how benefits vary between workers who are equally likely to be found on large and small farms. PSM balances the distributions of observed covariates between the treatment group and a control group based on their propensity scores. After matching, the treatment and comparison groups will be drawn from observationally equivalent distributions. The method allows us to compare the size-wage effect at various points on the distribution of workers. We have a particular interest in comparing wages of observationally equivalent workers in large and small farms at various education levels, regions, time periods and technologies.

The Assumptions Underlying Propensity Score Matching

The treated group is composed of workers who are employed on large farms (denoted as $D_i = 1$) and the control group is composed of workers on small farms ($D_i = 0$). Subscript *i* indicates the i^{th} worker in the sample. Workers select the realized log wages by utility maximization. Let U be utility: $U = U(x, V_U)$ where x is a vector of observed workers' characteristics and V_U is a vector of unobservable factors.[8] Workers self select into the large farms $D=1$ and receive the log wage $\ln W_1$ if $U>0$; and are otherwise employed on small farms, $D=0$ and paid $\ln W_0$. Subscripts 1 and 0 denote large and small farms respectively.

(2A) $$\ln W_1 = f(x, V_1)$$

(2B) $$\ln W_0 = f(x, V_0)$$

where V_1 and V_0 are unobserved factors related to the wage variation in the treatment group and the control group, respectively.

We wish to measure the treatment effect on the treated: $E(\ln W_1 - \ln W_0 \mid D=1, x)$. $E(\ln W_1 \mid D=1, x)$ in the large farms is known, however, its counterfactual, $E(\ln W_0 \mid D=1, x)$, needs to be constructed by matching. As we observe the selection process into large and small farms, the probability of being hired by a large farm $\Pr(D=1 \mid x)$ is known. Matching is based on the propensity score:

(3) $P(x_i) = \Pr(D_i = 1 \mid x_i); 0 < P(x_i) < 1$ for individual *i*.

According to Rosenbaum and Rubin's (1983) ignorability of treatment assumption, if

(i) $0 < P(x_i) < 1$; and if

(ii) outcomes (in this case wages) are independent of D_i given x_i. Using $\perp$ to denote independence, if $(\ln W_{1i}, \ln W_{0i}) \perp (D_i \mid x_i)$, then the ($\ln W$) is also independent of D_i conditional on the propensity score $P(x_i)$, $(\ln W_{1i}, \ln W_{0i}) \perp (D_i \mid P(x_i))$[9]. This allows us to construct the counterfactual mean: $E(\ln W_0 \mid D=1, P(x)) = E(\ln W_0 \mid D=0, P(x))$.

Under the maintained hypothesis of independence, individuals in the two groups that share the same probability of working on a large farm can be viewed as being drawn from the same universe. Under the maintained hypothesis of ignorability, exact matching on $P(x_i)$ will eliminate the bias caused by unobserved individual heterogeneity across the samples of workers in large and small farms.

Matching

We define the binary outcome D as follows: farms producing 10,000 or fewer pigs are defined as small farms; those producing more than 10,000 pigs are large farms. The size break is chosen to have sufficient numbers of incumbents in both groups —selecting smaller farm sizes would result in too few workers in the later years. We estimate the propensity scores as the fitted values of a probit model[10] that predicts the probability that each individual works on a large hog farm. The regression results are shown in Table 1.6. The characteristics of the workers include gender, the education level, age, tenure, agricultural background, geographical location and time. Workers with higher education, more previous experience and those in the Southeast or the West will be more likely to work on a large farm. These findings are consistent with those reported by McBride and Key (2003). Persons raised on a hog farm are also less likely to be employed on a large farm.

Matching on fitted probabilities $\hat{P}(x_i)$ seems to work quite well. As seen in Figure 1. 3, there is substantial overlap in the distributions of the estimated propensity scores $\hat{P}(x_i)$ for workers in large and small farms, and so for every employee on a large farm, we have a control group member that works on small farms but has a similar propensity score[11]. The average probability of working on a large farm for those who actually do work on a large farm is 0.59. The average probability of working on a large farm for those who actually work on a small farm is 0.31.

Given $\hat{P}(x_i)$, we can employ several methods to get the PSM estimator. Applying Smith and Todd (2005) to our application, the size impact estimator takes the form:

$$\hat{\tau} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} [\ln W_{1i} - \ln \hat{W}_{oi}] \tag{4}$$

$$\ln \hat{W}_{oi} = \sum_{j \in I_o} \hat{w}(i,j) \ln W_{0j}$$

where n_1 is the number of individuals in the treated group, I_1 denotes the set of observations with $D_i = 1$, I_0 is the set of control group with $D_i = 0$, S_P is the region with common support, and $\hat{w}(i,j)$ are weights depending upon the distance between the propensity scores for individual *i* in the treatment group and individual

j in the control group. For robustness, we use three variations on matching which are commonly used in literature.

Matching 1. Nearest neighbor matching.

$$\hat{w}(i,j) = \begin{cases} 1 & j = \arg\min_{k \in I_0} \left\| \hat{P}(x_i) - \hat{P}(x_k) \right\| \\ 0 & otherwise \end{cases}$$

Matching 2. Caliper matching. $\hat{w}(i,j) = \begin{cases} \frac{1}{n_i} & \left\| \hat{P}(x_i) - \hat{P}(x_k) \right\| < c \\ 0 & otherwise \end{cases}$ where n_i is the number of caliper matches for i and c is the window width that we take as 0.05.

Matching 3. Kernel matching. $$\hat{w}(i,j) = \frac{G\left(\frac{\hat{P}(x_j) - \hat{P}(x_i)}{a}\right)}{\sum_{k \in I_0} G\left(\frac{\hat{P}(x_k) - \hat{P}(x_i)}{a}\right)}$$

where $G(s)$ is a kernel function. Following Heckman et al (1997, 1998), we use the Epanechnikov kernel function, $G(s) = \frac{3}{4}(1 - s^2)$ and a is a bandwidth parameter, which we take as 0.06.[12]

Matching is with replacement in the control group in order to reduce the bias and avoid the deterioration in quality of matches (Dehejia and Wahba 2002). In order to measure the accuracy of these estimates, we must utilize the bootstrap method, re-sampling the data with replacement m times to approximate the standard errors (Becker and Ichino 2002).

Estimated Size and Technology Effects using Matching Estimators

Using the full sample, we calculated the size-wage effect using the matching methods above. The results are very consistent across methods. The mean effects using Methods 1-3 respectively are 0.307, 0.329, and 0.293. All three estimates have one standard deviation bounds that contain the least-squares estimate of 0.33 from Model (3) in Table 1.4. Estimated effects of about 0.3 imply that the salary paid on the largest farms is 35% higher than that on small farms.

We can use the matching methods to explore the size-wage effect for subsamples of interest. Table 1.7 reports the size-wage premium for different education, region, and technology groups as well as for groups employed in different years. The size-wage difference is largest for the least educated and smallest (and imprecisely estimated in some cases) for the most educated. Nevertheless, all size-wage premia are large, ranging from 20% for the four year college degree holders to 53% for high school dropouts using the nearest neighbor and Kernel matching methods. The Caliper matching method finds the same pattern of estimates but with higher returns for more educated workers: ranging from 31% for the worker who has at least a master degree to 46% for the high school dropouts.

The size-wage premium is large in all parts of the country, but largest in the West at about 55%. The premium is smallest and sometimes insignificant in the Northeast. There is no consistent pattern of the size-wage effect over time. It is large and significant in every time period, ranging from 28% in 2000 to returns exceeding 40% in both the earliest and latest periods.

We also estimate the size wage premium for large and small farm workers employing the most commonly employed technologies. Workers on large farms using Phase Feeding, All-In-All-Out and Computer Usage, get the largest wage premium of over 30% over the pay on small farms employing the same technologies. The smallest size-wage premium of from 19% to 23% is associated with Artificial Insemination which is also the most commonly employed technology across farm sizes. It is plausible that AI has more ubiquitous productivity effects across farm sizes than do the other technologies.

The size-wage premium is alive and well in the hog industry. Despite producing a relatively undifferentiated product with many substitutes, larger farms pay more than smaller farms, regardless of location, education level or type of technology used. The size-wage premium has persisted over 20 years with no evidence of decline.

Model of Employment on Farms by Number of Technologies

We can use the same methods to test for corroborating evidence that workers on farms using multiple technologies earn more than their counterparts on less technologically advanced farms. We expect that if technologies raise farm productivity, some of the inframarginal rents earned by adopting technologies in the early stages of diffusion may be shared with the workers.

The binary outcome D now indicates that a farm adopts at least six advanced technologies out of the ten possible. A probit model is again used to predict the propensity score for each observation. The regression results are shown in Table 1.8. Farms employing workers with more education, more previous work experience and that are located in the West are the most likely to be heavy adopters of technologies. Figure 1.4 reports histograms of the estimated propensity scores $\hat{P}(x_i)$ for workers in the two technology groups. Again, there is substantial overlap in the propensity score distributions, and so we have good comparisons for workers employed on the technologically intensive farms.

Using the same matching methods yields a technology wage effect of 0.248; 0.281; and 0.230 using matching methods 1-3, respectively. The implied salary differential paid on the technology intensive farms varies between 26% and 32%.

Table 1.9 reports the detailed outcomes of the matched comparisons for technology wage premiums. Again, it is the least educated workers who benefit the most from working on farms using more complex technologies, and the technology-wage premium decreases with years of schooling. The wage returns to more intensive technology use exceed 23% in all regions. The ranking of returns varies by estimation method, with marginally lower returns in the Midwest and marginally higher in the Northeast. However, the general conclusion is that workers consistently earn substantial returns to technological intensity in every part of the country. The technology-wage premium has trended downward over time, although with only three years of data, we will characterize that conclusion as suggestive. Even the lowest returns are large at just under 20%.

We know that large farms are more likely to adopt multiple technologies than are small farms. Nevertheless, the small farms that adopt technologies more intensively pay a larger premium to attract workers than do larger, technology intensive farms.

Regardless of how we cut the sample, workers earn substantial rents from the use of more technologies on hog farms. The higher wages are paid whether the worker is educated or not, regardless of where the farm is located, and whether the farm is large or small. These returns have persisted over 15 years with only modest evidence that the returns have fallen over time.

Conclusion

This study examined evidence of the size-wage premium on U.S. hog farms from 1990-2005. We examine whether the premium exists within narrowly defined industries, whether the premium persists over time, and whether it can be explained by correlation with other differences across farm size such as differences in technological adoption or differences in the sorting process of workers across large and small firms. We find that regardless of methodology employed, from simple least-squares analysis to various propensity score matching strategies, there are large and persistent wage differentials favoring workers on large hog farms. The magnitude of the premium differs across various groups. It is larger for the least skilled, for workers in the Western U.S. and for workers using technologies more intensively. However, the general finding is that regardless of worker attributes, they receive a premium for working on large hog farms.

We also find substantial returns to the use of technologies on hog farms. These positive returns are also found for all education levels, regions of the country and farm sizes. Nevertheless, controlling for technology use has almost no impact on the magnitude of the size-wage effect. Additional research will be needed to determine why large farms persistently pay more to their employees regardless of worker attributes.

Endnotes

[1] These findings have been confirmed by numerous studies. See Oi and Idson(1999) for a review.

[2] Our employment trends are consistent with evidence reported by Lawrence *et. al*. (2001) that the share of hogs produced by firms marketing 50,000 head or more increased from 7% in 1988 to 37% in 1997.

[3] These technologies are relatively new and were not used frequently in 2005. Thus, we can presume that they were even less important before that.

[4] USDA accounts originally include 18 regions and four size classifications. Since some region-size cells included very few observations in our samples, we aggregated some of the cells. The eight regions are 1. IL 2. IN 3. IA 4. MN 5. MO, TX, OK and AR 6. OH, WI and MI 7. NE 8 other states(including ND, SD, PA, CT, ME, MD, MA, VT, NJ, NH, NY, RI, DE, NC ,KY, WV, VA, GA, SC, FL, AL, TN, MS, LA, WA, ID, OR, NV, CA, AZ, UT, HI, AK, KS, MT, WY, CO and NM). Farm sizes have three levels for the 1990 and 1995 surveys: small if fewer than 3,000 pigs

produced per year, medium if 3000 to 9,999 pigs produced per year and large: more than 10,000 pigs produced per year. For the 2000 and 2005 year surveys, farm size is further aggregated into two levels: small if fewer than 10,000 pigs produced per year and large if more than 10,000 pigs produced per year.

[5] Weights based on the 1992 Census were used for 1990 and 1995 survey responses, while the 1997 Census were used for weighting 2000 and 2005 survey responses.

[6] States included in the Midwest: 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 the 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.

[7] Exp(0.32) -1 = 0.38

[8] The model represents a given worker and the subscript *i* is suppressed for notational ease in the following analysis.

[9] Heckman et al (1998) argue that the second condition in the ignorability assumption is too strong. Instead, the weaker assumption $ln W_{0i} \perp (D_i \mid x_i)$ is sufficient to construct the counterfactual mean.

[10] Logit specification can also be imposed to obtain the propensity score. The results are shown to be consistent with those estimated from a probit model.

[11] Common support conditions are examined at radius 0.05 and they are shown to be satisfied.

[12] The kernel is $G(s) = \frac{3}{4}(1 - s^2)$ if $-1<s<1$, and zero otherwise.

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Table 1. 1 Distribution of employees and technology adoption intensity on hog farms by size of farm

Code	Size Class (pigs per year)	Weighted Frequencies (%)				Number of technologies	
		1990	1995	2000	2005	Mean	Std Dev
1	Less than 500	14.87	8.86	4.41	.	2.760	1.886
2	500 to 999 / less than 1000 in 2005	16.48	11.75	3.05	16.53	2.986	1.589
3	1,000 to 1,999	23.51	26.04	6.47	8.64	2.763	1.772
4	2,000 to 2,999	15.06	23.28	16.80	7.99	3.472	1.815
5	3,000 to 4,999	9.05	8.86	16.70	13.78	4.083	1.847
6	5,000 to 9,999	13.09	13.28	26.94	27.43	3.818	1.872
7	10,000 or more (1990) /10,000 to 14,999 (1995)	7.94	2.09	4.55	3.08	4.618	1.638
8	15,000 to 24,999	.	1.83	3.50	2.65	4.898	1.807
9	25,000 or more / 25,000 to 49,999 (2005)	.	4.02	17.58	4.63	5.263	1.788
10	50,000 to 99,999(2005)	.	.	.	3.3	4.844	2.044
11	100,000 or more (2005)	.	.	.	11.96	6.322	2.080

Note: Employee responses are weighted to reflect the distribution of employment on the US hog farms by the size and regions as reported by the USDA. Dot(.) represents that the category is not asked in the survey.

Figure 1.1 Size wage effect: Log of salary distribution in different size categories

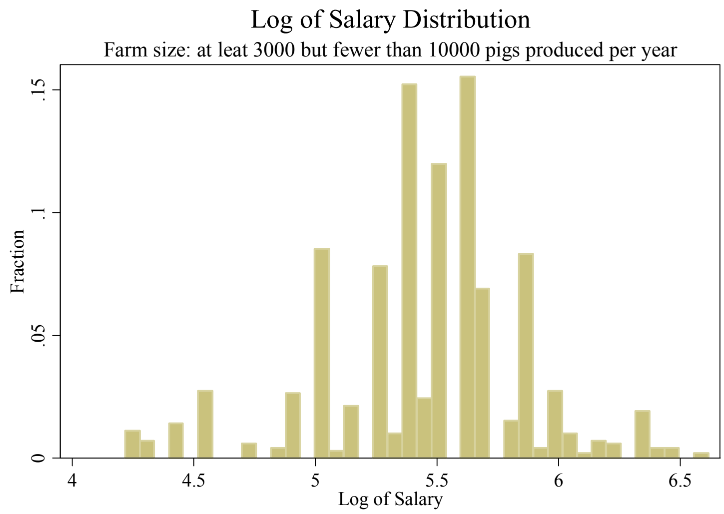
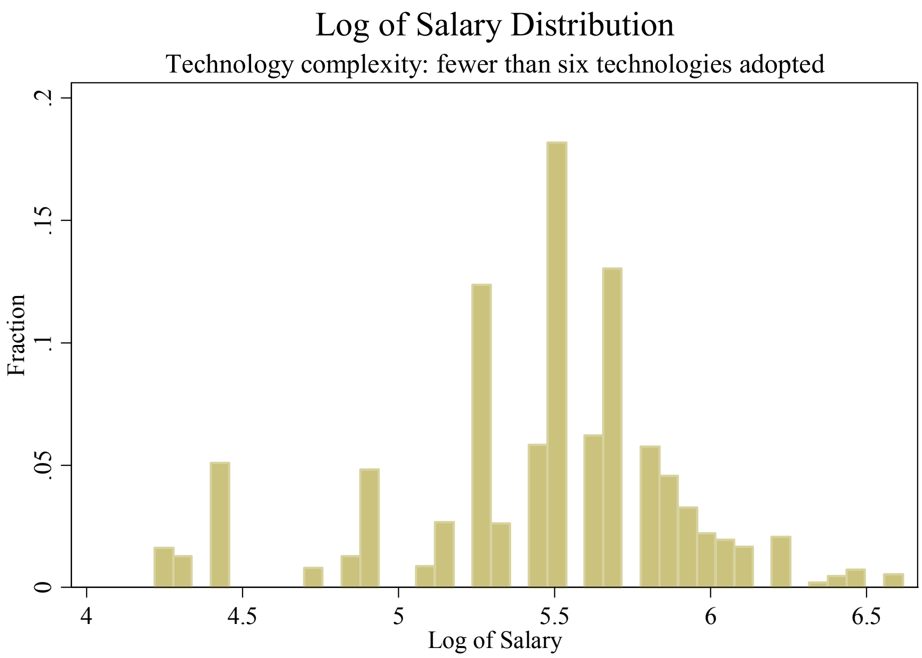


Table 1. 2 Fraction of employees on hog farms using various technologies

Number	Name	Notation	1995		2000		2005	
			Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
1	Artificial Insemination	AI	0.407	0.492	0.606	0.489	0.687	0.464
2	Split Sex Feeding	SSF	0.321	0.467	0.450	0.498	0.345	0.476
3	Phase Feeding	PF	0.479	0.500	0.535	0.499	0.492	0.500
4	Multiple Site Production	MSP	0.220	0.414	0.329	0.470	0.287	0.453
5	Early Weaning	EW	0.147	0.355	0.246	0.431	0.234	0.424
6	All in / All out	AIAO	0.572	0.495	0.638	0.481	0.568	0.496
7	Auto Sorting Systems	AS	.	.	.	.	0.025	0.158
8	Parity Based Management	PBM	.	.	.	.	0.186	0.389
9	Formal Management	FM	0.479	0.500	0.582	0.494	0.688	0.464
10	Computer Use	CU	0.589	0.492	0.686	0.464	0.721	0.449
-	Number of Technologies	-	3.214	1.839	4.072	1.978	4.233	2.085

Note: Statistics are weighted. Dot (.) represents that the category is not asked in the survey.

Figure 1.2 Workers on farms adopting more technologies earn more



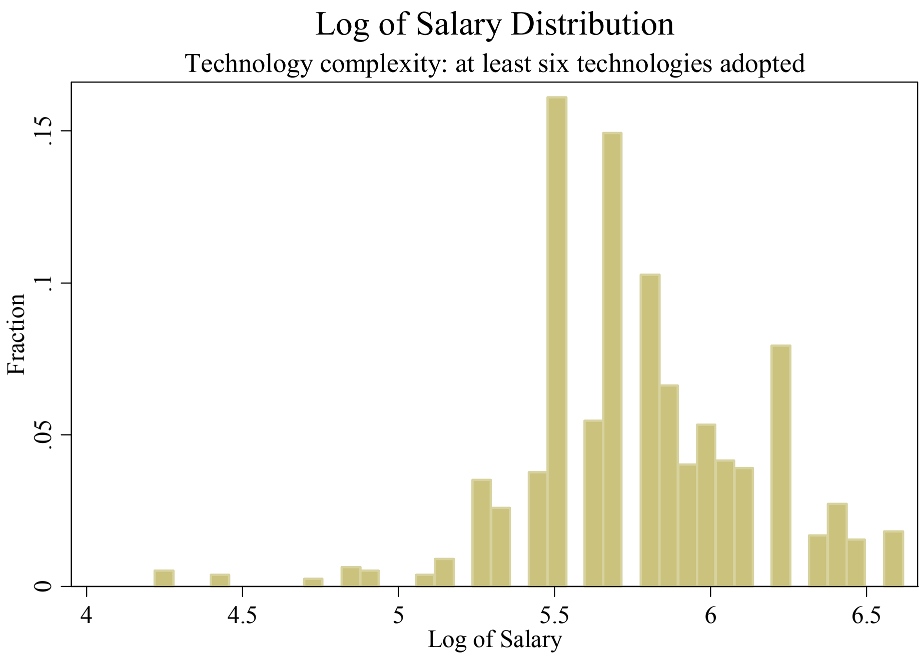


Table 1. 3 Characteristics of Employees and farms in the U.S. Hog Industry

Variables	Description	Full sample		Large Farms		Small Farms	
lnW	Log of salary	5.41	(0.54)	5.73	(0.38)	5.35	(0.55)
lnW[a]	Log of salary	5.44	(0.55)	5.73	(0.39)	5.37	(0.56)
Female	Gender of workers	0.09	(0.28)	0.11	(0.31)	0.08	(0.28)
Edu12	High school graduate	0.30	(0.46)	0.26	(0.44)	0.31	(0.46)
Edu14	2 year college diploma or equivalent	0.21	(0.40)	0.21	(0.41)	0.21	(0.40)
Edu16	4 year university degree or equivalent	0.34	(0.47)	0.43	(0.50)	0.33	(0.47)
Edu18+	Higher degree education level	0.09	(0.28)	0.06	(0.23)	0.09	(0.29)
Age	Age of workers	36.64	(10.85)	36.63	(10.09)	36.64	(10.98)
Tenure	Experience in the current farm	8.94	(8.18)	6.29	(5.95)	9.41	(8.42)
PrevExp	Dummy variable, equal to one if previously working in a hog farm	0.41	(0.49)	0.57	(0.50)	0.39	(0.49)
Raise	Dummy variable, equal to one if raised in a hog farm	0.53	(0.50)	0.45	(0.50)	0.55	(0.50)
Northeast	Dummy variable, equal to one if located in the northeast	0.09	(0.28)	0.06	(0.23)	0.09	(0.29)
Southeast	Dummy variable, equal to one if located in the southeast	0.14	(0.35)	0.21	(0.41)	0.13	(0.33)
West	Dummy variable, equal to one if located in the west	0.14	(0.35)	0.20	(0.40)	0.13	(0.34)
Farm Size	Number of pigs produced (unit: 10,000 heads)	0.77	(1.41)	3.32	(2.26)	0.31	(0.26)
Farm Size[a]	Number of pigs produced (unit: 10,000 heads)	0 .953	(1.63)	3.71	(2.26)	0.35	(0.26)
Number of technologies[a]	Number of technologies used	3.75	(2.01)	5.28	(1.92)	3.42	(1.86)

Note: The number is the weighted mean. The number in the parenthesis is the standard deviation. The statistics of the variables are weighted and are based on the surveys in 1990, 1995, 2000 and 2005. Salaries are discrete categories in the survey. We define the *salary* as a continuous variable by taking the mid-point of the range for each category, adjusted by the consumer price index. And the salary is adjusted by the consumer price index (CPI) from the Labor Statistics Bureau. CPI in 1990, 1995, 2000 and 2005 is 79.9975, 91.2177 98.8768 110.4758 respectively. *lnW* is the natural log of the real salaries. Education variables are dummies based on high school dropout. Higher degree includes a master degree, a Ph.D. degree or a Doctor of Veterinary Medicine. Farm size is defined in the following way: farms producing greater than or equal to 10,000 pigs each year is large, otherwise small if producing fewer than 10,000 pigs. [a] Statistics of the variable are based on the surveys in 1995, 2000 and 2005.

Table 1. 4 Traditional wage regression for U.S. hog industry employees (1990-2005)

	Model (1)	Model (2)	Model (3)	Model (4)
Female	-0.203	-0.193	-0.201	-0.173
	(3.84)**	(3.59)**	(3.75)**	(2.69)**
Edu12	0.211	0.200	0.204	0.225
	(2.71)**	(2.63)**	(2.71)**	(2.37)*
Edu14	0.353	0.332	0.334	0.350
	(4.51)**	(4.35)**	(4.41)**	(3.64)**
Edu16	0.439	0.423	0.418	0.420
	(5.62)**	(5.57)**	(5.56)**	(4.42)**
Edu18+	0.745	0.784	0.764	0.710
	(7.31)**	(7.75)**	(7.62)**	(5.63)**
Age	0.044	0.042	0.042	0.044
	(5.23)**	(5.08)**	(5.09)**	(4.10)**
Age^2	-0.000	-0.000	-0.000	-0.000
	(4.35)**	(4.22)**	(4.24)**	(3.43)**
Tenure	0.003	0.007	0.007	0.005
	(0.63)	(1.58)	(1.51)	(0.97)
Tenure^2	-0.000	-0.000	-0.000	-0.000
	(0.64)	(1.05)	(1.10)	(0.89)
PrevExp	0.170	0.153	0.157	0.135
	(6.03)**	(5.56)**	(5.71)**	(3.84)**
Raise	-0.067	-0.064	-0.062	-0.103
	(2.50)*	(2.42)*	(2.36)*	(3.01)**
Northeast	0.053	0.071	0.062	0.077
	(0.99)	(1.32)	(1.17)	(1.08)
Southeast	0.071	0.041	0.033	0.048
	(1.89)	(1.10)	(0.89)	(0.99)
West	-0.068	-0.092	-0.088	-0.140
	(1.49)	(2.04)*	(1.97)*	(2.42)*
Year 1995	-0.032	-0.041	-0.027	
	(1.17)	(1.49)	(0.98)	
Year 2000	0.101	0.024	0.052	0.063
	(2.88)**	(0.66)	(1.44)	(1.55)
Year 2005	0.074	-0.041	0.011	0.020
	(1.79)	(0.87)	(0.27)	(0.45)
Farm Size		0.145		
		(12.28)**		
Farm Size^2		-0.004		
		(8.03)**		
Size^a*>10.000*			0.330	0.258
			(14.25)**	(8.83)**
Technologies^b *>5*				0.240
				(5.86)**
Constant	4.051	4.057	4.063	4.001
	(25.86)**	(26.69)**	(26.27)**	(19.36)**
Observations	3934	3934	3934	2266
R-squared	0.21	0.25	0.25	0.29

Note: Dependent variable is natural log of salary. Number in the parentheses is absolute value of *t* statistics. Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1% respectively.

a. Size is defined as a dummy variable, equal to one if farms produce greater than or equal to 10,000 pigs each year, otherwise zero if farms produce fewer than 10,000 pigs. Model (4) use year 1995, 2000 and 2005 data and the other three models use four year survey data.

b. Dummy variable for the number of technologies is equal to one if the farms use more than five advanced technologies otherwise equal to zero if farms use no more than three technologies.

Table 1. 5 Characteristics of Employees and farms in the U.S. Hog Industry

Variables	Description	Full sample		Large Farms		Small Farms	
lnW	Log of salary	5.41	(0.54)	5.73	(0.38)	5.35	(0.55)
lnW[a]	Log of salary	5.44	(0.55)	5.73	(0.39)	5.37	(0.56)
Female	Gender of workers	0.09	(0.28)	0.11	(0.31)	0.08	(0.28)
Edu12	High school graduate	0.30	(0.46)	0.26	(0.44)	0.31	(0.46)
Edu14	2 year college diploma or equivalent	0.21	(0.40)	0.21	(0.41)	0.21	(0.40)
Edu16	4 year university degree or equivalent	0.34	(0.47)	0.43	(0.50)	0.33	(0.47)
Edu18+	Higher degree education level	0.09	(0.28)	0.06	(0.23)	0.09	(0.29)
Age	Age of workers	36.64	(10.85)	36.63	(10.09)	36.64	(10.98)
Tenure	Experience in the current farm	8.94	(8.18)	6.29	(5.95)	9.41	(8.42)
PrevExp	Dummy variable, equal to one if previously working in a hog farm	0.41	(0.49)	0.57	(0.50)	0.39	(0.49)
Raise	Dummy variable, equal to one if raised in a hog farm	0.53	(0.50)	0.45	(0.50)	0.55	(0.50)
Northeast	Dummy variable, equal to one if located in the northeast	0.09	(0.28)	0.06	(0.23)	0.09	(0.29)
Southeast	Dummy variable, equal to one if located in the southeast	0.14	(0.35)	0.21	(0.41)	0.13	(0.33)
West	Dummy variable, equal to one if located in the west	0.14	(0.35)	0.20	(0.40)	0.13	(0.34)
Farm Size	Number of pigs produced (unit: 10,000 heads)	0.77	(1.41)	3.32	(2.26)	0.31	(0.26)
Farm Size[a]	Number of pigs produced (unit: 10,000 heads)	0 .953	(1.63)	3.71	(2.26)	0.35	(0.26)
Number of technologies[a]	Number of technologies used	3.75	(2.01)	5.28	(1.92)	3.42	(1.86)

Note: The number is the weighted mean. The number in the parenthesis is the standard deviation. The statistics of the variables are weighted and are based on the surveys in 1990, 1995, 2000 and 2005. Salaries are discrete categories in the survey. We define the *salary* as a continuous variable by taking the mid-point of the range for each category, adjusted by the consumer price index. And the salary is adjusted by the consumer price index (CPI) from the Labor Statistics Bureau. CPI in 1990, 1995, 2000 and 2005 is 79.9975, 91.2177 98.8768 110.4758 respectively. *lnW* is the natural log of the real salaries. Education variables are dummies based on high school dropout. Higher degree includes a master degree, a Ph.D. degree or a Doctor of Veterinary Medicine. Farm size is defined in the following way: farms producing greater than or equal to 10,000 pigs each year is large, otherwise small if producing fewer than 10,000 pigs.

[a]. Statistics of the variable are based on the surveys in 1995, 2000 and 2005.

Table 1.5(continued)

	1995	**2000**	**2005**	**Pooled**	**Pooled**	$\beta_T^{1995} = \beta_T^{2000}$	$\beta_T^{2000} = \beta_T^{2005}$	$\beta_T^{1995} = \beta_T^{2000} = \beta_T^{2005}$
West	-0.078	-0.034	-0.357	-0.154	-0.147	0.500	0.121	1.898
	(0.84)	(0.54)	(3.66)**	(2.82)**	(2.71)**	(0.480)	(0.728)	(0.150)
AI	0.132	0.170	0.435	0.217	0.213	0.241	4.560	3.368
	(2.89)**	(2.74)**	(4.05)**	(5.11)**	(5.00)**	(0.624)	(0.033)*	(0.035)*
SSF	-0.001	0.084	-0.094	0.001	-0.000	1.174	3.303	1.652
	(0.03)	(1.26)	(1.31)	(0.02)	(0.00)	(0.279)	(0.069)	(0.192)
PF	0.075	-0.063	0.149	0.052	0.055	3.251	5.559	2.908
	(1.78)	(0.98)	(2.35)*	(1.43)	(1.53)	(0.072)	(0.019)*	(0.055)
MSP	0.020	-0.061	-0.092	-0.023	-0.020	1.073	0.081	0.827
	(0.38)	(1.05)	(1.01)	(0.60)	(0.53)	(0.301)	(0.777)	(0.438)
EW	0.095	0.061	0.073	0.077	0.081	0.179	0.016	0.091
	(1.63)	(1.16)	(0.99)	(1.92)	(2.03)*	(0.672)	(0.901)	(0.913)
AIAO	0.055	0.010	0.122	0.074	0.075	0.328	1.352	0.676
	(1.15)	(0.17)	(1.67)	(1.97)*	(2.02)*	(0.567)	(0.245)	(0.509)
FM	0.182	0.136	0.031	0.137	0.133	0.319	1.109	1.493
	(3.87)**	(2.02)*	(0.41)	(3.68)**	(3.55)**	(0.572)	(0.293)	(0.225)
CU	0.078	0.027	-0.180	-0.016	-0.015	0.419	3.996	3.714
	(1.65)	(0.43)	(2.19)*	(0.42)	(0.39)	(0.518)	(0.046)*	(0.025)*
Year 2000				0.032	0.036			
				(0.79)	(0.88)			
Year 2005				-0.047	-0.023			
				(0.98)	(0.52)			
Farm Size	0.237	0.136	0.056	0.082		3.213	6.162	3.138
	(2.66)**	(0.95)	(3.06)**	(6.35)**		(0.073)	(0.013)*	(0.044)*

Table 1.5(continued)

	1995	**2000**	**2005**	**Pooled**	**Pooled**	$\beta_T^{1995} = \beta_T^{2000}$	$\beta_T^{2000} = \beta_T^{2005}$	$\beta_T^{1995} = \beta_T^{2000} = \beta_T^{2005}$
Farm Size^2	-0.050 (1.95)	-0.015 (0.37)	-0.001 (1.16)	-0.002 (4.01)**		2.605 (0.107)	5.414 (0.020)*	2.715 (0.066)
Size >10,000					0.210 (6.72)**			
Constant	3.888 (17.70)**	4.449 (12.43)**	3.069 (8.46)**	3.867 (18.71)**	3.863 (18.54)**			
Observations	1149	617	500	2266	2266			
R-squared	0.29	0.34	0.52	0.33	0.33			
Joint test of technology adoptions	1.65 (0.117)	1.87 (0.073)	3.96* (0.00)**	4.22* (0.00)**	3.98** (0.00)**			

Note: Dependent variable is natural log of salary. Numbers in parentheses for the column two to column six are absolute values of t statistics. Column seven to nine reports the joint F test for each variable, along with the P-value in the parenthesis. Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1% respectively.

a. Joint F-test. The numbers in the last three columns are F-values of joint test and number in the parenthesis is the P-value of the F statistic.

Table 1. 6 Probit model of employment on large and small hog farms

Variables	Coefficient	t-Statistic
Female	0.040	0.49
Edu12	0.186	1.73
Edu14	0.255	2.29*
Edu16	0.386	3.61**
Edu18+	-0.218	-1.53
Age	0.051	3.69**
Age^2	-0.001	-3.33**
Tenure	-0.052	-6.18**
$Tenure^2$	0.001	2.42*
PrevExp	0.205	4.30**
Raise	-0.109	-2.31*
Northeast	-0.017	-0.17
Southeast	0.696	9.83**
West	0.415	5.74**
Year 1995	0.689	12.88**
Year 2000	1.376	20.33**
Year 2005	1.571	20.69**
Constant	-1.984	-7.24**
Observations	3934	
LR $\chi^2(17)$	1200.84	

Note: Dependent variable is a dummy variable indicating employment on a farm producing 10000 or more hogs. Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1% respectively. The data are year 1990 – 2005 surveys.

Figure 1.3 Propensity score distribution in large and small hog farms

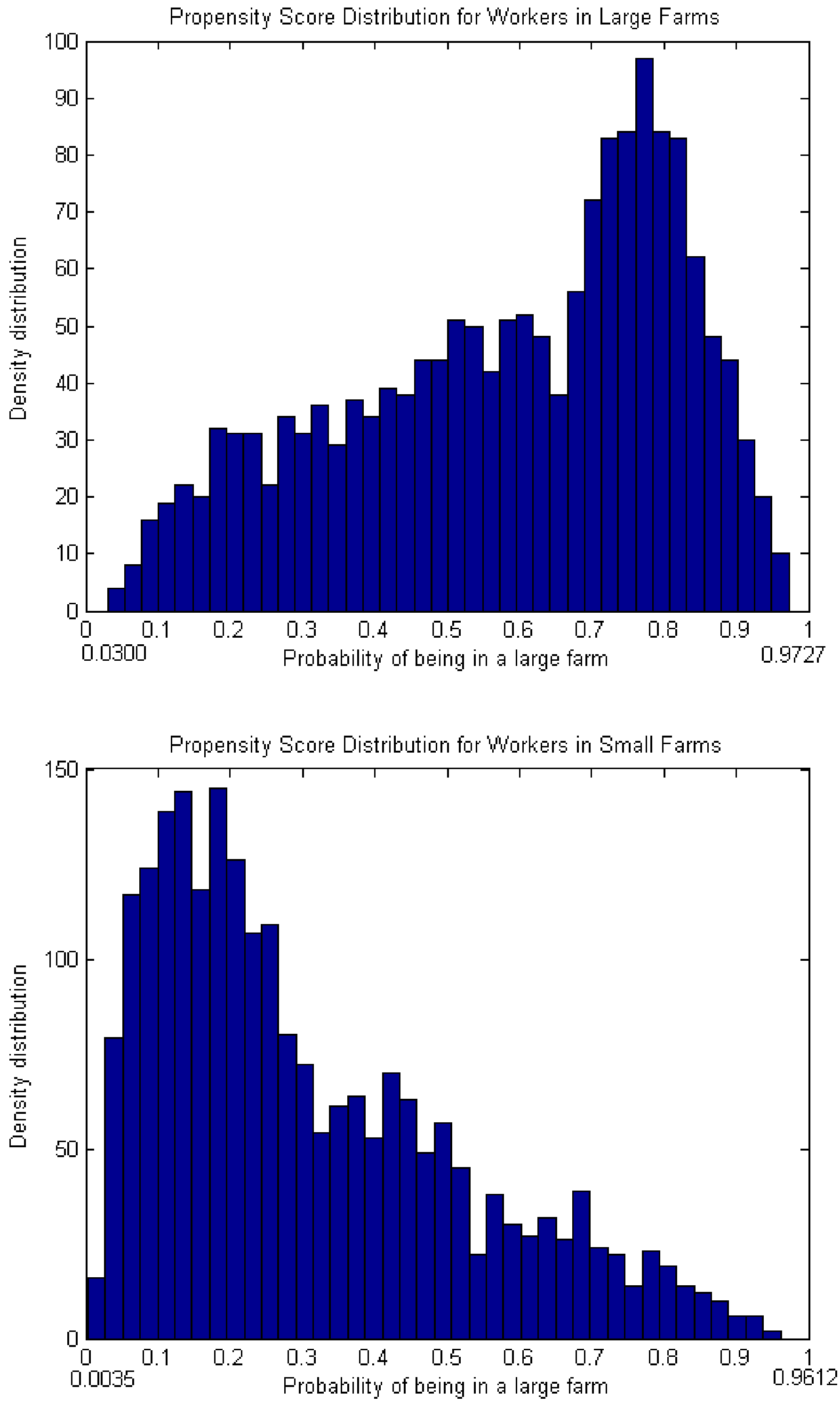


Table 1. 7 Estimated wage premium on hog farms producing 10,000 or more hogs, by worker and farm attributes

	Nearest			***Caliper***			***Kernel***			**Mean *ln*(Wage)** [a]	
	Premium (Log wage)	Std Err	Premium (%)	Premium (Log wage)	Std Err	Premium (%)	Premium (Log wage)	Std Err	Premium (%)	D=1	D=0
					1.7a. Estimation by education group						
Edu9	0.422	0.164	52.5%	0.377	0.099	45.8%	0.416	0.129	51.6%	5.533	4.960
Edu12	0.312	0.042	36.6%	0.331	0.022	39.2%	0.315	0.026	37.0%	5.607	5.232
Edu14	0.175	0.052	19.1%	0.319	0.027	37.6%	0.201	0.048	22.3%	5.691	5.327
Edu16	0.296	0.035	34.4%	0.310	0.022	36.3%	0.283	0.028	32.7%	5.786	5.429
Edu18+	0.239	0.185	27.0%	0.271	0.093	31.1%	0.217	0.134	24.2%	6.111	5.820
					1.7b. Estimation by region group						
Mid-west	0.265	0.030	30.3%	0.327	0.017	38.7%	0.264	0.022	30.2%	5.712	5.332
Northeast	0.124	0.120	13.2%	0.189	0.071	20.8%	0.140	0.086	15.0%	5.596	5.396
Southeast	0.298	0.044	34.7%	0.316	0.033	37.2%	0.294	0.044	34.2%	5.775	5.465
West	0.427	0.093	53.3%	0.431	0.066	53.9%	0.446	0.084	56.2%	5.749	5.298
					1.7c. Estimation by year						
1990	0.381	0.043	46.4%	0.361	0.025	43.5%	0.353	0.024	42.3%	5.694	5.304
1995	0.222	0.038	24.9%	0.299	0.023	34.9%	0.249	0.024	28.3%	5.673	5.320
2000	0.246	0.048	27.9%	0.253	0.050	28.8%	0.247	0.043	28.0%	5.727	5.427
2005	0.422	0.072	52.5%	0.364	0.067	43.9%	0.336	0.072	39.9%	5.763	5.415
					1.7d. Estimation by the often used individual technologies						
AI	0.204	0.032	22.6%	0.180	0.025	19.7%	0.173	0.026	18.9%	5.748	5.568
PF	0.302	0.040	35.3%	0.310	0.027	36.3%	0.293	0.030	34.0%	5.811	5.445
AIAO	0.303	0.036	35.4%	0.305	0.025	35.7%	0.288	0.036	33.4%	5.792	5.432
FM	0.249	0.041	28.3%	0.250	0.022	28.4%	0.229	0.030	25.7%	5.745	5.491
CU	0.328	0.033	38.8%	0.291	0.020	33.8%	0.285	0.026	33.0%	5.757	5.429

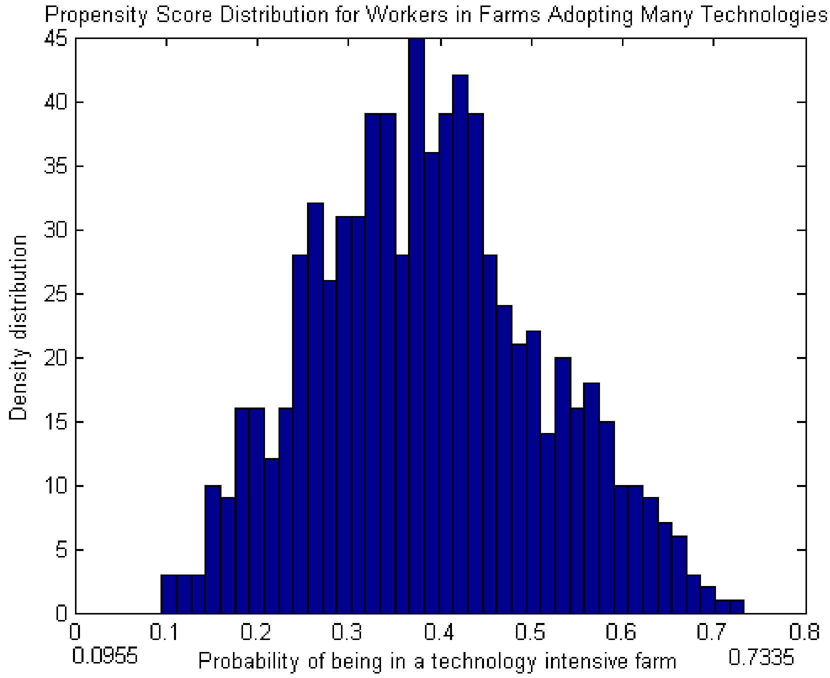
Note: The estimated mean is the difference of log of salary between large farms and small farms. Standard error is obtained by bootstrapping 100 times. Table 1.7a, 1.7b and 1.7c use the data set in all of four survey years. All results about technologies in table 1.7d uses the data in 1995, 2000 and 2005 except Formal Management, which uses all of the four survey data sets. [a] weighted mean log of the annual wage

Table 1. 8 Probit model of employment on farm by adoption of many or few technologies

Variables	Coefficient	t-Statistic
Female	-0.092	-0.98
Edu12	0.352	2.27*
Edu14	0.621	3.97**
Edu16	0.810	5.33**
Edu18+	0.948	5.10**
Age	0.046	2.62**
Age^2	-0.001	-2.66**
Tenure	-0.025	-2.47**
$Tenure^2$	0.001	1.65
PrevExp	0.234	3.94**
Raise	0.054	0.93
Northeast	-0.224	-1.68
Southeast	-0.074	-0.84
West	0.220	2.53*
Year 1995	-0.456	-6.18**
Year 2000	-0.342	-4.23**
Constant	-1.588	-4.41**
Observations	2266	
LR $\chi^2(16)$	167.76	

Note: Dependent variable is a dummy variable indicating employment on a farm using 6 or more technologies Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1% respectively. The data are year 1995 – 2005 surveys.

Figure 1.4 Propensity score distribution of hog farms adopting either many or few technologies



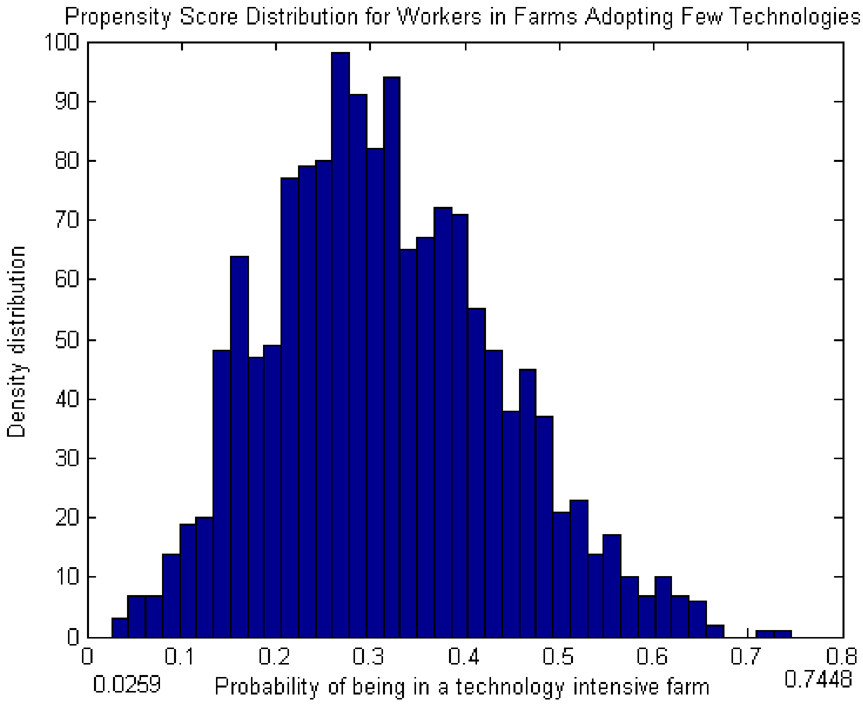


Table 1. 9 Estimated wage premium on hog farms using 6 or more technologies, by worker and farm attributes

	Nearest			***Caliper***			***Kernel***			**Mean *ln*(Wage) [a]**	
	Premium (log of wage)	Std Err	Premium (%)	Premium (log of wage)	Std Err	Premium (%)	Premium (log of wage)	Std Err	Premium (%)	D=1	D=0
1.9a. Estimation by education group											
Edu9	0.485	0.233	62.4%	0.470	0.089	60.0%	0.518	0.121	67.9%	6.005	4.934
Edu12	0.300	0.050	35.0%	0.308	0.026	36.1%	0.284	0.031	32.8%	5.628	5.266
Edu14	0.228	0.041	25.6%	0.263	0.033	30.1%	0.231	0.034	26.0%	5.698	5.349
Edu16	0.174	0.030	19.0%	0.204	0.026	22.6%	0.181	0.023	19.8%	5.712	5.457
Edu18+	0.251	0.137	28.5%	0.267	0.110	30.6%	0.164	0.085	17.8%	6.008	5.726
1.9b. Estimation by region group											
Mid-west	0.222	0.034	24.9%	0.260	0.022	29.7%	0.214	0.020	23.9%	5.740	5.334
Northeast	0.354	0.164	42.5%	0.318	0.098	37.4%	0.238	0.098	26.9%	5.625	5.438
Southeast	0.296	0.064	34.4%	0.295	0.046	34.3%	0.266	0.042	30.5%	5.890	5.484
West	0.206	0.062	22.9%	0.300	0.056	35.0%	0.253	0.056	28.8%	5.754	5.214
1.9c. Estimation by year											
1995	0.265	0.033	30.3%	0.293	0.024	34.0%	0.272	0.023	31.3%	5.668	5.303
2000	0.168	0.040	18.3%	0.193	0.027	21.3%	0.166	0.031	18.1%	5.710	5.433
2005	0.176	0.058	19.2%	0.237	0.039	26.7%	0.221	0.039	24.7%	5.853	5.353
1.9d. Estimation by farm size											
Large	0.162	0.024	17.6%	0.167	0.019	18.2%	0.151	0.017	16.3%	5.841	5.637
Small	0.217	0.062	24.2%	0.301	0.044	35.1%	0.229	0.038	25.7%	5.704	5.311

Note: The first column under each matching method is the difference of log of salary between farms adopting many and few technologies. Standard error is obtained by bootstrapping 100 times. Estimation is based on 1995, 2000 and 2005 surveys.
a: weighted mean of log of wage.

Appendix 1A

An alternative way is to estimate the propensity score through a probit model by weighted data, which corrects the sample selection. We further apply these three matching methods using the estimated propensity scores. According to Becker and Ichino(2002), the standard error is obtained

$Var(\hat{\tau}) = \frac{1}{N^T} Var(\ln w_{1i}) + \frac{1}{N^{2T}} \sum_{j \in I_0} \hat{w}(i,j)^2 Var(\ln w_{0j})$. However, the standard errors of kernel matching estimators can not be obtained by using this formula. Since we have already regarded the weighted data as a representative from the population, bootstrapping the data does not make any sense.

The following tables A1a and A1b list the probit estimation of propensity scores for the size treatment and technology treatments respectively. The size premium is 0.313(standard error of 0.023), 0.349(0.014) and 0.322 for Nearest Neighbor matching, Caliper matching and Kernel matching respectively .The technology premium is 0.239(0.026), 0.285(0.019) and 0.271 for Nearest Neighbor matching, Caliper matching and Kernel matching respectively.

The corresponding wage premiums in the subset of the data are reported in Table 1.A2a and Table 1.A2b.

Table 1.A1a: Probit model of employment on large and small hog farms

Variables	**Coefficient**	**t-Statistic**
Female	-0.004	-0.040
Edu12	0.148	1.140
Edu14	0.280	2.120*
Edu16	0.339	2.650**
Edu18+	-0.263	-1.640
Age	0.029	1.840
Age^2	0.000	-1.610
Tenure	-0.054	-4.950**
$Tenure^2$	0.001	1.800
PrevExp	0.201	3.480**
Raise	-0.088	-1.520
Northeast	-0.252	-2.250*
Southeast	0.446	4.850**
West	0.282	3.260**
Year 1995	1.648	29.060**
Year 2000	0.671	9.250**
Year 2005	0.866	10.400**
Constant	-2.021	-6.37**
Observations	3934	
F(17, 3917)	63.54	

Note: * Significant at 5%; ** significant at 1%.
The data are year 1990 – 2005 weighted survives.

Table 1.A1b Probit model of employment on hog farms which adopt many and few technologies

Variables	Coefficient	t-Statistic
Female	-0.211	-1.550
Edu12	0.409	1.730
Edu14	0.839	3.460**
Edu16	0.948	4.090**
Edu18+	1.395	5.040**
Age	0.037	1.360
Age^2	-0.001	-1.670
Tenure	0.007	0.440
$Tenure^2$	-0.001	-0.930
PrevExp	0.271	3.020**
Raise	0.146	1.680
Northeast	-0.545	-3.020**
Southeast	-0.117	-0.840
West	0.301	2.460*
Year 2000	-0.335	-3.560**
Year 2005	-0.136	-1.240
Constant	-1.850	-3.250**
Observations	2266	
F(16, 2250)	7.60	

Note:* significant at 5%; ** significant at 1%
The data are year 1995 – 2005 weighted surveys.

Table 1.A2a Large hog farm premium estimated wage

	Nearest		***Caliper***		***Kernel***		**Mean of Log Wage** [a]	
	Mean	Std	Mean	Std	Mean	Std	D=1	D=0
			1.A2a.a Estimation by education group					
Edu9	0.397	0.138	0.404	0.090	0.423	.	5.477	4.934
Edu12	0.319	0.040	0.336	0.024	0.308	.	5.585	5.240
Edu14	0.316	0.047	0.345	0.027	0.298	.	5.698	5.338
Edu16	0.284	0.034	0.331	0.022	0.314	.	5.748	5.439
Edu18+	0.341	0.127	0.195	0.077	0.236	.	6.068	5.905
			1.A2a.b Estimation by region group					
Mid-west	0.278	0.027	0.341	0.016	0.308	.	5.672	5.353
Northeast	0.094	0.119	0.193	0.073	0.160	.	5.602	5.403
Southeast	0.314	0.060	0.318	0.044	0.302	.	5.763	5.467
West	0.478	0.086	0.418	0.052	0.454	.	5.729	5.307
			1.A2a.c Estimation by year					
1990	0.301	0.038	0.372	0.023	0.361	.	5.694	5.304
1995	0.262	0.038	0.294	0.026	0.256	.	5.648	5.347
2000	0.237	0.066	0.272	0.046	0.243	.	5.727	5.427
2005	0.370	0.090	0.364	0.069	0.343	.	5.763	5.415
			1.A2a.d Estimation by the often used individual technologies					
AI	0.213	0.033	0.197	0.027	0.186	.	5.717	5.592
PF	0.314	0.037	0.324	0.026	0.308	.	5.754	5.474
AIAO	0.325	0.033	0.322	0.024	0.300	.	5.740	5.476
FM	0.214	0.030	0.267	0.020	0.234	.	5.717	5.492
CU	0.293	0.028	0.293	0.018	0.284	.	5.724	5.435

Note: *a*: weighted mean of log of salary. Table 1.A2a.a, 1.A2a.b and 1.A2a.c use the data set in whole four survey years. All results about technologies in Table 7d uses the data in 1995, 2000 and 2005 except Formal Management, which uses four survey data sets.

Table 1.A2b. Technology Wage Effect Estimation of Hog Farms

	Nearest		***Caliper***		***Kernel***		**Mean Log of Wage** [a]	
	Mean	Std	Mean	Std	Mean	Std	D=1	D=0
		1.A2b.a	Estimation by education group					
Edu9	0.625	0.213	0.566	0.112	0.553	.	6.002	4.902
Edu12	0.330	0.049	0.306	0.033	0.306	.	5.631	5.320
Edu14	0.273	0.050	0.268	0.035	0.274	.	5.743	5.423
Edu16	0.206	0.034	0.216	0.027	0.210	.	5.736	5.508
Edu18+	0.192	0.172	0.273	0.119	0.278	.	6.039	5.863
		1.A2b.b	Estimation by region group					
Mid-west	0.218	0.030	0.265	0.022	0.262	.	5.745	5.394
Northeast	-0.048	0.156	0.290	0.090	0.207	.	5.659	5.478
Southeast	0.326	0.057	0.314	0.046	0.302	.	5.927	5.539
West	0.304	0.075	0.275	0.060	0.269	.	5.765	5.258
		1.A2b.c	Estimation by year					
1995	0.286	0.035	0.293	0.024	0.280	.	5.730	5.420
2000	0.147	0.044	0.197	0.035	0.157	.	5.710	5.433
2005	0.166	0.061	0.266	0.045	0.213	.	5.853	5.353
		1.A2b.d	Estimation by farm size					
Large	0.134	0.028	0.156	0.020	0.149	.	5.795	5.598
Small	0.251	0.063	0.301	0.042	0.269	.	5.726	5.329

a: weighted mean of log of salary.

Testing for Complementarity and Substitutability among Multiple Technologies: The Case of U.S. Hog Farms

Li Yu, Terrance Hurley, James Kliebenstein and Peter F. Orazem

Abstract

We propose a strategy to identify the complementarity or substitutability among technology bundles. Under the assumption that alternative technologies are independent, we develop a hypothetical distribution of multiple technology adoptions. Differences between the observed distribution of technology choices and the hypothetical distribution can be subjected to statistical tests. Combinations of technologies that occur with greater frequency than would occur under independence are complementary technologies. Combinations that occur with less frequency are substitute technologies. This method is easily applied to simultaneous decisions regarding many technologies. We use the strategy to evaluate multiple technology adoptions on U.S. hog farms. We find that some technologies used in pork production are substitutable for one another while others are complementary. However, as the number of bundled technologies increases, they are increasingly likely to be complementary with one another, even if subsets are substitutes when viewed in isolation. This finding suggests that farmers have an incentive to adopt many technologies at once. Larger farms and farms run by more educated operators are the most likely to adopt multiple technologies. The complementarity among technologies in large bundles is contributing to a form of returns to scale that contributes to growth in average farm size.

Introduction

Since the publication of Griliches' (1957) seminal study on hybrid corn and Rogers (1962) seminal work on innovation diffusion, numerous studies have explored the process of technology adoption.[1] These studies have demonstrated the existence of a common sigmoidal trend in adoption rates and shown how the timing and pace of adoption is influenced by factors such as firm size; firm location; market structure; the human capital of the entrepreneur; and constraints on accessing labor or financial resources. Most of these studies focus on the decision to adopt a specific technology without explicitly considering other technologies. An aspect of technology adoption that has received less attention is the extent to which different technologies work well together and are adopted collectively or do not work well together and are adopted separately; or, in economic parlance, the extent to which combinations of technology are complementary or substitutable. This study develops and applies a tractable methodology that can show how technologies complement or substitute for each other, information that is critical to understanding the effect of technical innovation on industry growth and structure.

Several strategies have been employed to identify complementary and substitute relationships with multiple technology adoption. Wozniak (1993) and Dorfman (1996) simultaneously estimate adoption equations with two technologies. Although their methods differ, both studies use cross-correlation in regression errors to make inferences regarding technical relationships. Positive correlation is interpreted as a complementary relationship, while negative correlation is interpreted as a substitute relationship. The limitation is that the relationships can only be evaluated in bilateral comparisons, even when there are multiple technologies.

Efforts to incorporate more technologies have their own limitations. Stoneman and Toivanen (1997) estimate hazard rates for the adoption of five different technologies over time. A series of technology state dummy variables are constructed and included in the hazard rate equations. These technology state dummy variables reflect alternative bundles of technologies that have been adopted by the firm in addition to the technology under consideration. A significant positive effect attached to these dummy variables is interpreted as indicating a complementary relationship, while a significant negative effect indicates a substitute relationship. However, the technologies are jointly chosen with the technology being evaluated, and so there are clear endogeneity concerns. As an alternative, Caswell and Zilberman (1985) employ a multinomial logit model to allow selection of one of several potential technologies. However, the multinomial logit specification imposes that the technologies are substitutes, which was appropriate to their application but would not fit every circumstance.

Poppo and Zenger (2002) estimate the relationship between relational governance and formal contracts and Lokshin et al. (2004) estimate the relationship between multiple technology adoption and productivity. While Lokshin et al. treats technology as exogenous, Poppo and Zenger treat choices as endogenous. Both studies use the sign and significance of the effect of technology interactions on productivity to make inferences regarding complementary and substitute relationships between technologies or bundles of technologies.

While each of these strategies has its virtues, all share a common limitation — the curse of dimensionality. If there are K distinct technologies, there are 2^K possible technology bundles to choose from. This curse of dimensionality limits the practicality of applying these methods to cases where the number of available technologies is large. As a consequence, researchers may artificially restrict the number of technology choices to a subset of the universe, imposing independence between the included and excluded technologies. As we will demonstrate, imposing independence can lead to incorrect inferences regarding the true complementary or substitution relationships among technologies.

This paper proposes an alternative strategy for identifying complementary and substitute relationships in technology bundles. A key virtue of the proposed strategy is its broad applicability even when there are a large number of technologies that can be used in many different combinations. And the distributional forms of adoption are not required to be known. This virtue is demonstrated by applying the methodology to evaluate the adoption choices of eight separate technologies (or 256 potential technology bundles) used in U.S. hog production. An interesting insight gained from the application is that fewer than 10 percent of the technology bundles are complementary. However, over 80 percent of these complementary bundles include five or more different technologies, and so exploiting complementary relationships among technologies disproportionately involves the adoption of many technologies at once.

Because the adoption of multiple technologies can require substantial capital investment, we then examine the relationship between firm size and multiple technology adoption in the U.S. hog industry. Using a multinomial ordered probit model that allows the joint choices of the number of technologies and the size of farm, we find strong evidence of a complementary relationship between farm size and multiple technology adoption. This finding is consistent with the rapid growth in the market share of large farms coincident with rapid technology adoptions experienced by the U.S. hog industry over the past three decades.

The next section of the paper proposes an alternative strategy for determining if technology bundles are complementary, substitutable, or independent. The third section demonstrates the application of this method to data collected from a national longitudinal survey of U.S. hog producers. The fourth section first describes the multinomial ordered probit model used to estimate the relationship between multiple technology adoption and firm size, and then presents the results of the analysis. The final section concludes the paper.

Identifying Whether Technology Bundles Are Complements or Substitutes

Many previous studies of multiple technology adoption assume, either explicitly or implicitly, that complementary relationships result in positive correlation in adoption, while substitute relationships result in negative correlation. This assumption is intuitively appealing because if different technologies complement each other by increasing productivity or reducing costs, it is more likely that they will be used in combination. Alternatively, if different technologies substitute for each other such that the use of some makes the use of others either less productive or more costly, it is less likely that they will be used in combination. Nevertheless, the correlation between any two technology adoption rates may provide misleading inferences on whether the two technologies are complements or substitutes when there is even one more technology potentially in the mix.

The three technology illustration

Suppose any combination of three technologies can be adopted, leading to eight possible technology bundles. Let $X_k = 1$ if technology k is adopted and 0 otherwise for $k = 1, 2, 3$. If technology 1 is independent of technology 2, meaning that its adoption is just as likely as whether or not technology 2 is adopted, then the hypothesis

$$H_0^{(i)}: \Pr(X_1 = 1 | X_2 = 1) = \Pr(X_1 = 1) \text{ or } \Pr(X_1 = 1, X_2 = 1) = \Pr(X_1 = 1)\Pr(X_2 = 1)$$

will be true. Alternatively, if the adoption of technology 1 changes depending on whether technology 2 is adopted (i.e. there is positive or negative correlation in adoption), then

$$H_C^{(i)}: \Pr(X_1 = 1, X_2 = 1) > \Pr(X_1 = 1)\Pr(X_2 = 1) \text{ or}$$

$$H_S^{(i)}: \Pr(X_1 = 1, X_2 = 1) < \Pr(X_1 = 1)\Pr(X_2 = 1)$$

will be true. It is tempting to test hypothesis $H_0^{(i)}$ against its alternatives $H_C^{(i)}$ or $H_S^{(i)}$ in order to establish that the two technologies are complements (denoted by subscript C) or substitutes (denoted by subscript S). As shown by Lokshin et al. (2004), this strategy may be misleading when a third technology is present.

Suppose all three technologies are independent. Then the hypothesis

$$H_0^{(ii)}: \Pr(X_1 = 1, X_2 = 1, X_3 = 1) = \Pr(X_1 = 1)\Pr(X_2 = 1)\Pr(X_3 = 1) \text{ or}$$

$$\Pr(X_1 = 1, X_2 = 1 | X_3 = 1) = \Pr(X_1 = 1)\Pr(X_2 = 1)$$

will be true. Alternatively, if the three technologies are more or less likely to be adopted in combination, then

$$H_C^{(ii)}: \Pr(X_1 = 1, X_2 = 1 | X_3 = 1) > \Pr(X_1 = 1)\Pr(X_2 = 1) \text{ or}$$

$$H_S^{(ii)}: \Pr(X_1 = 1, X_2 = 1 | X_3 = 1) < \Pr(X_1 = 1)\Pr(X_2 = 1)$$

will be true.

If the three technologies are truly independent, then both $H_0^{(i)}$ and $H_0^{(ii)}$ will be true. However, if the three technologies are not independent, it is possible for both $H_C^{(i)}$ and $H_S^{(ii)}$ to be true. It is also possible for both $H_S^{(i)}$ and $H_C^{(ii)}$ to be true. In these circumstances, pairwise comparisons will lead to the wrong inference regarding the true relationships among the technologies.[2]

A proposed Test for Substitutability or Complementarity among Multiple Technologies

Our strategy begins with the realization that under the assumption of independent technologies, it is straightforward to construct the expected probability that a given bundle of technologies will be chosen by a random sample of agents. We can then compare the actual proportion of agents picking that technology bundle to the predicted proportion assuming independence. If the bundle is selected significantly more often than under the null hypothesis of independence, we can view the bundled technologies as mutually complementary. If the bundle is selected significantly less often than predicted under the null hypothesis of independence, we can view the bundled technologies as substitutes. Because of the tractability of the binomial distribution, the strategy applies easily to any number of technologies, and so the curse of dimensionality is avoided.

Suppose $K > 1$ technologies can be used alone or in combination. Let $X_k, k = 1, 2, \ldots K$, equal to 1 if the k^{th} technology is adopted and 0 otherwise. Define

$1 > p_k > 0$, for $k = 1, 2, \ldots K$ as the probability technology k is adopted. Let $Y = \{X_1, X_1, \ldots X_K\}$ be the set of technology bundles. The set has 2^K distinct elements denoted by Y_j for $j = 1, 2, \ldots 2^K$. Define $1 > q_j > 0$ for $j = 1, 2, \ldots 2^K$, such that $\sum_{j=1}^{2^K} q_j$ = 1, as the probability technology bundle j is adopted. Further define the set of technologies used in technology bundle Y_j as $\Omega_j^A = \{k \mid k = 1, 2, \ldots K \text{ and } X_k = 1\}$, while the set of technologies not used is $\Omega_j^N = \{k \mid k = 1, 2, \ldots K \text{ and } X_k = 0\}$.

Let $1 > p_{lk} > 0$, where $l, k = 1, 2, \ldots, K, l \neq k$, be the probability that k^{th} and l^{th} technologies are adopted jointly. To test if the k^{th} and l^{th} technologies are pairwise complements or substitutes, $H_0^{(i)}$, $H_C^{(i)}$ and $H_S^{(i)}$ can be generalized to $H_0^{(i)} : p_{kl} = p_{kl}^0$, $H_C^{(i)} : p_{kl} > p_{kl}^0$, and $H_S^{(i)} : p_{kl} < p_{kl}^0$ where $p_{kl}^0 = p_k p_l$. To test if the technologies adopted in technology bundle j are mutual complements or substitutes, $H_0^{(ii)}$, $H_C^{(ii)}$ and $H_S^{(ii)}$ can be generalized to $H_0^{(ii)} : q_j = q_j^0$, $H_C^{(ii)} : q_j > q_j^0$ or $H_S^{(ii)} : q_j < q_j^0$, where $q_j^0 = \prod_{k \in \Omega_j^A} p_k \prod_{l \in \Omega_j^N} (1 - p_l)$.

Implementing the pairwise hypothesis test for $H_0^{(i)}$, $H_C^{(i)}$ and $H_S^{(i)}$ or mutual hypothesis test for $H_0^{(ii)}$, $H_C^{(ii)}$ and $H_S^{(ii)}$ requires estimates of p_k assuming independence, and p_{kl} and q_j while relaxing the assumption of independence. It also requires estimates of the sampling distribution. Given a random sample of S firms denoted by $i = 1, 2, \ldots S$, let $X_k^i = 1$ if firm i adopts technology k and 0 otherwise; $X_{kl}^i = 1$ if firm i jointly adopts technologies k and l and 0 otherwise; and $Y_j^i = 1$ if firm i adopts technology bundle j and 0 otherwise. If technology adoption is in fact independent, maximum likelihood can be used to estimate p_k for $k = 1, 2, \ldots K$. The likelihood function is $L = \prod_{i=1}^{S} \prod_{k=1}^{K} p_k^{X_k^i} (1 - p_k)^{1 - X_k^i}$, which taking the natural log yields

$$(1) \qquad \ln L^O = \sum_{k=1}^{K} \left[\left(\sum_{1=1}^{S} X_k^i \right) \ln(p_k) + \left(S - \sum_{1=1}^{S} X_k^i \right) \ln(1 - p_k) \right].$$

Optimizing equation (1) with respect to p_k for $k = 1, 2, \ldots, K$ yields the estimates

(2) $$\hat{p}_k = \frac{\sum_{i=1}^{S} X_k^i}{S} \quad \text{for} \quad k = 1, 2, \ldots K .$$

The estimates in equation (2) indicate that the actual probability of adopting a given technology *k* can be calculated by the frequency of its occurrence in the random sample. Equation (2) implies

(3) $$\hat{p}_{kl}^0 = \hat{p}_k \hat{p}_l \text{ and } \hat{q}_j^0 = \prod_{k \in \Omega_j^A} \hat{p}_k \prod_{l \in \Omega_j^N} (1 - \hat{p}_l).$$

To estimate the probability that technologies *k* and *l* are jointly adopted, the log-likelihood function can be written as

(4) $$\ln L^{(i)} = \ln(p_{kl}) \sum_{i=1}^{S} X_{kl}^i + \ln(1 - p_{kl}) \left(N - \sum_{i=1}^{S} X_{kl}^i \right),$$

such that optimizing over p_{kl} yields the estimate $\hat{p}_{kl} = \frac{\sum_{i=1}^{S} X_{kl}^i}{S}$. More generally, to estimate the probability that technology bundle *j* is adopted, the log-likelihood function can be written as

(5) $$\ln L^{(ii)} = \sum_{j=1}^{2^K - 1} \ln(q_j) \sum_{i=1}^{S} Y_j^i + \ln\left(1 - \sum_{j=1}^{2^K - 1} q_j \right) \sum_{i=1}^{S} Y_{2^K}^i ,$$

such that optimizing over q_j yields the estimates

(6) $$\hat{q}_j = \frac{\sum_{i=1}^{S} Y_j^i}{S} \quad \text{for } j = 1, 2, \ldots 2^K - 1 \quad \text{and} \quad \hat{q}_{2^K} = 1 - \sum_{j=1}^{2^K - 1} \hat{q}_j .$$

Testing the null hypothesis that $\hat{p}_{kl} = \hat{p}_{kl}^{\,O}$ for a given pair of technologies or $\hat{q}_j = \hat{q}_j^{\,O}$ for a given technology bundle *j*, is complicated because $\hat{p}_{kl}$ and $\hat{p}_{kl}^{\,O}$, and $\hat{q}_j$ and $\hat{q}_j^{\,O}$ are correlated such that the sample variances are not easy to calculate. Plus, the usual statistic test based on Student's t distribution is not appropriate because the sampling distribution of the probability of $\hat{p}_{kl}$ and $\hat{q}_j$ are unknown. Percentile bootstrapping provides a good approximation to estimate the sampling distribution and the confidence intervals.

Suppose that M samples are drawn with replacement from the data. For each of these samples, $\hat{q}_j$ and $\hat{q}_j^{\,O}$ (or $\hat{p}_{kl}$ and $\hat{p}_{kl}^{\,O}$) are then calculated. Define $C = (C_1, C_2, \ldots, C_M)$ as the ordered vector of adoption rate differences $\hat{q}_j - \hat{q}_j^{\,O}$ (or $\hat{p}_{kl} - \hat{p}_{kl}^{\,O}$)

from samples such that $C_M \geq C_{M-1} \geq \ldots \geq C_1$. Locate the 2.5th and 97.5th percentiles of this ordered vector: $C^L = \left\lfloor \frac{0.05}{2}(M+1) \right\rfloor$ and $C^H = \left\lfloor (1-\frac{0.05}{2})(M+1) \right\rfloor$ where $\lfloor x \rfloor$ is the largest integer less than or equal to x. $[C^L, C^H]$ is the confidence interval for C at the significance level 95%. Consequently, if zero lies within the interval $[C^L, C^H]$, independence cannot be rejected. If C^L is positive, independence and a substitute relationship can be rejected, but a complementary relationship cannot. If C^H is negative, independence and a complementary relationship can be rejected, but a substitute relationship cannot.

A general test that technology bundles have a distribution predicted by technology independence

In general, multiple technology adoption can be regarded to have a standard multinomial distribution, where each combination of technologies occurs with a probability and the sum of the probability adds up to one. In S independent Bernoulli trials, the j^{th} technology bundle is adopted by producers with the probability $q_j^0, j = 1, 2, ..., 2^K, q_j^0 \geq 0$ and $\sum_{j=1}^{2^K} q_j^0 = 1$. Furthermore, define $F_j, j = 1, 2, ..., 2^K$ as the number of occurrence for the j^{th} technology bundle. $F = (F_1, F_2, \ldots, F_{2^K})$ follows a multinomial distribution with parameter S and $P = (P_1, P_2, \ldots, P_{2^K})$, denoted as $F \sim MN(S, P)$. In order to test if the technology bundles are selected with frequencies P, as predicted when technologies are independent, we use the G statistic, a log likelihood ratio statistic:

$$G = 2\sum_{j}^{2^K} F_j^1 \ln(\frac{F_j^1}{F_j^0}) = 2N\sum_{j}^{2^K} \hat{q}_j^1 \ln(\frac{\hat{q}_j}{\hat{q}_j^0}) \tag{7}$$

where F_j^1 and F_j^0 are respectively the frequencies that technology bundle j would be observed under H_1 and H_0. G is asymptotically distributed as a Chi- square with *$(2^K$-K-1)* degrees of freedom, $\chi^2(2^K - K - 1)$.

Multiple Technology Adoption on U.S. Hog Farms

The U.S. hog industry has experienced rapid technological innovation over last decade in the areas of nutrition, health, breeding and genetics, reproductive management, housing, and environmental management (McBride and Key, 2003). These technologies are used in four stages of the production process: breeding, gestation, farrowing, nursery and finishing. These technologies have been associated with improved feed efficiency, lower death loss, higher quality meat, more rapid weight gain, and other improved outcomes that raise farmer profits (Rhodes, 1995). The detailed benefits and targets of using specific technologies are shown in Table 2B.1 in the Appendix. Using our statistical method to compare observed adoption patterns against adoption patterns predicted under the null hypothesis of independence, we will be able to assess whether the observed technology bundles reflect an underlying complementary or substitute relationship among technologies.

We use data from random sample surveys of subscribers to *National Hog Farmer Magazine* (*NHFM*) conducted in years 1995, 2000 and 2005. Hog farmers across the United States were asked whether they use any of the ten technologies listed in Table 2.1. Each technology is treated as a dichotomous variable taking the value of 1 if the technology is used and 0 if it is not used. Information on Medicated Early Weaning and Modified Medicated Early Weaning was only available for 1995 and 2000. Questions regarding two other technologies, Auto Sorting and Parity Based Management, were only asked in 2005. We concentrate on the eight remaining technologies for which we have information in each of the three survey years. The most commonly used technologies are Phase Feeding (PF) and All In /All Out (AIAO) production. Artificial Insemination (AI) and Segregated Early Weaning (SEW) have been increasingly used by producers. Modified Medicated Early Weaning (MMEW) is the least often adopted in 1995, Medicated Early Weaning (MEW) is the least often adopted in 2000 and Auto Sorting (AS) is the least often used in 2005.

Because subscribers to *NHFM* are not a representative sample of all hog farmers and because the propensity to respond to surveys may differ by farm size and survey year, the survey data are weighted to conform to the size distribution of hog farms in the USDA Agricultural Census Data (ACD). Hog farm counts from 8 census regions and three size categories were taken as the population universe.[3] Each farmer in the *NHFM* sample was assigned a weight, w_i, that was the ratio of the proportion of USDA/ACD farms in the farmers region and size class[4]. Considering these weights, the adoption rate for technology k under independence is defined as

$$(8) \qquad \hat{p}_k = \frac{\sum_{i=1}^{S} X_k^i w_i}{\sum_{i=1}^{S} w_i}.$$

The adoption rate for technologies k and l jointly is $\hat{p}_{kl} = \frac{\sum_{i=1}^{S} X_{kl}^i w_i}{\sum_{i=1}^{S} w_i}$ and the adoption rate for technology bundle j is $\hat{q}_j = \frac{\sum_{i=1}^{S} Y_j^i w_i}{\sum_{i=1}^{S} w_i}$.

The number and size distribution of hog farms have changed dramatically across survey years, as shown in Table 2.2.[5] The number of farms has fallen by 61% in ten years. The surviving farms have tended to become larger or else have dropped to the smallest category.[6] In 1995, 6.7% of farms produced more than 5,000 hogs. By 2005, that proportion had risen to 12%. Respondents that were very large, producing over 25,000 hogs annually, more than doubled over the 10 year period.

Relationships among Multiple Technologies on U.S. Hog Farms

In this section, we show how our method can identify whether technologies adopted on U.S. hog farms are mutual complements or substitutes for individual technology bundles and also for all technology bundles jointly. Using equation (8), we utilize the raw data to estimate the adoption probability for each technology, $\hat{p}_k$, k = 1, 2,…, K. These are reported in Table 2.1. Some have had rapid growth in adoption rates such as Artificial Insemination (AI) and Segregated Early Weaning (SEW) whose usage doubled between 1995 and 2005. Other technologies such as Split Sex Feeding (SSF) and Phase Feeding (PF) have had a declining usage since 1995.

First, for a technology bundle j, the elements of the difference $\hat{q}_j - \hat{q}_j^0$ are calculated according to equations (2), (3) and (6). We then draw 5,000 samples with replacement to generate an approximate distribution of the differences. The results are summarized in Table 2.3a. Depending on the year, between 51-71 percent of possible technology bundles never occur in our data. The majority of the technology bundles that are selected occur with frequencies consistent with the independence assumption. Of the selected bundles, 72 of 125 cases (58%) are chosen with frequencies not significantly different from independence in 1995; 48 out of 73 (66%) in 2000; and 71 out of 101 (70%) in 2005. The remaining bundles can be categorized as either substitutes or complements with substitute relationships being more common at 23% of the selected bundles.

We have a particular interest in examining evidence of technology bundles that are mutually complementary. Previous studies of technology adoption have explicitly or implicitly restricted technologies to be independent or substitutes. As shown in Table 2.3b, we find evidence of mutually complementary technology bundles in each year.

When we add other technologies to a complementary bundle, the resulting bundles are also more likely to be complementary. For example, technologies SSF, PF and AIAO are complementary in 1995, when AI is added into the bundle, the new bundle is complementary. If we further add MSP into this bundle, the new bundle is also complementary. Furthermore, if any of the three early weaning technologies is added, the resulting six technology bundles are also mutually complementary. In particular, some technology combinations which we designate as T1= {AI, PF, AIAO} and T2= {SSF, PF, MSP, AIAO} appear atypically frequently among the complementary bundles in the sample. When only four technologies specified as T2 were adopted in 1995 and in 2005, these four technologies are independent. When T2 bundle is simultaneously adopted with any one of three Early Weaning technologies, the new bundles are complementary in 1995. When the T2 bundle is simultaneously adopted with Segregated Early Weaning technologies, the resulting bundles are complementary in 2005.

Another interesting result is that some technologies that may appear to be substitutes in isolation may become complementary when another technology is added to the bundle. For example, SSF and PF are substitutes in 1995, but SSF, PF and AIAO are complementary. AI, PF and AIAO appear to be mutual substitutes in 1995, but adding SSF results in a complementary bundle AI, SSF, PF, AIAO. This is one example of a general tendency we find in the data: as the number of bundled technologies increases, they are increasingly likely to be mutually complementary. This is true, even when subsets of the larger technology bundle are substitutes. This finding suggests that farmers that can adopt many technologies at once can take advantage of complementarities that would not occur if they adopted only a subset of those technologies.

Not all of the relationships among technologies are consistent or stable across time. The production function with elements of technologies, capital and labor inputs may change or correspond to the time horizon when new technologies diffuse, cost structures change, demand and preference for hogs alter or economic condition reverses and so on. For example, the bundle {AI, SSF, PF, MSP, AIAO, SEW} is mutually complementary in every year. However, {AI, PF, AIAO, MSP, SEW} is mutually complementary only in 1995 and 2000 but becomes independent in 2005.

Among early weaning technologies, Segregated Early Weaning is more frequently used in the complementary bundles than MEW and MMEW, as can be seen in Table 2.1. The three early weaning technologies are less likely to appear together in the technology combinations. None of the farms adopted the three technologies at the same time from 1995 to 2000. Furthermore, none of the farms adopted any two of the three technologies (SEW and MEW, MEW and MMEW, or SEW and MMEW) at the same time conditional on that no other technologies were used from 1995 to 2000 except that MEW and MMEW were independent in 1995. In particular, producers commonly adopt one of the three earning weaning technologies to complement with others. MEW and MMEW appeared more frequently in the complementary combinations in 1995 but declined dramatically in use in 2000 and were dropped from the survey in 2005. They were supplanted by SEW, which also incorporates the use of anti-biotic vaccines in early-weaned pigs combined with methods to keep litters of pigs separated to further suppress spread of diseases.[7]

Next, the *G* statistic from equation (7) allows an overall test of the null hypothesis that the pattern of technology bundle choices is consistent with expected distribution derived from independence assumption. By survey year, the *G* statistics are 1995: 94.7; 2000: 215.1; and 2005: 175.3. We easily reject technical independence.

Comparison with Inferences Drawn from Pairwise Comparisons

It is useful to compare our findings to the implied relationships we would have obtained between any two technologies, ignoring the existence of other potential technologies. Past studies have relied on the signs of the covariance matrix between residuals obtained from technology adoption regressions. Since conclusions from these approaches can be approximated by calculating simple correlation between two technologies, we can illustrate how conclusions differ when two technologies are viewed in isolation using simple correlations compared to our more general method.[8]

In Table 2.4, pairwise correlations lead to numerous incorrect inferences. For example, in 1995, bilateral correlations would imply that there are no substitute technologies whereas 13 of 28 possible cases are substitutes in conjunction with all the other technologies. Similarly, pairwise correlations imply numerous complementary technology pairs that are really independent or substitutes when viewed in the context of multiple technologies. For example, using survey data on employers in 2005, (SSF, MSP) and (PF, MSP) are complements using pair wise correlation method, but they turned out to be substitutes using our proposed method when the additional 6 technologies are available but not adopted. In addition, many of the presumptive complementary pairs implied by simple correlations, in fact never occur in the data — the pair of technologies is only chosen in combination with other technologies that are presumed to be irrelevant alternatives. For example, technology bundle (SEW, MMEW) had never been selected by farmers in 1995 but were shown to be complementary due to their positive correlation.

Simultaneous Technology Adoption and Farm Size Determination

The previous section demonstrates that certain technology bundles are mutually complementary, but that these bundles tend to have a relatively large number of technologies. This leads to the interesting possibility that the pattern of complementarities in high dimensioned technology bundles is contributing to the rising market share of large hog farms. Farm size may be complementary with multiple technology use because large holdings of land and facilities may be necessary to utilize multiple adoptions efficiently. Additionally, the skills necessary to manage large farms may be similar to the skills necessary to implement and manage multiple technologies effectively. Table 2.5 shows that it is indeed the larger farms that adopt more technologies in all three years. Farms with annual production levels below 1,000 pigs utilize fewer than two technologies on average. Farms producing more than 10,000 pigs use more than three technologies on average. Over time, there is modest growth in the number of technologies used within each size category, but the gap in technology use between the largest and smallest farms remains.

Previous studies have noted a correlation between firm size and technology adoption.[9] Several reasons have been advanced. Previous studies have also consistently shown that more educated agents more readily adopt new technologies, a finding that carries over to agriculture.[10]

We hypothesize that technology adoption and farm size are joint choices that are complementary with the human capital of the farmer. To investigate this relationship, we use a bivariate ordered probit model. We consider two latent dependent variables: t_i^* is the number of technologies used by producer i and s_i^* is the size of producer i's farm. We posit that the joint choice of t_i^* and s_i^* takes the form

$$(9)\quad \begin{aligned} t_i^* &= x_i\beta - u_{ti} \\ s_i^* &= x_i\gamma - u_{si} \\ \begin{pmatrix} u_{ti} \\ u_{si} \end{pmatrix} &\sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1+\lambda_t^2\sigma^2 & \lambda_t\lambda_s\sigma^2 \\ \lambda_t\lambda_s\sigma^2 & 1+\lambda_s^2\sigma^2 \end{pmatrix}\right). \end{aligned}$$

where β and γ are coefficient vectors to be estimated in the technology adoption and farm size equations, respectively. The error term $u_{ji} = \lambda_j\varepsilon_i + \mu_{ji},\ j = t, s$ is composed of two parts: unobserved ability ε_i for each producer i treated as random individual-specific effects distributed $N(0,\sigma^2)$; and a pure random factor $\mu_{ji},\ j = t, s$ that varies across choices and is assumed to be an independent draw from a standard normal distribution. The size and sign of the parameters λ_t and λ_t shows how and to what extent the managerial talents of producers affect their farm size and technology choices.

The latent and continuous number of technologies t_i^* is not observable by the analyst, but the number of technologies is observed as a discrete category, t_i defined as:

$$(10)\quad \begin{aligned} t_i &= 0 \quad if \quad t_i^* < a_0 \\ &= 1 \quad if \quad a_0 \le t_i^* < a_1 \\ &\ldots \\ &= 8 \quad if \quad a_7 \le t_i^* \quad , a_c > a_{c-1}, \forall c = \{1,2,\ldots,7\} \end{aligned}$$

where the a_c are unknown threshold parameters to be estimated. We similarly divide farm size into categories from 0 to 8. We impose that the two choices have the same thresholds a_c, $c = 0,1,...,7$. The model experienced convergence problems when we left all threshold parameters free to vary.

In order to identify the model, λ_t is normalized to be one. The remaining parameters to be estimated include $\beta, \gamma, \sigma^2, a_c$ and $\lambda_s, c = 0,1,...,7$. The μ_{ti} and μ_{si} can be regarded as draws from a bivariate normal distribution with correlation coefficient ρ, where

$$(11) \qquad \rho = \frac{\lambda_s \sigma^2}{\sqrt{1+\sigma^2}\sqrt{1+\lambda_s^2\sigma^2}}.$$

The probability for the producer *i* to adopt *k* technologies and produce amount of hogs in the size category *m* is given by

$$(12) \qquad \begin{aligned} &\Pr(t_i = k, s_i = m) = \Pr(a_{k-1} \le t_i < a_k, a_{m-1} \le s_i < a_m) \\ &= \Pr(t_i < a_k, s_i < a_m) - \Pr(t_i < a_{k-1}, s_i < a_m) \\ &- \Pr(t_i < a_k, s_i < a_{m-1}) + \Pr(t_i < a_{k-1}, s_i < a_{m-1}) \\ &k = 0, 1, ..., 8, \ \ m = 0, 1, ..., 8. \end{aligned}$$

and $\Pr(t_i = k, s_i = m)$ is the cumulative density function evaluated at individual producer i who adopts k technologies and operate a farm with size in the category m. $a_{-1} \to -\infty$ and $a_8 \to \infty$. When the normal distribution is assumed, the corresponding probability density function is

$$(13) \qquad \begin{aligned} &f_Y(k,m) = \frac{1}{(2\pi)^{2/n}\sqrt{\det\Sigma}} e^{-\frac{1}{2}(Y-\bar{y})^T \Sigma^{-1}(Y-\bar{y})} \\ &Y = (t^*, s^*)^T, \\ &\bar{y} = (x\beta, x\gamma)^T \end{aligned}$$

where Y is a vector of latent dependent variables, technology complexity and farm size; T denotes the transpose of the matrix; and Σ is the covariance matrix for Y, $\Sigma = \begin{pmatrix} 1+\sigma^2 & \lambda_s\sigma^2 \\ \lambda_s\sigma^2 & 1+\lambda_s^2\sigma^2 \end{pmatrix}$. The likelihood function to be maximized is

$$(14) \qquad LL = \prod_{i=1}^{N} \omega_i \ln[\Pr(t_i = k, s_i = m)], \quad k = 0, 1, ..., 8, m = 0, 1, ..., 8$$

where $\Pr(t_i = k, s_i = m)$ is defined in (12) and its probability density function is defined in equation (13). ω_i is the sampling weight assigned to individual producer i, as stated in the third section (Rabe-Hesketh *et al*. 2006).

We expect but do not restrict that the correlation coefficient ρ is positive. It will reflect the underlying correlation between the unobserved λ_t and λ_s. A finding that $\rho > 0$ (which implies that $\lambda_s > 0$) is consistent with the hypothesis that unobserved entrepreneurial skill positively affects both the number of technologies adopted and the size of farm. Finding that the β and γ attached to observable skills are also positive in both equations can be viewed as corroborating evidence that skills are complementary with both farm size and technology.

We use the Generalized Linear Latent and Mixed Models (GLLAMM) in STATA to estimate the model. The method uses the Newton–Raphson method and adaptive quadrature to approximate the likelihood function by numerical integration (Rabe-Hesketh et al. 2004). As before, sample weights are imposed. Regression results are shown in Table 2.7.

Producer human capital increases both the scale and the number of technologies used in hog production. Producers with more education are more likely to adopt at least two technologies, and are more likely to produce annually at least 2,000 hogs in 1995 and 2000 and at least 3,000 hogs in 2005. Consistent with past studies, producer experience has a small negative effect on the number of technologies adopted, presumably because younger farmers have more time to capture the benefits from the new technologies. The estimate for λ_s is statistically significant and positive (implied ρ =0.35) so that unobservable producer attributes, assumed to be unobserved managerial skills, significantly increase both farm size and the number of technologies used.

Conclusion and Discussion

This paper proposes a tractable statistical method to test for mutually complementary or substitute technologies. The method exploits the fact that profit maximizing producers will adopt technologies in groups if they are complements with greater frequency than would be predicted if the technologies were mutually independent. On the other hand, if the technologies are mutual substitutes, combinations will be bundled together with less frequency than would occur under mutual independence. This statistical method makes it simple and feasible to check the relationships between technologies which have high dimensional combinations. Our method therefore solves a series of problems in the current literature of technology adoption such as complex computation and endogeneity in simultaneous adoption of multiple technologies.

Applying the method to a data set that includes eight technologies adopted by U.S. hog farmers, we find that some technologies used in pork production are mutual substitutes while others are mutual complements. Several technologies including Sex Split Feeding, Phase Feeding, Multiple Site Production, and All In/ All are often bundled together. More importantly, as the number of bundled technologies increases, they are increasingly likely to be complementary with one another, even if subsets are substitutes when viewed in isolation. Ignoring the existence of other potential technologies and concluding from the simple correspondence based on the correlation between complementarity or substitutability is shown to be misleading. The application of our proposed method suggests that the usual correlation between any two technology adoption rates, ignoring other technologies may provide misleading inferences on whether the two technologies are complements or substitutes.

Our findings suggest that the complementarity among technologies in large bundles is contributing to a form of returns to scale that is leading to increasing growth in average farm size. Because the technologies are complementary, the productivity of one technology is enhanced by the adoption of the other technologies. This provides an incentive for multiple technology adoption, but not all farms are equally able to adopt. We find that large farms run by more educated operators are the most likely to adopt multiple technologies. This apparent size bias for multiple technologies is consistent with the view that new technologies are hastening the move toward larger farms in the U.S. pork industry.

The application of our newly proposed method to the case of hog production is appealing. One concern is that the technology adoption decision will be made simultaneously with the type of operation. Some farms produce pigs from farrowing stages to finishing stages while others specialize in farrowing pigs till feeder pigs. Not all technologies would be appropriate for the more specialized operations. For example, artificial insemination (AI) technology is only useful on farms whose production includes the farrowing stage while multi-site production might be expected to be most appropriate for farms that finish hogs.

The jointness of the decision on type of operation and mix of technologies means that it would not be appropriate to condition choice of technology bundle on operation type.

However, we can investigate the degree to which the technology bundle choice is dictated by the desired type of operation.

Table 2B.2 in Appendix 2B shows the adoption rates for single technologies by farm type. Except for AI and MMEW, technology usage does not vary significantly by the farm operation type. Therefore, it does not appear that choice of farm type constrains the technology mix sufficiently to alter our conclusions.

A second concern is that different hog production technologies require differing levels of capital and labor inputs. For example, Multiple Site Production (MSP) technology is relatively capital-intensive, while Medicated Early Weaning (MEW) technology is relatively labor-intensive. This suggests that farm size may be related to technology adoption because of the ability to attract funding rather than an underlying complementarity between farm size and technology. As indicated in Table 2B.2, feeder-to-finish farms tend to adopt fewer technologies than those of other types, perhaps due to differences in ability to fund capital investments.

We examined this issue by adding choice of operation as an added decision to a multivariate probit model including choices on technology adoption intensity and farm size. The results are shown in the Table 2B.3. The hypotheses that producer human capital increases probability of adopting multiple technologies and of operating a large farm still cannot be rejected, even after the selection of farm types is added as a choice. Unobserved factors that increase technology adoption and farm size are also positively correlated.

Interestingly, producer attributes do not affect choice of farm type. However, there is a strong negative relationship between errors in the choice to operate a feeder-to-finish farm and both number of technologies and farm size. That suggest that using operation type as an exogenous factor in either farm size or technology choice would incorrectly assign a causal role that feeder-to-finish operations lead to fewer technologies and smaller farms. Instead, unobserved factors that lead farmers to opt for feeder-to-finish operations also lead those farmers to adopt fewer technologies and to operate smaller farms.

Farmers, who are atypically interested in farrow-to-feeder operations, holding observed attributes constant, are also atypically prone to adopt larger farms. In this case, incorrectly treating farrow-to-feeder operations as an exogenous attribute would cause researchers to incorrectly interpret that farrow-to-feeder operations are complementary with farm size.

Endnotes

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[1] Examples include Hannan and McDowell (1984), Weiss(1994), Putler and Zilberman (1998), and Baker (2001). Sunding and Zilberman (2001) offer a good survey of the literature.

[2]Appendix contains a more formal discussion of the alternatives.

[3] USDA accounts originally include 18 regions and four size classifications. Since in some cells (region, size), there are only a couple of observations in our samples, we aggregate some of the regions and sizes. Eight regions are categorized in the following: 1. IL 2. IN 3. IA 4. MN 5. MO, TX, OK and AR 6. OH, WI and MI 7. NE 8 other states(including ND, SD, PA, CT, ME, MD, MA, VT, NJ, NH, NY, RI, DE, NC ,KY, WV, VA, GA, SC, FL, AL, TN, MS, LA, WA, ID, OR, NV, CA, AZ, UT, HI, AK, KS, MT, WY, CO and NM). Farm sizes have three levels: small if fewer than 3,000 pigs are produced per year, medium if 3,000 to 9,999 pigs are produced per year and large if more than 10,000 pigs are produced per year.

[4] Weights based on the 1992 Census were used to weight 1995 survey responses, 1997 Census were used for the survey in 2000 and 2002 Census for the survey in 2005.

[5] All of these market shares are computed using the sample weights.

[6] The size categories in the surveys are inconsistent over time in that the smallest category of less than 500 hogs produced annually is eliminated in the 2005 survey. The 2005 survey adds a new largest category of over 50,000 hogs produced per year.

[7]Additional information on these technologies is available at http://www.thepigsite.com.

[8] Lokshin, et.al (2004) also proposes a method to evaluate multiple technology choices rather than pairwise comparisons but their procedure is also limited to small dimensional problems.

[9] Examples include Colombo and Mosconi (1995); Kristen and Belman (2004);and Stoneman and Kwon (1994, 1996).

[10] 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 for examples of technology adoption in agriculture. Huffman (1999) presents a comprehensive review.

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Table 2. 1 Technologies used and adoption rate in the US hog industry

No.	Description	Notation	1995	2000	2005
1	Artificial Insemination	AI	0.236	0.350	0.407
			(0.425)	(0.477)	(0.492)
2	Split Sex Feeding	SSF	0.284	0.305	0.200
			(0.451)	(0.461)	(0.400)
3	Phase Feeding	PF	0.508	0.524	0.397
			(0.500)	(0.500)	(0.490)
4	Multiple Site Production	MSP	0.218	0.261	0.202
			(0.413)	(0.440)	(0.401)
5	Segregated Early Weaning	SEW	0.079	0.156	0.155
			(0.269)	(0.363)	(0.362)
6	Medicated Early Weaning	MEW	0.035	0.010	
			(0.183)	(0.101)	
7	Modified Medicated Early Weaning	MMEW	0.010	0.021	
			(0.097)	(0.144)	
8	All in / All out	AIAO	0.501	0.584	0.511
			(0.500)	(0.493)	(0.500)
9	Auto Sorting Systems	AS			0.020
					(0.139)
10	Parity Based Management	PBM			0.059
					(0.235)

Note: The estimates of the adoption rates of individual technologies are weighted using sampling weights. Number in the parenthesis is standard deviation.

Table 2. 2 Size class and frequencies

Code	Size Class (pigs per year)	Weighted Frequencies (%)		
		1995	2000	2005
1	Less than 500	2.93	4.69	.
2	500 to 999 / less than 1000 in 2005	6.41	1.97	27.64
3	1,000 to 1,999	35.39	37.3	27.5
4	2,000 to 2,999	42.28	36.43	27.74
5	3,000 to 4,999	6.27	6.35	5.46
6	5,000 to 9,999	5.67	9.18	8.36
7	10,000 to 14,999	0.47	1.23	0.99
8	15,000 to 24,999	0.3	1.02	0.75
9	25,000 or more / 25,000 to 49,999 (2005)	0.28	1.83	0.7
10	50,000 or more (2005)	.	.	0.85
Total	Number of farms	175,775	97,180	69,420

Source: Authors' compilation of weighted survey responses with weights defined in the text.

Table 2. 3 Results of the specific technology bundle test

Table 2.3a Summary of the results

Relations	*1995*	*2000*	*2005*
Do Not Exist in Sample	131	183	155
Substitutes	35	18	16
Independence	72	48	71
Complements	18	7	14

The statistics are based on M=5000 bootstrapped samples.

Table 2.3.b Complementary technologies

	1995	*2000*	*2005*
2 technologies	-	-	-
3 technologies	SSF & PF & AIAO	-	SSF & PF & AIAO
4 technologies	T1 & SSF AI, MSP,SEW, AIAO	-	SSF & PF & SEW & AIAO
5 technologies	T2 & MEW T2 & MMEW T2 & SEW T1 & SSF & MSP T1 & MSP & SEW T1 & SSF & MEW T1 & SSF & MMEW	T1 & MSP & SEW	T2 & AI T2 & SEW
6 technologies	T2 & AI & MEW T2 & AI & MMEW T2 & AI & SEW	T2 & AI & SEW	T2 & AI & SEW T2 & AI & AS T2 & AI & PM T1 & MSP & SEW & PM
7 technologies	-	-	T2 & AI & SEW & AS T2 & AI & SEW& PM
8 technologies	-	-	-

Note: The number of technologies in the first column is the number of technologies adopted which are significantly complementary. T1= {AI, PF, AIAO}. T2 = {SSF, PF, MSP, AIAO}. The case in which no technologies are adopted is excluded from the analysis, though it generates a higher frequency and is included into the category of "complements".

Table 2. 4 Comparison between bilateral correlation method and our statistical method in the context of more than two technologies available

Bilateral Correlation Method

Year	Substitutes	Complementary	Independence
1995	0	27	1
2000	2	14	11
2005	0	15	13

New Method for Multiple Technologies

Year	Substitutes	Complementary	Independence	Do Not Exist in Sample
1995	13	0	9	6
2000	4	0	11	13
2005	3	0	14	11

Note: the total number of cases when the bilateral relationship between two technologies is 28. Each number shows how many cases are predicted using one of the methods in each of survey years

Table 2. 5 Technology usage by size class and survey year: Mean and standard deviation

Technologies Adopted	Farm Size Category: Less Than 500	500 to 999	1,000 to 1,999	2,000 to 2,999	3,000 to 4,999	5,000 to 9,999	10,000 to 14,999	15,000 to 24,999	More Than 25,000
					1995				
Mean	1.21	1.07	1.56	2.02	2.58	2.87	3.34	3.56	3.88
Standard Deviation	1.28	0.92	1.21	1.37	1.54	1.61	1.64	1.76	1.86
					2000				
Mean	1.66	0.87	1.92	2.04	3.09	3.47	3.43	3.77	3.45
Standard Deviation	1.38	0.79	1.29	1.4	1.51	1.76	1.62	2.09	2.15
					2005				
Mean	1.34	1.76	2.1	2.64	2.97	3.1	3.72	3.93	4.27
Standard Deviation	0.86	1.29	1.29	1.38	1.58	1.64	2.1	2.11	2.1

Note: Number in the parenthesis is the standard deviation of the weighted mean

Table 2. 6 Characteristics of producers and farms

Variables	Description	Mean	(std dev)
Female	Gender of producer	0.068	-0.252
Edu	Schooling years	13.873	-2.429
Experience	Working experience	26.608	-11.936
Northeast	Dummy variable, equal to one if located in the northeast	0.087	-0.282
Southeast	Dummy variable, equal to one if located in the southeast	0.112	-0.316
West	Dummy variable, equal to one if located in the west	0.119	-0.323
Number of technologies	Number of technologies used	1.984	-1.44
Farm Size	Categories 0-8	2.483	1.371

Note: a. Farms with more technologies are defined as the ones adopting at least four technologies, other wise they are farms adopting fewer technologies.
* The statistics of the variables are weighted. The number is the weighted mean. The number in the parenthesis is standard deviation.
* Higher degree includes a master degree, a Ph.D. degree or a Doctor of Veterinary Medicine.
* Education variables are dummies based on high school dropout.
* Working experience is age of the producer minus schooling years minus six. The education level reflected in the survey is categorical. The schooling years (SY) of producer 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. SY = 16 if she is has a bachelor's degree. SY = 19 if she has a master degree. SY = 23 if she a Ph.D. degree hold or a Doctor of Veterinary Medicine.

Table 2.7 Technology adoption – bi-variate ordered probit regression

Dependent Variable:	**Number of technologies**	**Farm size**
Female	0.279	-0.660
	(1.41)	(3.93)**
Edu	0.034	0.038
	(1.97)*	(2.65)**
Experience	-0.027	0.019
	(1.97)*	(1.86)
Experience^2	-0.0001	-0.0003
	(0.36)	(1.92)
Northeast	-0.318	-0.186
	(1.67)	(1.45)
Southeast	-0.476	-0.038
	(2.49)**	(0.33)
West	-0.354	-0.458
	(2.22)*	(3.90)**
Year 2000	0.250	0.172
	(2.62) **	(2.13)*
Year 2005	0.266	-1.150
	(2.49) *	(11.6)**
a_0	-1.660	
	(6.86) **	
a_1	-0.531	
	(2.27) *	
a_2	0.549	
	(2.42)*	
a_3	1.616	
	(6.98)* *	
a_4	2.177	
	(9.32) **	
a_5	2.927	
	(12.49) **	
a_6	3.414	
	(14.34) **	
a_7	3.643	
	(15.14) **	
λ_2	0.575 [0.046]**	
σ^2	0.998 [0.111] **	
ρ	0.352 [0.026]**	

Note: Absolute value of *t* statistics in parentheses and standard error in square bracket.
* Significant at 5%; ** significant at 1%.
Probability weights are considered in the model and the standard errors are therefore robust.
Asymptotic standard error of ρ is obtained using Delta Method and shown in the parenthesis.

Appendix 2A

Proposition A: If technologies 1 and 2 are complements in pair wise comparison ($H_C^{(i)}$) and substitutes without technology 3 ($H_S^{(ii)}$), then technologies 1 and 2 must be complements with technology 3.

Proof :

Under $H_C^{(i)}$, $\Pr(X_1 = 1, X_2 = 1) > \Pr(X_1 = 1)\Pr(X_2 = 1)$;

Under $H_S^{(ii)}$, $\Pr(X_1 = 1)\Pr(X_2 = 1) > \Pr(X_1 = 1, X_2 = 1| X_3 = 0)$

$\Pr(X_1 = 1, X_2 = 1)$

$= \Pr(X_3 = 1)\Pr(X_1 = 1, X_2 = 1| X_3 = 1) + \Pr(X_3 = 0)\Pr(X_1 = 1, X_2 = 1| X_3 = 0)$

$> \Pr(X_1 = 1, X_2 = 1| X_3 = 0)$ according to $H_C^{(i)}$ and $H_S^{(ii)}$, which implies that

$\Pr(X_1 = 1, X_2 = 1| X_3 = 1) > \Pr(X_1 = 1, X_2 = 1| X_3 = 0)$ as long as $\Pr(X_3 = 1)>0$.

Then

$\Pr(X_1 = 1, X_2 = 1| X_3 = 1)\Pr(X_3 = 0) + \Pr(X_1 = 1, X_2 = 1| X_3 = 1)\Pr(X_3 = 1)$

$> \Pr(X_1 = 1, X_2 = 1| X_3 = 0)\Pr(X_3 = 0) + \Pr(X_1 = 1, X_2 = 1| X_3 = 1)\Pr(X_3 = 1)$.

So, $\Pr(X_1 = 1, X_2 = 1| X_3 = 1) > \Pr(X_1 = 1, X_2 = 1)$, technologies 1 and 2 together are complements with technology 3.

Q.E.D.

Corollary A: If technologies 1 and 2 are complements in pair wise comparison ($H_C^{(i)}$) and substitutes without technology 3 ($H_S^{(ii)}$), then technologies 1, 2 and 3 are mutual complements.

Proof:

According to proposition A and $H_C^{(i)}$,

$\Pr(X_1 = 1, X_2 = 1| X_3 = 1) > \Pr(X_1 = 1, X_2 = 1) > \Pr(X_1 = 1)\Pr(X_2 = 1)$. Q.E.D.

Proposition B: If technologies 1 and 2 are substitutes in pair wise comparison ($H_S^{(i)}$) and complements without technology 3 ($H_C^{(ii)}$), then technologies 1 and 2 must be substitutes with technology 3.

Proof :

Under $H_S^{(i)}$, $\Pr(X_1 = 1, X_2 = 1) < \Pr(X_1 = 1) \Pr(X_2 = 1)$;

Under $H_C^{(ii)}$, $\Pr(X_1 = 1) \Pr(X_2 = 1) < \Pr(X_1 = 1, X_2 = 1 | X_3 = 0)$.

$\Pr(X_1 = 1, X_2 = 1)$

$= \Pr(X_3 = 1) \Pr(X_1 = 1, X_2 = 1 | X_3 = 1) + \Pr(X_3 = 0) \Pr(X_1 = 1, X_2 = 1 | X_3 = 0)$

$< \Pr(X_1 = 1, X_2 = 1 | X_3 = 0)$ according to $H_S^{(i)}$ and $H_C^{(ii)}$, which implies that

$\Pr(X_1 = 1, X_2 = 1 | X_3 = 1) < \Pr(X_1 = 1, X_2 = 1 | X_3 = 0)$ as long as $\Pr(X_3 = 1)>0$.

Then

$\Pr(X_1 = 1, X_2 = 1 | X_3 = 1) \Pr(X_3 = 0) + \Pr(X_1 = 1, X_2 = 1 | X_3 = 1) \Pr(X_3 = 1)$

$< \Pr(X_1 = 1, X_2 = 1 | X_3 = 0) \Pr(X_3 = 0) + \Pr(X_1 = 1, X_2 = 1 | X_3 = 1) \Pr(X_3 = 1)$,

So, $\Pr(X_1 = 1, X_2 = 1 | X_3 = 1) < \Pr(X_1 = 1, X_2 = 1)$. Technologies 1 and 2 must be substitutes with technology 3.

Q.E.D.

Corollary B: If technologies 1 and 2 are substitutes in pair wise comparison ($H_S^{(i)}$) and complements without technology 3 ($H_C^{(ii)}$), then technologies 1, 2 and 3 must be mutual substitutes.

Proof:

According to proposition B and $H_S^{(i)}$,

$\Pr(X_1 = 1, X_2 = 1 | X_3 = 1) < \Pr(X_1 = 1, X_2 = 1) < \Pr(X_1 = 1) \Pr(X_2 = 1)$.

Q.E.D.

Appendix 2B

Table 2B.1 Description of technologies in the hog production

Technology	Description
AI	It focuses on enhancing hog reproductive efficiency and improving the gene pools
SSF	It feeds different rations to males and females. They have different diets for pigs of various weights and separate diets for gilts and barrows for maximum efficiency and carcass quality.
PF	It involves feeding several diets for a relatively short period of time to more accurately and economically meet the pig's nutrient requirements.
MSP	It produces hogs in separate places in order to curb disease spread.
SEW	The method gives the piglets a better chance of remaining disease-free when separated from their mother at about three weeks when levels of natural antibodies from the sow's milk are reduced. And at the same time, early weaning helps to produce more piglets each year.
MMEW	Its effect is same as MEW but less all-embracing. The range of infectious pathogens to be eliminated is not quite so comprehensive. MMEW can also be used to move pigs from a diseased herd to a healthy herd.
MEW	The method uses medication of the sow and piglets to produce excellent results in removing most bacterial infections.
AIAO	It allows hog producers to tailor feed mixes to the age of their pigs (instead of offering either one mix to all ages or having to offer several different feed mixes at one time). It also helps limit the spread of infections to new arrivals by allowing for cleanup of the facility between groups of hogs being raised.
AS	It helps in the way of labor savings, easier feed withdrawal, reductions in sort variation and sort loss, greater uniformity in pig market weight, and therefore more accurate marketing.
PBM	The specialization of labor in breeding, feeding and caring for pigs will benefit the production by reducing disease transmission and lowering the risk of new disease introductions.

Note: the technology the notation stands for is referred in the Table 2.1 or Table 2B.2. Information is based on the USDA animal and plant health inspection service and ERS; http://www.thepigsite.com/; and National Hog Farmer http://nationalhogfarmer.com/.

Table 2B.2 Technology adoption rate by farm type

No.	Description	Notation	Farrow to Finishing	Farrow to Feeder Pigs	Feeder Pigs to Finishing
1	Artificial Insemination	AI	0.316	0.474	0.027
			(0.465)	(0.500)	(0.163)
2	Split Sex Feeding	SSF	0.279	0.172	0.327
			(0.448)	(0.378)	(0.470)
3	Phase Feeding	PF	0.551	0.305	0.448
			(0.498)	(0.461)	(0.498)
4	Multiple Site Production	MSP	0.251	0.214	0.139
			(0.434)	(0.411)	(0.347)
5	Segregated Early Weaning	SEW	0.096	0.144	0.107
			(0.295)	(0.352)	(0.310)
6	Medicated Early Weaning	MEW	0.025	0.025	0.005
			(0.157)	(0.157)	(0.067)
7	Modified Medicated Early Weaning	MMEW	0.006	0.019	0.000
			(0.075)	(0.136)	(0.000)
8	All in / All out	AIAO	0.521	0.529	0.592
			(0.500)	(0.500)	(0.492)
9	Auto Sorting Systems	AS	0.001	0.000	0.018
			(0.028)	(0.011)	(0.133)
10	Parity Based Management	PBM	0.013	0.007	0.003
			(0.111)	(0.084)	(0.050)
-	Total number of technologies	-	2.059	1.891	1.666
			(1.460)	(1.492)	(1.295)

Note: numbers in the parentheses are standard errors.

Table 2B.3 Multivariate probit model of technology, farm size and farm type

Variables	Equation 1: Technology Adoption Intensity	Equation 2: Farm size	Equation 3: Farrow to Feeder	Equation 4: Feeder to Finishing
Female	0.138	-0.100	-0.029	-0.197
	(0.62)	(0.78)	(0.11)	(0.79)
Education	0.076	0.074	-0.031	0.003
	(3.14)**	(4.61)**	(1.36)	(0.13)
Experience	-0.002	0.001	-0.014	0.011
	(0.11)	(0.13)	(1.02)	(0.68)
Experience^2	-0.000	-0.000	0.000	-0.000
	(1.48)	(0.82)	(0.82)	(0.29)
Northeast	0.079	-0.092	0.377	-0.142
	(0.30)	(0.68)	(1.70)	(0.81)
Southeast	-0.523	0.410	0.013	-0.000
	(2.63)**	(3.22)**	(0.08)	(0.00)
West	-0.526	-0.144	0.058	-0.143
	(2.75)**	(1.15)	(0.34)	(0.80)
Year 2000	0.303	0.538	-0.402	0.227
	(2.25)*	(6.75)**	(2.66)**	(1.79)
Year 2005	0.224	0.529	0.025	0.309
	(1.63)	(6.58)**	(0.16)	(2.27)*
Constant	-1.686	-3.333	-0.432	-1.325
	(4.47)**	(11.42)**	(1.06)	(3.44)**
Correlation Coefficients				
ρ_{12}	0.533			
	(17.00)**			
ρ_{13}	0.026			
	(0.44)			
ρ_{14}	-0.123			
	(2.18)*			
ρ_{23}	0.199			
	(2.80)**			
ρ_{24}	-0.162			
	(2.06)*			
ρ_{34}	-0.428			
	(8.03)**			

Note: Absolute value of *t* statistics in parentheses and standard error in square bracket. * Significant at 5%; ** significant at 1%.

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.

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

Li Yu and Peter F. Orazem

Abstract

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's value. The theory has relevance in agricultural settings where mistakes have led to large recalls of organic spinach, pet food, chicken, beef and other products. This paper tests the predictions of the O-Ring theory in the context of hog production in the United States. Empirical results show that, consistent with the theory, distributions of wages, technology adoptions, and farm size are all skewed to the right. The most skilled workers concentrate in the largest and most technologically advanced farms. Workers on the larger and more technologically advanced farms are paid more than comparably skilled workers on smaller and less technology intensive farms. Positive correlations among the unmeasured factors that lead to higher wages, more complex technologies and larger farms suggest that, as with observed skills, workers with the greatest endowments of unobserved skills also sort themselves into the largest and most technology intensive farms.

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 Brown and Medoff (1989), Idson and Feaster(1990), Troske(1999), Bayard and Troske(1999), Oi and Idson(1999), and Lluis(2003). 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; Monaco and Belman, 2004; 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 firm numbers since 1995, there were still 69 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. 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.

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. The number of tasks t represents 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) $$\underset{t,\{q_i\}}{Max} \quad (\prod_{i=1}^{t} q_i)\, tB(t) - \sum_{i=1}^{t} w(q_i) \quad .$$

$B(t)$ 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 $q_i = q_j = q,\ i, j = 1, 2, \ldots, t,\ \ i \neq j$. These preliminaries can be shown to imply regularities that we should be able to confirm or reject in the data.

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

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

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

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

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

The zero profit condition implies

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

Inserting condition (5) into (4) implies that

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

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 (4) 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 (4), 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(5),

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

where $q = g(t)$ and $g(t)$ is the inverse function of $t(q)$ which is increasing in *t* according to (6). Taking derivatives with respect to w on (8), we obtain $\frac{\partial w}{\partial t} = w(-t\frac{B''}{B} + (\frac{B'}{B})) > 0$.

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].

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). 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[9]. 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 $\frac{n_j}{s_j}$.[10]

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 3.1, 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 asked in the 2005 questionnaire. Because AS and PBM technologies are new and still not commonly used, we constrain the available technology set at the eight options. 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 3.1 shows the distribution of employment in farms with different numbers 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 3.2. The size categories varied across surveys. Reflecting that the market share of large firms increased over the decade (McBride and Key, 2003), the smallest farms are defined as producing fewer than 500 pigs in the 1995 and 2000 surveys and less than 1,000 pigs in 2005. The largest farm is 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 3.2. 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 3.2. 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 3.3. The distribution of employees earning different levels of salaries is shown in Figure 3.3. The distribution is also right skewed and has similar statistics with those of the farm size distribution. Moreover, Table 3.3 shows an apparent positive relationship among salary level and farms sizes 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 3.4 summarizes the other variables included in our analysis. *Female* is a self-defining dummy variable. Only 8.8% of hog farm employees are female. *Education* is measured by years of schooling completed and 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. Average tenure is nearly nine years with 41% 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[11]. These are captured by three dummy variables with the base being the Midwest region where 63% of employees are found.

Among these characteristics, education level of workers is positively related with the technology complexity, farm size and wages. Figure 3.4 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 3.4 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.

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. That larger and more technologically complex farms have more educated workers has been found in other studies. However, larger farms may also require workers with unmeasured skills that are nevertheless demanded by farmers such as dependability, accuracy, care and ambition. In another context, Abowd *et al* (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

$$
\begin{aligned}
&t_i^* = x_i\beta - u_{ti} \\
&s_i^* = x_i\gamma - u_{si} \\
(9) \qquad &w_i^* = x_i\delta - u_{wi} \\
&\begin{pmatrix} u_{ti} \\ u_{si} \\ u_{wi} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1+\lambda_t^2\sigma^2 & \lambda_t\lambda_s\sigma^2 & \lambda_t\lambda_w\sigma^2 \\ \lambda_t\lambda_s\sigma^2 & 1+\lambda_s^2\sigma^2 & \lambda_w\lambda_s\sigma^2 \\ \lambda_t\lambda_w\sigma^2 & \lambda_w\lambda_s\sigma^2 & 1+\lambda_w^2\sigma^2 \end{pmatrix}\right).
\end{aligned}
$$

where x_i is a vector of person attributes and farm characteristics specified in Table 3.4 with coefficient vectors β, γ and δ to be estimated in technology adoption, farm size and wage rate equations respectively. The random disturbance term $u_{ji} = \lambda_j e_i + \mu_{ji}, j = t, s, w$ is composed of two parts: the unobserved ability component of skill, $e_i \sim N(0, \sigma^2)$, and a pure random factor μ_{ji}, $j = t, s, w$ that varies across choices and is assumed to be an independent draw from a standard normal distribution. The observed workers skills h_i are included in the vector x_i. *Hypothesis 1* can be tested based on the signs of the β, γ and δ 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

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

A finding that $\rho_{ts} > 0$, $\rho_{sw} > 0$, and $\rho_{tw} > 0$ is consistent with the second hypothesis 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 conceptual variable t_i^*, which is continuously latent, is not directly observed by analysts, but the number of technologies used on the farm is observed as a discrete category, t_i defined as:

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

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

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

$\Phi(\cdot)$ denotes the cumulative density function of the standard normal distribution. Farm size and wages are also divided into categories from 0 to 8. In principle, we can allow separate cut-points for each equation, but as discussed below, we found that the model was more tractable when we impose the same thresholds a_c, $c = 0, 1, \dots, 7$. The corresponding probability 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

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

where

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

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

$$
\begin{aligned}
&f_Y(k,m,l) = \frac{1}{(2\pi)^{2/n}\sqrt{\det\Sigma}} e^{-\frac{1}{2}(Y-\bar{y})^T \Sigma^{-1}(Y-\bar{y})} \\
&Y = (t^*, s^*, w^*)^T, \\
&\bar{y} = (x\beta, x\gamma, x\delta)^T \\
&\Sigma = \begin{pmatrix} 1+\lambda_t^2\sigma^2 & \lambda_t\lambda_s\sigma^2 & \lambda_t\lambda_w\sigma^2 \\ \lambda_t\lambda_s\sigma^2 & 1+\lambda_s^2\sigma^2 & \lambda_w\lambda_s\sigma^2 \\ \lambda_t\lambda_w\sigma^2 & \lambda_w\lambda_s\sigma^2 & 1+\lambda_w^2\sigma^2 \end{pmatrix}
\end{aligned} \tag{14}
$$

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[12].

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 $\beta, \gamma, \delta, \sigma^2, a_c, \lambda_s$ and $\lambda_w, c = 0, 1, \ldots, 7$ are estimated subject to that normalization. Second, we simplify the parameter estimation by constraining the threshold parameters to be the same across the technology adoption equation, farm size equation and earning equation. 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 separate cut points. We allow some flexibility by allowing different variances across three equations while assuming that the errors are jointly normally distributed[13]. 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 and the conclusions do not be altered.

Farms specializing in farrow-to-feeder or feeder-to-finish operations would be expected to have relatively fewer technology options than would farms that take pigs all the way from farrowing to finishing pigs. This could alter the results of our estimation if type of farm operation is correlated with the unobservable employee attributes that also affect farm size and wages. We replicated our analysis of model (9) using a restricted sample that included only farrow-to-finish farms. The results are shown in Table 3B.2 in the Appendix[14]. Although the estimated parameters have different magnitudes, the predictions of the O-Ring production hypotheses are still confirmed.

Marginal Effect of Human Capital

The post estimation unconditional marginal effect of worker skills on technology adoption, farm size, and wages is given by:

(15)

$$ME_j(x_c) \equiv \frac{\partial \Pr(j=k)}{\partial x_c} = \begin{cases} -\phi(\frac{x\beta - a_0}{\sqrt{1+\lambda_j^2\sigma^2}})\beta_c & k=0, \\ \phi(\frac{x\beta - a_{j-1}}{\sqrt{1+\lambda_j^2\sigma^2}})\beta_c - \phi(\frac{x\beta - a_j}{\sqrt{1+\lambda_j^2\sigma^2}})\beta_c & k=2,...,7 \\ \phi(\frac{x\beta - a_{j-1}}{\sqrt{1+\lambda_j^2\sigma^2}})\beta_c & k=8 \end{cases}$$

$j = t, s, w$

Equation (15) defines the marginal effect of a continuous variable on one of the categorical dependent variables (technology t, size s and wage w). The marginal effect is evaluated at the average of individual employee attributes. The corresponding estimated marginal effect from a discrete covariate is defined as:

$$(16) \qquad ME_j(x_d) \equiv \Pr(j=k \mid x_d = 1) - \Pr(j=k \mid x_d = 0), \quad j = t, s, w$$

where x_d is a discrete variable(Greene, 2006).

Empirical Findings

Coefficient estimates from the trivariate ordered probit are shown in Table 3.5. Observed measures of human capital behave largely as expected. Years of schooling simultaneously raise wages, farm size and the number of technologies on the farms on which they work. A similar result holds for prior experience on hog farms—more sector-specific experience increases all three dependent variables. The implied marginal effects reported in Table 3.6 illustrate progressively higher likelihood of moving to the upper tail of the wage, technology and farm size distributions as education and experience increase.

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 relative 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 estimated to be significantly less than one. The variance of the pure random factor μ_{ji} is normalized to be one. Consequently, $\sigma^2 < 1$ indicates that the random effect from individual unobserved abilities constitutes a small part of the total random factors influencing the three choices.

With λ_t restricted to be one the finding that λ_s and λ_w are both significantly positive means that unmeasured individual abilities affect the technology adoption, farm size and thereafter the wage rate 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 3.1-3.3.

The implied pairwise correlation coefficients among the errors in the technology adoption, farm size and wage rate equations are reported at the bottom of Table 3.5. The standard errors are calculated using the delta method. All three correlations are significantly positive, consistent with hypothesis 2. 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. Our results show that with explainable exceptions, both observed and unobserved measures of human capital affect these dependent variables as predicted by the theory.

There are two other interesting results. First, women are paid less than observationally equivalent men, but 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 significant increase in real earnings experienced 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, but production processes have become increasingly more reliant on those complementarities over time.

Conclusion

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 *et al* (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, Iranzo *et al* (2008) did not perform the tests that we employ in this paper.

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, and importantly, the O-Ring specification allows firms with multiple production stages to use workers of different skills in different stages. It is possible that their 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.

Endnote

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[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 for examples of technology adoption in agriculture. Huffman (1999) presents a comprehensive review.

[5] Examples include Krueger, 1993; Reily, 1995; Dunne and Schmitz, 1995; Caselli and Coleman II, 2001 and Dunne, Foster and Troske, 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 are shown the predicted distributions.

[9] The USDA cells originally included 18 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.

[10] 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.

[11]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.

[12] 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).

[13] We also attempted a trivariate probit model to accommodate the possible differences in distribution shapes among the error terms In this case, the model uses less informative dependent variables: more (>5) technologies versus less technologies; Large (>10,000 head) versus small farms; and high (>$34,999) versus low pay. The results are shown in Table 3B.1. Consistent with the earlier findings, the errors are positively correlated and prior experience increases the likelihood of technological complexity, farm size and high wages. One exception is that schooling of workers is not significantly correlated with farm size although it still is positively related to wages and number of technologies. Tenure is negatively related with farm size.

[14] Similarly, a trivariate probit model is estimated based on the subsample of farms with farrow–to-finishoperations. Estimation results are shown in Table 3B.3 in the Appendix. Results do not change relative to those obtained with the broader sample.

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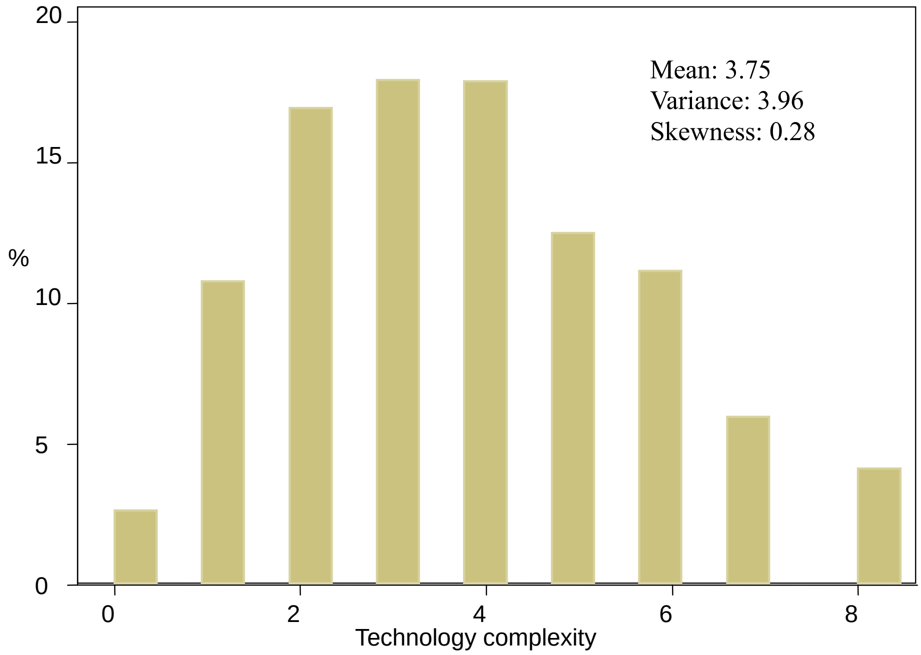
Table 3. 1 Fraction of employees on hog farms using various technologies

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.

Figure 3.1 Distribution of technology complexity



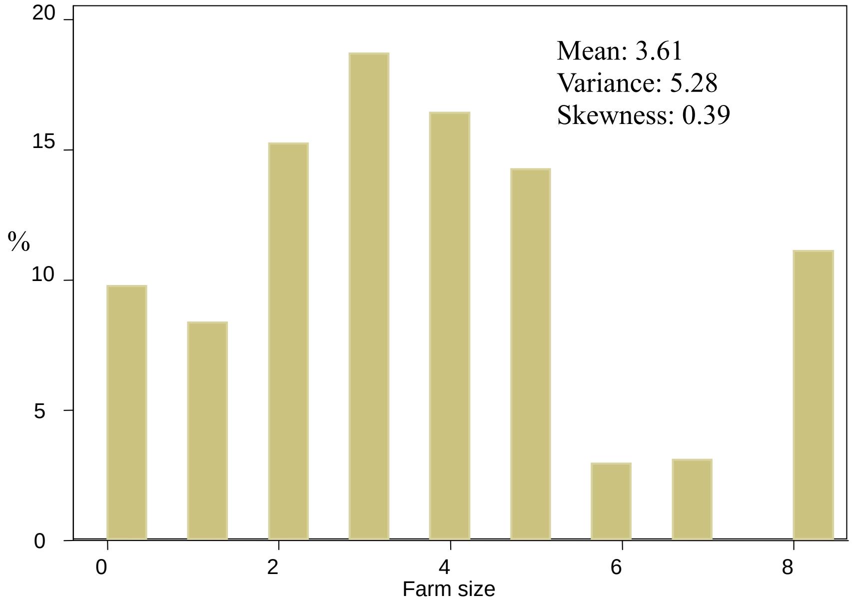
Note: Technology complexity is represented by the number of technologies adopted on hog farms. The distribution is weighted by sampling weights such that it reflects the population distribution of hog farms. Auto Sorting system technology (AS) and Parity Based Management (PBM) in 2005 are censored in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

Table 3. 2 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.

Figure 3.2 Distribution of firm size



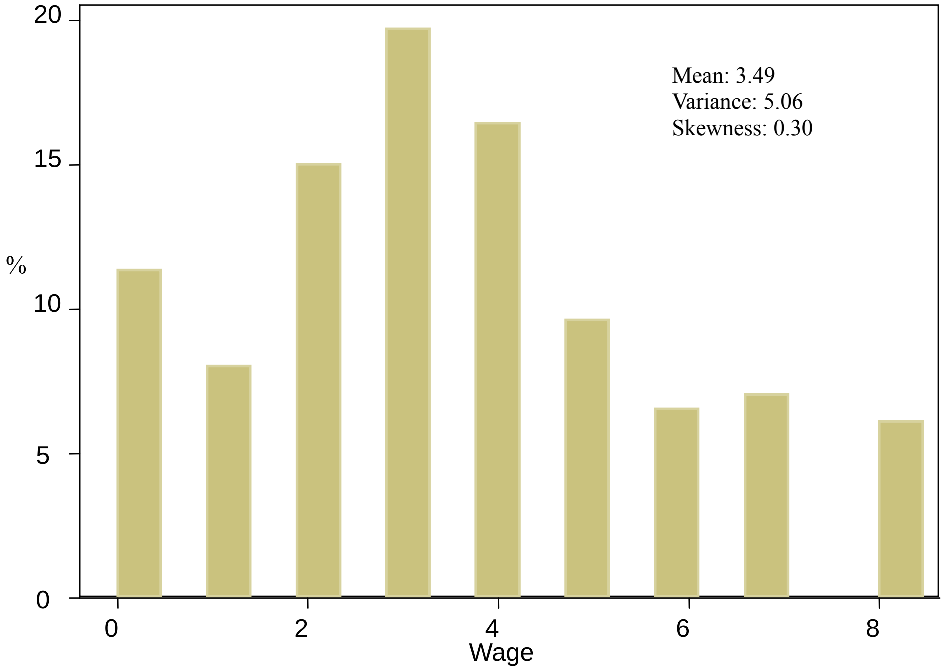
Note: The size class is defined in the Table 3.2. The size distribution is weighted by sampling weights farms.

Table 3. 3 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.

Figure 3.3 Distribution of wages



Note: The corresponding wage range is defined in the Table 3.3**Error! Reference source not found.**. The wage distribution is weighted by sampling weights farms.

Table 3. 4 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.

Figure 3.4 Relationships of worker skills with technology complexity, farm size and wages

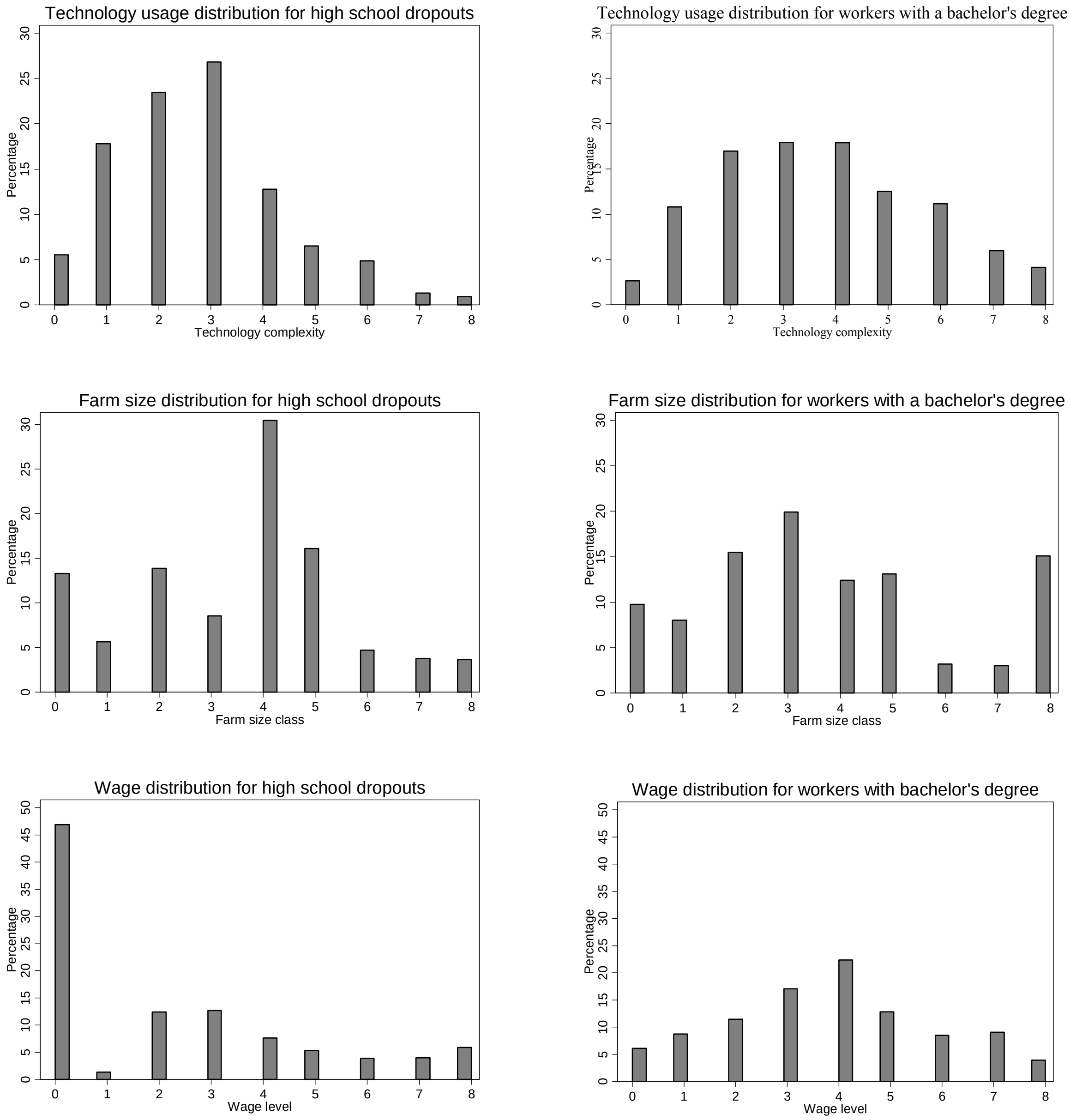


Table 3.5 Weighted tri-variate ordered probit model results

	Technology		**Farm Size**		**Wage**	
Variables	β	t-value	γ	t-value	δ	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 (8) with estimated standard errors obtained using delta method.

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

Table 3.6 Marginal effects of workers' human capital on the technology adoption, farm size and salary level

	Education	Previous working experience	Raised on hog farms
		Technology Complexity	
Pr(t=0)	-1.05%	-2.52%	-0.75%
Pr(t=1)	-1.08%	-2.62%	-0.76%
Pr(t=2)	-1.31%	-3.23%	-0.92%
Pr(t=3)	-0.50%	-1.33%	-0.35%
Pr(t=4)	0.59%	1.36%	0.42%
Pr(t=5)	1.01%	2.46%	0.72%
Pr(t=6)	0.79%	1.95%	0.56%
Pr(t=7)	0.71%	1.77%	0.50%
Pr(t=8)	0.84%	2.17%	0.59%
		Farm Size	
Pr(s=0)	-0.85%	-6.58%	-4.14%
Pr(s=1)	-0.40%	-3.20%	-1.94%
Pr(s=2)	-0.32%	-2.69%	-1.55%
Pr(s=3)	-0.02%	-0.31%	-0.07%
Pr(s=4)	0.25%	1.90%	1.25%
Pr(s=5)	0.34%	2.66%	1.64%
Pr(s=6)	0.27%	2.14%	1.29%
Pr(s=7)	0.26%	2.13%	1.26%
Pr(s=8)	0.47%	3.95%	2.25%
		Salary	
Pr(w=0)	-1.19%	-4.54%	4.23%
Pr(w=1)	-1.05%	-4.10%	3.76%
Pr(w=2)	-1.07%	-4.32%	3.87%
Pr(w=3)	-0.16%	-0.85%	0.63%
Pr(w=4)	0.77%	2.85%	-2.68%
Pr(w=5)	0.96%	3.76%	-3.43%
Pr(w=6)	0.66%	2.65%	-2.38%
Pr(w=7)	0.54%	2.20%	-1.95%
Pr(w=8)	0.55%	2.35%	-2.04%

Appendix 3A

Expected distribution shape for technology complexity, firm size and wages

The production function is $y = q^t tB(t) \equiv f(q^*, t^*(q^*))$. Holding technology usage constant, output is homogeneous of degree *t* in *q*. As long as *t* is greater than one, output y will be convex in *q*. Whenever skills of worker are normally or symmetrically distributed (or even right skewed distributed), output *y* will be skewed to the right.

The zero profit condition $q^t\, B(t) - w(q) = 0$ similarly implies that wage is also homogeneous of degree *t* in *q*, holding technology usage fixed. In the same fashion, if skills of worker are normally or symmetrically distributed (or even right skewed distributed), wage *w* will be skewed to the right.

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 $E = -\frac{B'''}{B} + \frac{3B'B''}{B^2} - \frac{(B')^3}{B^3}$, $\frac{\partial A}{\partial q} = E\frac{\partial t}{\partial q} = E\frac{1}{qA}$.

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

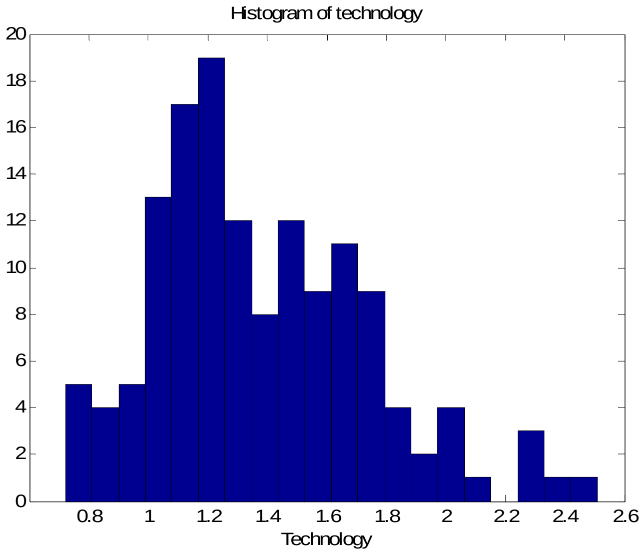
Technology complexity *t* is convex in *q* if $\frac{\partial^2 t}{\partial q^2} > 0 \Leftrightarrow A + \frac{E}{A} < 0 \Leftrightarrow E < -A^2$.

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 examples from simulation, 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.

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

Figure 3A.1 Simulated histograms of production process complexity, output



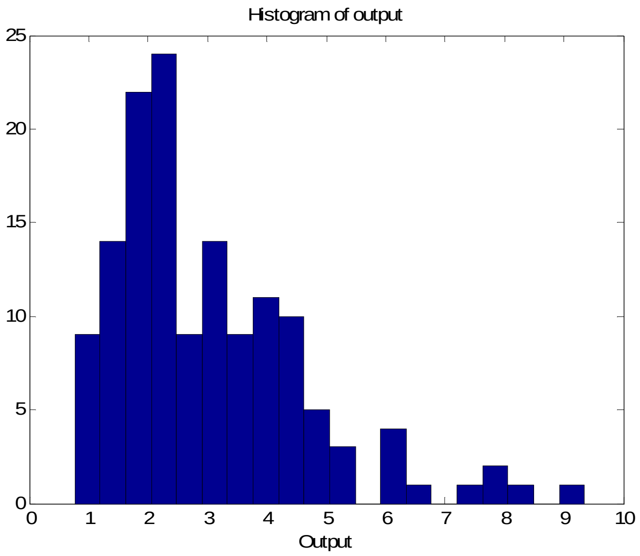
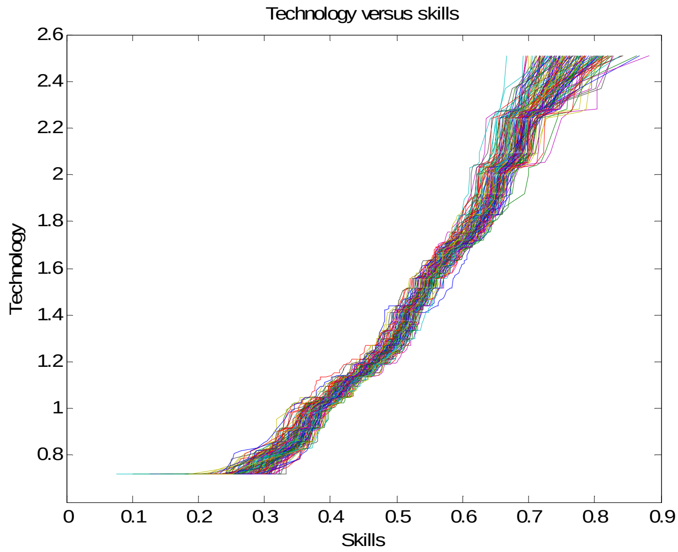


Figure 3A.2 Simulated relationship between production process complexity and skills



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

Figure 3A.3 Simulated histograms of production process complexity, output

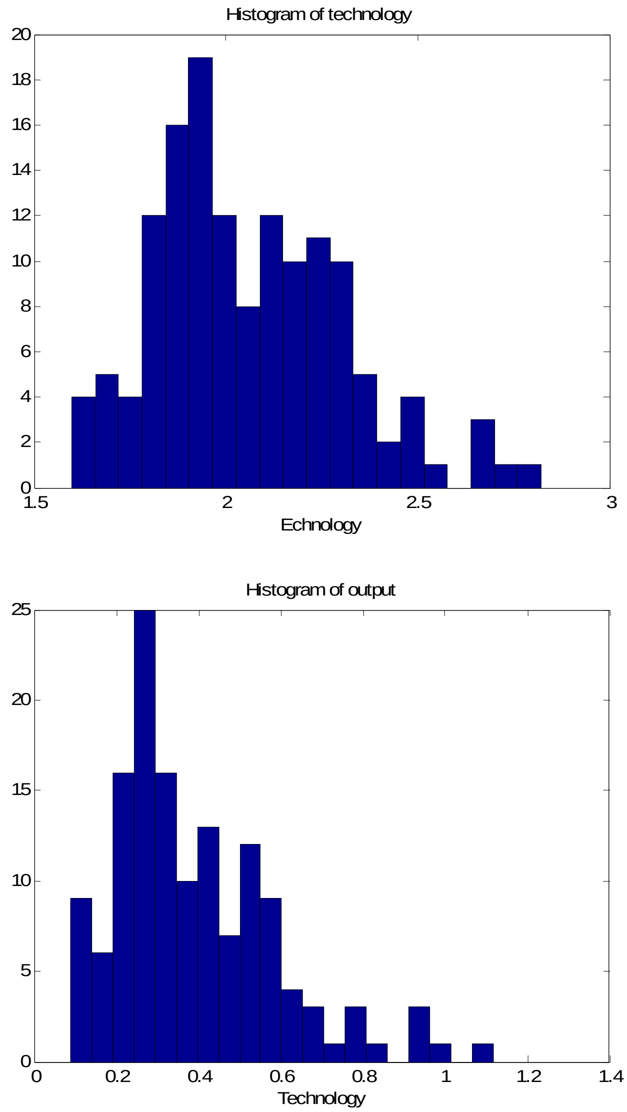
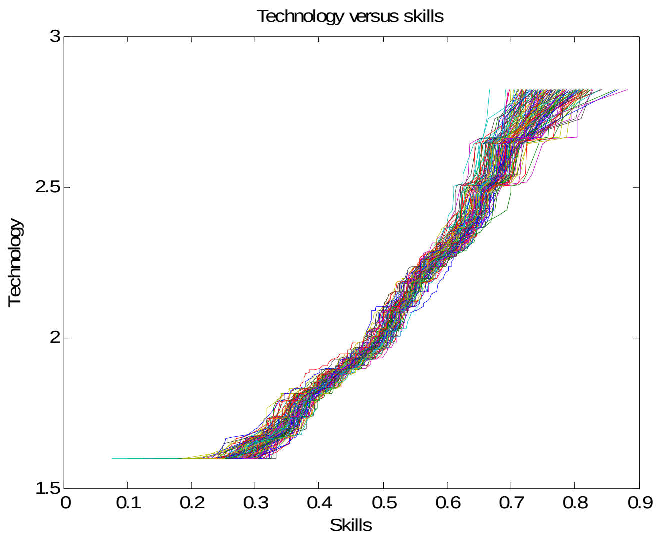


Figure 3A.4 Simulated histograms of production process complexity, output



Appendix 3B

Table 3B.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 3B.2 Trivariate orderd probit model of technology adoption, farm size and wages for employees working on farms which have farrow-to-finish operations

	Technology		Farm Size		Wage	
Variables	β	t-value	γ	t-value	δ	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 3B.3 Trivariate probit model of technology adoption, farm size and wages 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.

General Conclusion

The dissertation consists of three essays of analysis on the US hog farms in the last two decades. It provides a deeper look into the issues related with farm size, technology adoption, wages and human capital and their interrelationship as well. The research is based on four surveys on producers and employees in the US hog industry. It is found that larger farms pay higher wages than comparable workers on smaller farms. The size wage premium persists over time, differs by geographic regions, carries over individual technologies and remains significantly across workers with different skill levels. One of the hypotheses is that more educated producers in the larger farms tend to use more technologies, which are complementary with worker skills. The hypothesis can not be rejected in the pork sector. Technology complexity and farm size are positively correlated. Decision on the level of technology complexity and the elements of technology bundles is as critical as decision on output quantity for hog producers because technologies are related to some extent. A method easy to be applied is proposed in my dissertation to identify complementarity or substitutability among multiple technologies. It finds that technologies are increasingly likely to be complementary with one another as the number of bundled technologies increases and farmers have an incentive to adopt many technologies at once. The last chapter is motivated by summarizing the findings in the previous two chapters and hypothesizing that hog production is of an O-Ring type. Even a single mistake in any one of several tasks in the firm's production process can lead to catastrophic failure of the whole product. More skilled workers are matched together to more complex production process. They are at the same time in the larger firms and paid higher. After controlling observed workers skills, unobserved abilities and other firm specific characteristics, firm size, technology adoption intensity and wages are positively correlated. Size wage premium remains and is inseparable from technologies. The US hog industry is empirically investigated in the dissertation, however, the econometric model and statistical method can be applied to other analyses.

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