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September 2008

Working Paper # 08026

Department of Economics
Working Papers Series

Ames, Iowa 50011

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

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August, 2008

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.

JEL: O33; L25; C12

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This paper has benefited from comments from seminar participants at Iowa State University and at meetings of the Midwest Economics Association and the American Association of Agricultural Economists. Funding support from the U.S. Department of Agriculture and the National Pork Board/Primedia Business is gratefully acknowledged.

I. 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. treat technology as exogenous, Poppo and Zenger treat these 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% of the technology bundles are complementary. However, over 80% 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 market share of large farms coincident with rapid technology adoptions experienced by the U.S. hog industry over the past two decades. Consistent with earlier work on technology adoption, it is the younger but most educated farmers that most readily adopt multiple technologies.

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 three national surveys 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.

II. 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.

Suppose there are three technologies. 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 whether or not technology 2 is adopted, then the hypothesis

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

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

$$H_0^{(ii)}: \Pr(X_1 = 1, X_2 = 1, X_3 = 0) = \Pr(X_1 = 1)\Pr(X_2 = 1)\Pr(X_3 = 0)$$

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

$$H_C^{(ii)}: \Pr(X_1 = 1, X_2 = 1, X_3 = 0) > \Pr(X_1 = 1)\Pr(X_2 = 1)\Pr(X_3 = 0) \text{ or}$$

$$H_S^{(ii)}: \Pr(X_1 = 1, X_2 = 1, X_3 = 0) < \Pr(X_1 = 1)\Pr(X_2 = 1)\Pr(X_3 = 0)$$

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 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, so the curse of dimensionality is avoided.

Suppose $K > 1$ technologies can be used alone or in combination. Let X_k, $k = 1, 2, ...K$, equal to 1 if the k^{th} technology is adopted and 0 otherwise. Define $1 > p_k > 0$, for $k = 1, 2, ...K$ as the probability technology k is adopted. Let $Y = \{X_1, X_1, ...X_K\}$ be the set of technology bundles. The set has 2^K distinct elements denoted by Y_j for $j = 1, 2, ...2^K$. Define $1 > q_j > 0$ for $j = 1, 2, ...2^K$, 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 $\Omega_j^A = \{k \mid k = 1, 2, ...K \text{ and } X_k = 1\}$, while the set of technologies not used is $\Omega_j^N = \{k \mid k = 1, 2, ...K \text{ and } X_k = 0\}$.

Let $1 > p_{lk} > 0$, where $l, k = 1, 2, ..., K, l \neq k$, 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 $i = 1, 2, ...S$, 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 $k = 1, 2, ...K$. The likelihood function is

$L = \prod_{i=1}^{S} \prod_{k=1}^{K} p_k^{X_k^i} \left(1 - p_k\right)^{1 - X_k^i}$, which taking the natural log yields

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

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

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

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

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

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

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

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

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

such that optimizing over q_j yields the estimates

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

Testing the null hypothesis that $\widehat{p}_{kl} = \widehat{p}_{kl}{}^O$ for a given pair of technologies or $\hat{q}_j = \hat{q}_j{}^O$ for a given technology bundle j, is complicated because $\widehat{p}_{kl}$ and $\widehat{p}_{kl}{}^O$, 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 the Student's t distribution is not appropriate because the sampling distributions of the probabilities of $\widehat{p}_{kl}$ 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 $\widehat{p}_{kl}$ and $\widehat{p}_{kl}{}^O$) 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 $\widehat{p}_{kl} - \widehat{p}_{kl}{}^O$) 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 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, the number of trails and $P = (P_1, P_2, \ldots, P_{2^K})$, the frequency vector. It is 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:

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

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, $\chi^2(2^K - K - 1)$.

III. Multiple Technology Adoption on U.S. Hog Farms

The U.S. hog industry has experienced rapid technological innovation over the 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 five 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 B.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 10 technologies listed in Table 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. Therefore, we have eight possible technologies in each survey year.

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 3 size categories were taken as the population universe.[3] Each farmer in the *NHFM* sample was assigned a weight, w_i, representing the inverse of the probability of each individual farm sampled from the population in region and size class.[4] Considering these weights, the adoption rate for technology k under independence is defined as

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

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 $\hat{q}_j = \frac{\sum_{i=1}^{S} Y_j^i w_i}{\sum_{i=1}^{S} w_i}$.

Using equation (8), we utilize the raw data to estimate the adoption probability for each technology, $\hat{p}_k$, $k = 1, 2, \ldots K$, shown in Table 1. The usage of Artificial Insemination (AI) and Segregated Early Weaning (SEW) doubled between 1995 and 2005. Other technologies such as Split Sex Feeding (SSF) and Phase Feeding (PF) have had a declining usage since 1995. The most commonly used technologies are Phase Feeding (PF) and All In /All Out (AIAO) production. 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.

At the same time, the number and size distribution of hog farms have changed dramatically across survey years, as shown in Table 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.

IV. 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.

First, for a technology bundle *j*, the elements of the difference $\hat{q}_j - \hat{q}_j^0$ are calculated using 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 3a. Depending on the year, about 51% to 71% 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 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 bundle is also mutually complementary.

Two technology combinations, designated T1= {AI, PF, AIAO} and T2= {SSF, PF, MSP, AIAO} appear atypically frequently among the complementary bundles in the sample. When the four technologies in T2 were adopted in 1995 and in 2005, they appear to be independent. When the T2 bundle is simultaneously adopted in combination 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 mutually complementary. AI, PF and AIAO appear to be mutual substitutes in 1995, but adding SSF results in the complementary bundle {AI, SSF, PF, AIAO}.

These are examples 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 interrelationships among the technologies are consistent or stable across time. One reason may be that new technologies are developed while others are discarded, changing the menu of available bundles. Changes in adoption costs and changes in the market demand and packer capacity could also affect the interrelationships between technologies. An example of this phenomenon is that the bundle {AI, SSF, PF, MSP, AIAO, SEW} is mutually complementary in every year. However, {AI, PF, MSP, AIAO, SEW} is mutually complementary only in 1995 and 2000 but becomes independent in 2005. They remain mutual complements when the new technologies PBM and AS, made available in 2005, are added to the bundle.

Among early weaning technologies, Segregated Early Weaning is more frequently used than MEW and MMEW, as can be seen in Table 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, only rarely were any two of the three technologies adopted, and then only in combination with other available technologies. Producers commonly adopted only one of the three early weaning technologies in complementary bundles with others. MEW and MMEW 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.

One concern with our method is that the technology adoption decision is made simultaneously with the type of operation. Some farms produce pigs from farrowing stages to finishing stages. Others specialize in farrowing pigs which are sold as feeder pigs and others specialize in purchasing feeder pigs for finishing as market hogs. 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 only finish hogs. Because farmers are choosing type of operation jointly with technology mix, it is not appropriate to condition the technology choice on type of operation. Nevertheless, we can investigate the degree to which the technology bundle choice is dictated by the desired type of operation. Table B.2 in the appendix 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.

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 the predicted frequencies based on technical independence.

Testing Pairwise Relationships

Past studies[8] have relied on the correlation between technology adoption or the between the residuals from technology adoption equations to assess whether technologies are substitutes or complements. As shown in section II, these bivariate relationships may yield misleading inferences in the presence of other technologies not included in the analysis. We can compare bivariate relationships derived from our method with those from traditional methods to demonstrate the frequency of these errors.

In Table 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 when these bivariate relationships are couched in context 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 the pairwise correlation method, but they turned out to be substitutes using our method. Further, many of the presumptive complementary pairs implied by simple correlations never occur in the data — the pair of technologies is only chosen in combination with other technologies that are presumed to be irrelevant alternatives. One example of this is that in 1995, the technology bundle (SEW, MMEW) was never selected unless other technologies were also included in the bundle, but the bivariate correlation implied that they were complements.

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 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.[8] 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.[9]

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

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

where β and γ are coefficient vectors to be estimated in the technology adoption and farm size equations, respectively. The description and statistics of the covariates x are shown in Table 5. 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 μ_{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:

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

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 λ_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

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

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

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

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

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

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

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

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 6.

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.

Another 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 B.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 of technology adoption intensity and farm size.[10] 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.[11]

V. Conclusion

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 Split Sex Feeding, Phase Feeding, Multiple Site Production, and All In/ All Out production 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 simple correlation between any two technologies 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 younger and 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.

Endnotes

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[1] Examples include Hannan and McDowell (1984), Weiss(1994), Putler and Zilberman (1986), Baker (2001), and Caswell and Zilberman (1985). Sunding and Zilberman (2001) offer a good survey of the literature.

[2] A formal proof that bivariate relationships yield biased inferences regarding substitute or complement relationships in the presence of a third technology is shown in the Appendix A.

[3] USDA counts 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. 8 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 size has 3 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 was eliminated in the 2005 survey. The 2005 survey adds a new largest category of over 50,000 hogs produced per year.

[7] 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.

[8] Examples include Dorfman(1996); Poppo and Zenger(2002); Colombo and Mosconi (1995); and Stoneman and Kwon (1994).

[9] 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 on the role of human capital on technology adoption in agriculture.

[10] Technology adoption intensity is indicated by a dummy variable, equal to 1 if at least six technologies are adopted, or 0 otherwise. Farm size is a dummy variable, equal to 1 if more than 10,000 pigs producer annually or 0 otherwise. Farm types are a series of dummy variables. Regression results are shown in Table B.3.

[11] Another interesting result is that 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 technology complexity and farm size. This 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.

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TABLE 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.— SIZE CLASS, FREQUENCIES AND RELATIONSHIP BETWEEN FARM SIZE AND TECHNOLOGY ADOPTION INTENSITY

Code	Size Class (pigs per year)	Farm distribution (%)			Average number of technologies adopted
		1995	2000	2005	
1	Less than 500	2.93	4.69	.	1.42 (0.12)
2	500 to 999 / less than 1000 in 2005	6.41	1.97	27.64	1.22 (0.88)
3	1,000 to 1,999	35.39	37.3	27.5	1.70 (1.25)
4	2,000 to 2,999	42.28	36.43	27.74	2.04 (1.36)
5	3,000 to 4,999	6.27	6.35	5.46	2.74 (1.52)
6	5,000 to 9,999	5.67	9.18	8.36	3.11 (1.67)
7	10,000 to 14,999	0.47	1.23	0.99	3.32 (1.63)
8	15,000 to 24,999	0.3	1.02	0.75	3.71 (2.00)
9	25,000 or more / 25,000 to 49,999 (2005)	0.28	1.83	0.7	3.62 (2.09)
10	50,000 or more (2005)	.	.	0.85	4.27 (2.10)
Total	Number of farms	175,775	97,180	69,420	-

Source: Authors' compilation of weighted survey responses with weights defined in the text.
Numbers in the parentheses are standard deviations for the average number of adopted technologies.

TABLE 3. — RESULTS OF THE SPECIFIC TECHNOLOGY BUNDLE TEST

TABLE 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 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 4.— COMPARISON BETWEEN BILATERAL CORRELATION METHOD AND OUR STATISTICAL METHOD IN THE CONTEXT OF MORE THAN TWO TECHNOLOGIES AVAILABLE

Bilateral Correlation Method				
Year		Substitutes	Complements	Independent
1995		0	27	1
2000		2	14	11
2005		0	15	13
New Method for Multiple Technologies				
Year	Not in Sample	Substitutes	Complements	Independent
1995	6	13	0	9
2000	13	4	0	11
2005	3	3	0	14

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 5.— CHARACTERISTICS OF PRODUCERS AND FARMS

Variables	Description	Mean	Standard Deviation
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 6. — 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 A

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 B

TABLE B.1.— DESCRIPTION OF TECHNOLOGIES IN THE HOG PRODUCTION

Technology	Description
AI	Artificial Insemination focuses on enhancing hog reproductive efficiency and improving the gene pools.
SSF	Split Sex Feeding 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	Phase Feeding involves feeding several diets for a relatively short period of time to more accurately and economically meet the pig's nutrient requirements.
MSP	Multiple Site Production produces hogs in separate places in order to curb disease spread.
SEW	Segregated Early Weaning 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. At the same time, early weaning helps to produce more piglets each year.
MEW	Medicated Early Weaning uses medication of the sow and piglets to produce excellent results in removing most bacterial infections.
MMEW	Modified Medicated Early Weaning is same as MEW but less all-embracing. The range of infectious pathogens to be eliminated is not quite as comprehensive. MMEW can also be used to move pigs from a diseased herd to a healthy herd.
AIAO	All In/All Out 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 helps limit the spread of infections to new arrivals by allowing for cleanup of the facility between groups of hogs being raised.
AS	Auto Sorting System helps with labor savings, easier feed withdrawal, reductions in sort variation and sort loss, greater uniformity in pig market weight, and therefore more accurate marketing.
PBM	Parity Based Management uses specialized labor in breeding, feeding and caring for pigs. In addition to returns from specialization, this method reduces disease transmission and lowers the risk of new disease introduction.

Note: the technology the notation stands for is referred in the Table 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 B.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. The statistics of the variables are weighted.

TABLE B.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.