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

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Abstract: The hypothetical distribution of multiple technology adoptions under the assumption that technologies are mutually independent is compared against the actual observed distribution of technology adoptions on hog farms. Combinations of technologies that occur with greater frequency than would occur under independence are mutually complementary technologies. Combinations that occur with less frequency are substitute technologies. This method is easily applied to simultaneous decisions regarding many technologies. We find that some technologies used in pork production are mutually 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. 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.

1. Introduction

Numerous studies have examined the choice of whether or not to adopt a given technology (Griliches (1957), Putler and Zilberman (1998), etc.). In most of these settings, the decision is whether or not to adopt a specific technology, ignoring the presence of other potential technologies. Even papers that evaluate the choice between two practices or technologies typically consider these choices as separable from the possible existence of other technologies. However, if these other technologies are not truly independent, treating the adoption of a given technology as an independent choice or a choice relative to a single alternative can yield misleading results.

The analysis of multiple technology adoptions is complicated by the curse of dimensionality -- if there are n technologies, there will be 2^n potential technology combinations. The computational burden of analyzing these adoption decisions simultaneously requires that researchers impose simplifying assumptions. For example, Stoneman and Toivanen (1997) and Wozniak (1993) treated each technology as an independent choice. This ignores the possibility that technologies may be substitutes or complements. Even when one technology is adopted from a menu of many options, as with a multinomial logit specification for example, the researcher imposes that the agent select only one technology. This implicitly imposes that the technologies are substitutes for one another. The possibility that technologies are complements in production is not allowed. Dorfman (1996) proposed but did not test a method which can be extended to check adoption rates of some multiple technology bundles. The method utilizes Gibbs sampling to reduce the computational burden of adding additional choices to a multinomial probit model. His method also requires that the technology adoptions be ordered. Still, the method does not essentially exam the whether these multiple technologies are substitutes or complements.

This paper proposes a statistical method that identifies complementarity or substitutability relationships from among a large menu of technologies. This method is applied to the technology adoption decisions of hog farmers in the United States. The data strongly reject the null hypothesis of independence among technologies. Of 256 possible combinations of technologies, only one-quarter occur at the frequency within 2 standard deviations of the projected occurrence under independence. Almost 60% of the combinations never occur. Of the remaining 15%, 11% of the combinations are mutual substitutes and 4% are mutual complements. However, while the number of complementary combinations is small, these tend to be combinations of large numbers of technologies. In fact pairs of technologies may be substitutes, but in combinations with other technologies, they become mutually complementary. That large technology bundles tend to be complements suggests that large farms may have a comparative advantage in technology adoption. Smaller farms may not have the capacity to use multiple technologies. Smaller farms may also be unable to attract sufficient loans borrowed against future income to allow them to adopt large numbers of technologies. These findings suggest that multiple adoptions may be complementary with farm size.

We test the hypothesis that farm size is complementary with multiple technology adoptions using an ordered probit equation with number of technologies used as the dependent variable. We find that it is the larger farms that are the most likely to adopt multiple technologies. In addition, more educated producers are more likely to adopt multiple technologies.

The next section of the paper will propose our strategy for statistically modeling whether groups of technologies are mutually complementary or substitutes for one another. The third section proposes a mechanism to establish statistical bounds that can be applied to establish whether the observed pattern of multiple technology adoption can reject the null hypothesis of independence among the technologies and whether the groups are complements or substitutes. The method is applied to data on technologies adopted in the US hog industry in the third section. The fourth section further relates the multiple technology adoption to the farm sizes and human capital. The final section concludes the paper.

2. Complements or Substitutes among Technologies Adopted?

In this section, we formally derive a method that can distinguish whether a particular pattern of multiple technology adoptions is consistent with mutual independence, mutual substitutability or mutual complementarity. The method follows this logic: Suppose K ($K>1$) technologies are mutually independent so that adopting one of the technologies does not affect or is not influenced by the presence of any other technologies. The probability of adopting each of K technologies will equal the product of the adoption probabilities of each of the K technologies. In reality, these technologies may be complements or substitutes. If a set of technologies are mutually complementary, then producers will select that combination of technologies with greater frequency than would occur under the null hypothesis of mutual independence. On the other hand, if the technologies are mutually substitutable for one another, the combination will be bundled together less frequently than would occur under mutual independence. This strategy is computationally simple and remains feasible even as the number of technologies expands.

We further check whether or not the data as a whole is consistent with the independence assumption. If technologies are adopted independently, we can decompose the production function into technology specific functions. The technology adoption decision can be made independently, ignoring the effects from other technologies. However, if technologies are not mutually independently adopted, we cannot decompose the production function because firms have to incorporate the effects from simultaneous multiple technology adoption, such as economy scales and complemented labor inputs.

- **Independence test for a specific technology bundle**

The null hypothesis (H_0) is that *K* technologies in bundle *j* are independent. The alternative hypothesis (H_1) is two sided: either they are substitutes or they are complements.

H_0: The *n* technologies are mutually independent.

H_1: The *n* technologies are not mutually independent and may be complements or substitutes.

Each technology adoption decision can be regarded as a *Bernoulli* trial, a common assumption employed in the single technology adoption literature. Define X_k as a random variable which reflects this binary technology adoption decision. X_k has a *Bernoulli* distribution if

$$X_k = \begin{cases} 1 & \textit{Adopted with probability } p_k \\ 0 & \textit{Not Adopted with probability } 1 - p_k \end{cases} \tag{1}$$

where $0 \le p_k \le 1$. X_k can be a single technology adoption decision variable, and can also be a random variable in the multiple technology combination context.

The matrix *T* below illustrates all possible adoption combinations from a menu of *K* technologies, where each column represents a specific technology and each row represents a possible combination of technologies. The matrix is $2^K \times K$. Element "1" in the j^{th} row and i^{th} column represents that technology *i* is adopted in combination ***j***.

$$T = (X_1, X_2, ..., X_K) = \begin{bmatrix} 0 & 0 & . & . & . & . & 0 & 0 & 0 \\ 0 & 0 & . & . & . & . & 0 & 0 & 1 \\ 0 & 0 & . & . & . & . & 0 & 1 & 0 \\ 0 & 0 & . & . & . & . & 0 & 1 & 1 \\ 0 & 0 & . & . & . & . & 1 & 0 & 0 \\ 0 & 0 & . & . & . & . & 1 & 0 & 1 \\ 0 & 0 & . & . & . & . & 1 & 1 & 0 \\ . & . & . & . & . & . & . & . & . \\ 1 & 1 & . & . & . & . & 1 & 1 & 1 \end{bmatrix}_{2^K \times K}$$

Define the j^{th} row of matrix T as (X_{j1}, X_{j2}, X_{j3},… X_{jK}). Suppose that the first m ($m \le K$) technologies are adopted and that the remaining K-m technologies are not. Define a new random variable Y_j where j indexes the j^{th} adoption combination:

$$Y_j = \begin{cases} 1 \quad if \;\; X_{j1} = ... = X_{jm} = 1 \; and \;\; X_{jm+1} = ... = X_{jK} = 0 \; with \; \Pr obability \; q_j \\ 0 \quad otherwise \; with \; \Pr obability \; 1 - q_j \end{cases}$$

Under H_0, the probability is denoted as q_j^0: $q_j^0 = E(Y_j |$ Independent) =

$$\prod_{k \in \Omega_j^A} E(X_k) \prod_{l \in \Omega_j^N} (1 - E(X_l))$$

where Ω_j^A and Ω_j^N are the set of technologies adopted and not adopted for the j^{th} technology bundle. We can think of specific technology choices as coming from K independent Bernoulli trials where p_k^0 is the probability a producer adopts technology k. The likelihood function for the null hypothesis can then be written as

$$L^0 = \prod_{i=1}^{N} \prod_{k=1}^{K} p_k^{0\,X_k^i} \left(1 - p_k^0\right)^{1 - X_k^i} = \prod_{k=1}^{K} p_k^{0 \sum_{1=1}^{N} X_k^i} \left(1 - p_k^0\right)^{N - \sum_{1=1}^{N} X_k^i}$$ where i indexes the i^{th} observation in the sample and N is the total observations in the sample. The log likelihood function is then

$$\ln L^0 = \sum_{k=1}^{K} \left[\left(\sum_{1=1}^{N} X_k^i \right) \ln\left(p_k^0\right) + \left(N - \sum_{1=1}^{N} X_k^i \right) \ln\left(1 - p_k^0\right) \right]. \qquad (2)$$

It can be shown that the MLE estimators are

$$\hat{p}_k^0 = \frac{\sum_{i=1}^{N} X_k^i}{N}, \; k=1, 2, \ldots, K, \qquad (3)$$

which means that the actual probability of adopting a given technology *k* can be calculated by the frequency of its occurrence in a random sample. The probability to adopt technology bundle *j* is hence easy to obtain,

$$\hat{q}_j^0 = \prod_{k \in \Omega_j^A} \hat{p}_k^0 \prod_{l \in \Omega_j^N} \left(1 - \hat{p}_l^0\right). \tag{4}$$

Under H_1, The Likelihood function is $L^1 = \prod_{i=1}^{N} P_i$ where

$$P_i = \begin{cases} q_j^1 \;\; if \;\; individual\, i\, chooses\, technology\, bundle\, j,\; j = 1,2,...,2^K - 1 \\ 1 - \sum_{j=1}^{2^K - 1} q_j^1 \;\; if \;\; individual\, i\, chooses\, technology\, bundle\, 2^K \end{cases}.$$

It can be also shown that MLE estimate of probability of adopting technology bundle *j* is

$$\hat{q}_j^1 = \frac{N_j}{N} \tag{5}$$

where N_j is the number of individuals in the sample adopting technology bundle *j*.

In order to test null hypothesis $\hat{q}_j^1 = \hat{q}_j^0$ for a given technology bundle *j*, usual statistics are not available or are very difficult to obtain mainly because $\hat{q}_j^o$ and $\hat{q}_j^1$ are correlated such that sample variances are not easy to calculate. Percentile Bootstrapping provides a good tool to accomplish our goal. Suppose that *M* samples are drawn with replacement from our raw data. *M* $\hat{q}_j^o$ s and $\hat{q}_j^1$ s are calculated according to equations (4) and (5) for each new drawn sample. Define C_j as a vector of adoption rate difference $\hat{q}_j^1 - \hat{q}_j^o$. Sort C_j according to an ascending order. Redefine the new data as $\tilde{C}_j$. We then get rid of the smallest 2.5% of the elements and the biggest 2.5% of the elements in $\tilde{C}_j$. The confidence interval of C_j at the significance level 5% is therefore constructed as [$\tilde{C}_j^L$, $\tilde{C}_j^H$] where $\tilde{C}_j^L = \tilde{C}_j^{M*2.5\%^{th}}$ and $\tilde{C}_j^H = \tilde{C}_j^{M*97.5\%^{th}}$.

If zero falls into the interval [$\tilde{C}_j^L$, $\tilde{C}_j^H$], we cannot reject the hypothesis that technologies in bundle *j* are independent. If $\tilde{C}_j^L$ and $\tilde{C}_j^H$ are both positive, the technologies in bundle *j* are regarded as complements, because it is more likely that these technologies go together. If $\tilde{C}_j^L$ and $\tilde{C}_j^H$ are both negative, the technologies in bundle *j* are regarded as substitutes, because it is less likely that these technologies go together than the situation where technologies are independent.

- **Independence test for technology bundles in general**

G test, a log likelihood ratio test of independence, is given by

$$G = 2\sum_{j}^{2^K} F_j^1 \ln(\frac{F_j^1}{F_j^0}) = 2N\sum_{j}^{2^K} \hat{q}_j^1 \ln(\frac{\hat{q}_j^1}{\hat{q}_j^0}) \qquad (6)$$

where F_j^1 and F_j^0 are frequency if the technology bundle *j* observed under H^1 and H^0 respectively. *G* is asymptotically distributed as a Chi- square with *(2^K-K-1)* degrees of freedom, $c^2(2^K - K - 1)$. For those technology bundles which do not exist in the data, define $0 \times \ln(\frac{0}{\hat{q}_j^o}) = 0$.

3. 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 and 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). Using our statistical method comparing observed adoptions against that predicted under the null hypothesis of independence, we will be able to assess whether the adoption patterns reflect an underlying complementrarity or substitutability among the technologies.

- **Data**

This paper uses survey data from a random sample of subscribers to *National Hog Farmer Magazine*. The surveys were 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 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 obtained in 1995 and 2000 while questions regarding Auto Sorting and Parity Based Management were only asked in 2005. Consequently, we have information on the use of eight different technologies in each of the three survey years. The most commonly used technologies are Artificial Insemination technology (AI), Phase Feeding technology (PF) and All In / All Out (AIAO) production. Modified Medicated Early Weaning (MMEW) is the least often utilized in 1995 and 2000 and Auto Sorting (AS) is the least often utilized in 2005.

Because subscribers to *National Hog Farmer Magazine* are not a representative sample of all hog farmers 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 hog farms in the USDA Agricultural Census Data (ACD). USDA counts of hog farms in 18 census regions and four farm size classifications were taken as the population universe.[1] Farm size ranges from fewer than 1000 pigs, 1000 to 1999, 2000 to 4999 and more than 5000 pigs. The weights are computed as follows: there are N hog farms in total in the US and n_j farms in region and size cell j. The proportion of all hog farms in the j^{th} cell is n_j/N. The comparable number of farms in the same region and size group in our sample is s_j. Each farm in our sample is then assigned a probability weight by $\frac{s_j}{n_j / N}$.[2]

[1] 1. IL 2. IN 3. IA 4. MN 5. MO 6. NE 7. OH 8. WI 9. ND and SD 10. PA, CT, ME, MD, MA, VT, NJ, NH, NY, RI and DE 11. MI 12. NC 13. KY, WV and VA 14. GA, SC, FL, AL, TN, MS and LA 15. WA, ID, OR, NV, CA, AZ, UT, HI and AK 16. TX, OK and AR 17. KS 18. MT, WY, CO and NM.

[2] Weights based on the 1992 Census were used for 1995 survey responses and the 1997 Census was used to construct weights for the 2000 and 2005 survey responses. 2002 Census data were not available at the time of the analysis.

When the probability weight is considered, the adoption rate for technology *k* under independence assumption is redefined as

$$\hat{p}_k^o = \frac{\sum_{i=1}^{N} X_k^i w_i}{\sum_{i=1}^{N} w_i} \quad . \qquad (7)$$

w_i is the weight assigned to observation *i* in the sample. The adoption rate of technology bundle *j* is calculated from equation (4) in which $\hat{p}_k^o$ is defined as equation (7) now.

At the same time, the adoption rate of technology bundle *j* under alternative hypothesis needs correction by the probability weights,

$$\hat{q}_j^1 = \frac{\sum_{i=1}^{N} w_i 1(i, j)}{\sum_{i=1}^{N} w_i} \qquad (8)$$

, where $1(i, j)$ is an indicator function, equal to one if individual *i* adopts technology bundle *j*, otherwise, zero.

Hog farm size ranges from less than 500 heads in 1995 to more than 100,000 in 2005. The size categories varied across survey years, as shown in Table 2. In 2005, the smallest farm is defined as producing fewer than 1000 pigs rather than 500 in 1995 and 2000. The 2005 survey adds an additional category for the largest farms, distinguishing farms producing 25,000 to 49,999 from those producing 50,000 or more. The market share of large farms has grown rapidly over time. In 1995, about 30 percent of farms produced more than 10, 000 pigs. By 2000, that proportion of farms had risen to 43 percent; and to 54 percent by 2005. On the other hand, 29% of farms were producing fewer than 5,000 pigs in 1995; 27 percent by 2000; and only 11 percent by 2005.[3]

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

- **Findings**

In this section, we show how our method can identify whether technologies adopted in the U.S. hog industry are complements or substitutes.

Using equation (7), we use the raw data and estimate the adoption probability for each technology *k*, $\hat{p}_k^0$, *k=1,2,…,K r*espectively, as reported in Table 1. Some have had rapid growth in adoption rates such as AI and Segregated Early Weaning (SEW) whose usage doubled between 1995 and 2005. Others, such as MEW and MMEW, have decreased in usage from 1995 to 2000. The adoption rate $\hat{q}_j^0$ of technology bundle *j* is calculated from equation (4), $j=1,2,\ldots,2^K$. We then calculate $\hat{q}_j^1$, $j = 1,2...,2^K$ according to the equation (5). Difference between $\hat{q}_j^1 - \hat{q}_j^0$ is obtained.

Using bootstrapped method, we draw new data sets with replacement for M = 2000 times. And redo the procedure above to obtain a matrix with 2000 elements of differences $\hat{q}_j^1 - \hat{q}_j^0$. The matrix is now $M \times 2^K$. The basic results of multiple technology relations for each case are shown in the Table3a. Some cases of technology bundles never occur in our data. Except the non-existence cases, technologies in most bundles are independent. For example, 76 out of 133 cases are independent in 1995, 45 out of 79 in 2000 and 67 out of 102 in 2005. The remaining bundles indicate that technologies are either substitutes or complements and the substitute relations prevail.

Technologies with mutual complementarity are what we are more interested in. We further look at the results in the Table 3b where we present the specific technologies adopted which are regarded as complementary in each year. The case in which no technologies are adopted generates a higher frequency than that under independence assumption. One of the explanations is that very small farms do exist in the market and survive the competition even if they do not use any advanced technologies. We excluded the zero adoption case from the following analysis.

In each survey year, there are some single technologies adopted at a higher rate than under the independence assumption. These farms only utilize one of the advanced technologies to produce hogs. Among these eight technologies, Artificial Insemination and All In/ All Out are the two technologies often used by farmers in all three survey years. Split Sex Feeding and Phase Feeding technologies are also often used by farms in 1995 and 2000. In 1995, Multiple Site Production is another technology frequently used by farmers who only use a single technology.

Other rows in the Table 3b show the adoption of multiple technologies. Certain specific technology combinations such as (AI, SSF, PF, MSP, SEW, AIAO) and (AI, SSF, PF, MSP, MEW, AIAO) appear very frequently in the sample with the former selected by almost 8% of all farms in 1995, 14% in 2000, and 6% in 2005. When we add a certain new technology to some technology bundles which appear to be complementary, the new technology bundles are still more likely to be complementary. For example, technologies SSF, PF, MSP, SEW and AIAO are complementary in 1995 and 2005. When we add AI into the bundle, the new bundle is also a complementary combination.

However, we still find that some technologies appear to be substitutes. After a new technology is added into the bundle, the new bundle may become complementary. For example, AI, PF and AIAO appear to be a substitute combination in 1995, but after SSF is used, the new bundle (AI, SSF, PF, AIAO) becomes complementary. 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.

Among early weaning technologies, Segregated Early Weaning technology is more frequently used in the complementary bundles than MEW and MMEW. The three early weaning technologies are less likely to appear together in the technology bundles. However, when farms adopt at least seven technologies, they become necessary elements in the complementary bundles to increase productivity. 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 the close substitute technology 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 disease.[4] As newly introduced technologies in 2005, Parity Based Management and Auto-Sorting System technologies, adopted along with other often used technologies, are regarded as complementary with each other.

As far as the relationship between two technologies is concerned, several studies have examined correlations between two practices or technologies to assess whether the technologies are subsititutes or complements. For example, Poppo and Zenger (2002) interpret a positive correlation between relational governance and formal contracts as evidence that the two choices are complementary. Dorfman (1996) interpreted a negative correlation in the errors across probit equations explaining the adoption of various irrigation and integrated pest management techniques to suggest that the technologies are substitutes. However, the simple correspondence between correlations and complementarity or substitutability breaks down when more than two technologies are selected simultaneously.

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

We compare the conclusions that would result from bilateral correlations to the conclusions that are derived from our more general method in Table 4. The bilateral correlations suggest numerous occurrences of complementary technology pairs that are really independent or are subsets of more complex technology combinations. For example technology bundle of AI and AIAO, or the bundle of AI and SSF are regarded as substitutes by the simple correlations in 2005, but both of the bundles are independent when evaluated in conjunction with all the other technologies. Many of the presumptive complementary pairs, based on simple correlations, in fact never occur in the data—the pair always occurs in conjunction with other technologies that are presumed to be irrelevant alternatives when computing the bilateral correlations.

Finally, the *G* statistics from equation (6) of the independence of the multiple technology adoption in general are constructed using probabilities defined according euqaiton (4) and (5). The G statistics are 2850.8，843.84 and 937.21 in 1995, 2000 and 2005 data respectively using our raw data. P-value for each test is less than 0.01. Therefore we reject the hypothesis that technology adoption in general is independent. Multiple technology adoption in the US hog industry is not mutually independent.

4. Simultaneous Technology Adoption and Farm Size Determination

The adoption of each technology requires fixed investment in land, equipment and human capital. Not all farms will be equally positioned to adopt. Small farms may face liquidity constraints that prevent them from incurring large capital investments or they may not have sufficient land to enable multiple adoptions. Farmers with better human capital endowments, presumably those with more education, may be better positioned to learn about new technologies or to learn how to implement them effectively.

Table 5 provides additional detail on the persistence of the farm size-adoption relationship. It is apparent that larger farms adopt more technologies in all three years. Farms with fewer than 2,000 pigs utilize fewer than two technologies on average, while farms producing more than 25,000 pigs use more than four 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 the correlation between firm size and technology adoption. Several reasons have been advanced. Larger firms have more educated workers who are more easily adapt to new technologies, meaning that larger farms have a comparative advantage in training costs (Idson and Oi, 1999). Adoption of new technologies is risky, and large farms may be better able to diversify that risk across more technologies or across greater volume of output. Finally, large farms may face fewer liquidity constraints in absorbing the fixed costs of technology adoption. Kristen and Belman (2004) found that firms with more than 250 drivers are between 44 percent and 62 percent more likely to use Satellite Based Systems than firms with less than 25 employees. Stoneman and Kwon (1994, 1996) and Colombo and Mosconi (1995) also find a positive relationship between firm size and technology adoption. Firms adopting multiple technologies tend to have higher profits (Stoneman and Kwon, 1996), consistent with the presumption that these technologies are mutually complementary.

Previous studies have also consistently shown that more educated agents adopt technologies more readily. This apparent complementarity between human capital and technological innovations has been used to explain the positive correlation between average wages and information technology investments at the firm or individual levels.[5] Numerous papers have also found a positive correlation between farmer education and technology adoption in agriculture.[6] More educated or more skilled farmers may have a comparative advantage in adopting new or more advanced technologies. They may learn of new technologies more quickly or they may have skills that complement the productivity of the new technologies.

To investigate the roles of human capital and farm size in multiple technology adoption, assume a bi-variate ordered - response probit model, considering the correlation between the technology adoption and farm size. The bivariate ordered – response probit model considers two latent dependent variables t_i^* and s_i^* with the following form shown in equation (9), assuming that the purely random error terms m_{1i} and m_{2i} have independently and identically standard normal distribution, where t_i^* is the number of technologies used by the producer i, s_i^* is the farm i's size, b is a coefficient vector to be estimated in technology adoption equation and g is the coefficients to be estimated in the size equation. e_i is the random specific individual effect common to each equation which is distributed as $N(0, s^2)$.

$$\begin{aligned} t_i^* &= x_i b - e_i - m_{1i} \\ s_i^* &= x_i g - e_i - m_{2i} \\ \begin{pmatrix} m_{1i} \\ m_{2i} \end{pmatrix} &\sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right). \end{aligned} \tag{9}$$

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[5] Examples include Krueger, 1993; Dunne and Schmitz, 1995; Caselli and Coleman II, 2001 and Dunne, Foster and Troske, 2004. Dinardo and Pishke (1997) suggest that the correlation may not be causal. Acemoglu (2002) reviews the literature.

[6] 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.

t_i^* is the unobserved latent and continuous number of technologies used by the producer i, unobserved to the analysts but the number of technologies is observed as a discrete category, t_i given as:

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

where the a_c are unknown parameters to be estimated. The size equation, which is categorized from 0 to 8, is specified in analogous manner to (10). Its threshold series b_c, $c = 0,1,\dots,7$ in the size equation, is the counterpart of a_c in technology adoption equation.

The random disturbance term can be redefined as $u_{ji} = e_i + m_{ji}$, $j = 1,2$. Therefore, u_{1i} and u_{2i} can be regarded as a bivariate normal distribution with correlation coefficient r, where $r = \frac{s^2}{1+s^2}$. The regression model is reduced to

$$\begin{aligned} t_i^* &= x_i b - u_{1i} \\ s_i^* &= x_i g - u_{2i} \\ \begin{pmatrix} u_{1i} \\ u_{2i} \end{pmatrix} &\sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & r \\ r & 1 \end{pmatrix}\right). \end{aligned}$$

The probability is given by

$$\begin{aligned} \Pr(t_i = k, s_i = m) = {} & \Phi_2(x_i b - a_{k-1}, x_i g - b_{m-1}, r) - \Phi_2(x_i b - a_{k-1}, x_i g - b_m, r) \\ & - \Phi_2(x_i b - a_k, x_i g - b_{m-1}, r) + \Phi_2(x_i b - a_k, x_i g - b_m, r) \end{aligned}$$

where $\Phi_2(.)$ is the standard bivariate normal cumulative distribution function, $a_{-1}, b_{-1} \to -\infty$ and $a_8, b_8 \to \infty$. We expect that the correlation coefficient r is positive since the unobserved entrepreneurial skill of producers positively affects both decisions regarding technology adoption decision and farm sizes. The more able the producer, the more technologies utilized and the larger her farm is. Elements related to the human capital of producers in b and g are also expected to be greater than zero.

In our application, we use GLLAMM (generalized linear latent and mixed models) in STATA that uses the Newton – Raphson method and adaptive quadrature to approximate the likelihood function by numerical integration (Rabe-Hesketh et al. 2004). Regression results are shown in Table 7. The correlation coefficient between the error terms is 0.468 and is statistically significant, which verifies that technology adoption and farm size growth go hand in hand. Coefficients of all education dummy variables are significantly positive in the technology adoption equation. In the size equation, having at least a four year college degree raises farm size significantly, and so for holding a post-graduate degree. The higher educated the producer, the more likely to adopt more technologies and the larger the farm is. However, farm experience is not an important factor in both the technology adoption and farm size decision.

Females have a significantly lower probability of operating large farms, but do not have a significantly different propensity to adopt technologies.[7] Farms in the mid-west are using more technologies but have smaller farms than those in the northeast, southeast and west. One possible reason is farms in the mid-west have a comparative advantage in obtaining input feeds at a lower cost. They may not need to be large. On the contrary, newer farms in the southeast and west regions, operated by younger producers have higher feed prices, and the improved productivity and size economies can offset this disadvantage (McBride and Key, 2003).

5. Conclusion

[7] Fortin (2005) has argued that women are less likely to be entrepreneurs because usually they lack the "soft factors" such as greediness, ambition, confidence and leadership.

This paper proposes a tractable statistical method to test for mutual complementarity or substitutability among 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 mutually substitutable for one another, the 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.

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 mutually substitutable for one another, while others are complementary. Several technologies including Artificial Insemination, Sex Split Feeding, Phase Feeding, Multiple Site Production, Segregated Early Weaning and All In/ All are often bundled together. What is a more important finding is that 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.

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 at once, 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.

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Table 1. Technologies used in the US hog industry

			Adoption Rate (std)		
Number	Name	Notation	1995	2000	20005
1	Artificial Insemination	AI	.549 (.5)	.764 (.425)	.767 (.423)
2	Split Sex Feeding	SSF	.469 (.499)	.465 (.499)	.393 (.489)
3	Phase Feeding	PF	.553 (.497)	.509 (.500)	.498 (.500)
4	Multiple Site Production	MSP	.382 (.486)	.470 (.5)	.459 (.499)
5	Segregated Early Weaning	SEW	.146 (.353)	.288 (.453)	.318 (.466)
6	Medicated Early Weaning	MEW	.083 (.276)	.038 (.190)	.
7	Modified Medicated Early Weaning	MMEW	.018 (.133)	.007 (.478)	.
8	All in / All out	AIAO	.670 (.470)	.647 (.478)	.606 (.489)
9	Auto Sorting Systems	AS	.	.	.059 (.237)
10	Parity Based Management	PBM	.	.	.261 (.440)

Table 2. Size class and frequencies

Code	Size Class (pigs per year)	Weighted Frequencies (%)		
		1995	2000	20005
1	Less than 500	0.01	1.61	.
2	500 to 999 / less than 1000 in 2005	0.02	0.08	1.42
3	1,000 to 1,999	3.18	4.34	1.71
4	2,000 to 2,999	14.90	9.21	3.51
5	3,000 to 4,999	10.66	11.48	4.03
6	5,000 to 9,999	41.79	29.77	35.36
7	10,000 to 14,999	13.12	14.81	16.98
8	15,000 to 24,999	8.67	12.33	13.13
9	25,000 or more / 25,000 to 49,999 (2005)	7.66	16.33	12.07
10	50,000 or more (2005)	.	.	11.79

Table 3. Results of specific technology bundle test

Table 3a. Summary of the results

Relations	*1995*	*2000*	*2005*
No existence [a]	123	177	154
Substitutes	44	24	24
Independent	78	45	67
Complements	13	10	11

a, based on the raw data.

The statistics are based on M = 2,000 bootstrapped samples. Probability Weights are considered.

Table 3b. Complementary technologies

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

The number of technologies in the first column is the number of technologies adopted which are significantly complementary.

T = 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		Our Method for Multiple Technologies			
	Substitutes	Complementary	Substitutes	Complements	Independent	Nonexistent
1995	1	27	8	0	14	6
2000	0	28	6	1	10	11
2005	3	25	6	1	10	11

Table 5. Technology usage by Size Class and Survey Year: Mean and Standard Deviation

	Size(1995)								
Variable	< 500	[500, 999]	[1000, 1999]	[2000, 2999]	[3000, 4999]	[5000, 9999]	[10000, 14999]	[15000, 24999]	>25000
number of technologies	1.12	1.22	1.57	2.10	2.51	3.02	3.59	3.94	4.37
	(1.27)	(1.17)	(1.20)	(1.42)	(1.51)	(1..63)	(1.61)	(1.68)	(1.79)
	Size(2000)								
number of technologies	1.23	0.12	1.61	2.07	2.77	3.49	3.55	4.04	4.20
	(0.70)	(0.43)	(1.43)	(1.33)	(1.39)	(1.69)	(1.70)	(1.83)	(2.16)
	Size(2005)								
	< 1000	[1000, 1999]	[2000, 2999]	[3000, 4999]	[5000, 9999]	[10000, 14999]	[15000, 24999]	[25000, 49999]	>50000
number of technologies	1.49	1.61	2.22	2.66	2.85	3.18	4.13	4.56	4.40
	(0.54)	(1.22)	(1.37)	(1.37)	(1.58)	(1.61)	(2.00)	(1.90)	(2.06)

The number in the parentheses is the standard deviation.

Table 6. Characteristics of producers and farms

		Whole sample	*Sample with more technologies* [a]	*Sample with fewer technologies*
Variables	*Description*	*Mean (std)*	*Mean(Std)*	*Mean(Std)*
Female	Gender of producers	0.039 (0.193)	0.036(0.187)	0.040(0.197)
Education	Schooling of producers	14.125(2.301)	14.540(2.213)	13.839(2.316)
Experience	Working experience	23.832(11.187)	21.594(9.992)	25.345(11.684)
Firm Size	Number of pigs produced (unit: 10,000 heads)	1.005 (0.861)	1.322(0.981)	0.787(0.686)
Northeast	Dummy variable, equal to one if located in the northeast.	0.045(0.208)	0.030(0.170)	0.0560(0.230)
Southeast	Dummy variable, equal to one if located in the southeast.	0.057(0.231)	0.032(0.175)	0.074(0.262)
West	Dummy variable, equal to one if located in the west.	0.081(0.273)	0.048(0.214)	0.104(0.305)
Number of technologies	Number of technologies used by the farmers	3.059 (1.745)	-	-

a. Farms with more technologies are defined as the ones adopting at least four technologies, other wise categorized into the sample composed of farms with fewer technologies.

The number in the parenthesis is the standard deviation.

The statistics of the variables are weighted.

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 master degree. SY = 23 if she a Ph.D. degree hold or a Doctor of Veterinary Medicine.

Table7. Technology adoption – bi-variate ordered probit regression

Dependent Variable:	*number of technologies*	Farm Size
Femaler	-0.105	-0.333
	(1.04)	(3.29) *
Edu12	0.248	-0.028
	(2.17) *	(0.25)
Edu14	0.392	-0.009
	(3.24)* *	(0.07)
Edu16	0.721	0.330
	(6.25)**	(2.90)**
Edu18+	0.718	0.425
	(4.94)**	(2.94)**
Experience	-0.010	0.003
	(1.47)	(0.41)
Experience^2	-0.0003	-0.0002
	(2.22) *	(1.87)
Northeast	-0.277	0.121
	(2.95)**	(1.30)
Southeast	-0.490	0.960
	(6.00)**	(11.61)**
West	-0.352	0.242
	(3.97)**	(2.73)**
Year 2000	0.541	0.673
	(8.11) **	(10.00) **
Year 2005	0.606	0.084
	(9.97) **	(1.38)
a_0	-1.761	-0.741
	(12.24) **	(4.69) **
a_1	-0.508	-1.367
	(3.59) **	(8.95) **
a_2	0.250	-0.923
	(1.77)	(6.15) **
a_3	0.972	-0.776
	(6.84)* *	(5.16)
a_4	1.684	-0.827
	(11.71) **	(5.45) **
a_5	2.388	-0.740
	(16.25) **	(4.78) **
a_6	3.700	-1.600
	(21.92) **	(9.14)) **
a_7	4.490	-1.880
	(20.48) **	(8.38) **
s^2	0.881 (19.93) **	
Log likelihood	-16147.566	

NOTE: Absolute value of *t* statistics in parentheses

a. Thresholds for technology adoption equation are shown in the first column. Thresholds for size determination equation are the summation of the cutoff points in the first and second columns (Rabe-Hesketh, et.al. 2004).

* Significant at 5%; ** significant at 1%