Do Large Firms with More Technologies Pay More?

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Abstract

Investigation of size wage premium in earning's literature neglects the important role played by technology adoption. This study models the size selection corrected earning's function by introducing an extra dimension of selection of technology complexity, using a sample from workers in US hog farms. The estimated wage gap between large and small farms is reduced once correction in selection is controlled. Workers compensate monetary income for better work environment, better health and more job security, in which large farms and technologically advanced farms have advantages.

Key Words: size; technology adoption; wage; double selection, agriculture and health

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I. Introduction

It is commonly observed that larger firms pay higher wages than smaller firms. This size-wage premium was first documented by Henry Moore (1911), and corroborated by others, among them, Brown and Medoff (1989) and Oi and Idson(1999). At the same time, Abowd, Kramarz and Margolis (1999) found that individual heterogeneity explains a large proportion of the wage variation between different firm size categories. There is a mixed result on the positive size-wage premium after endogenous employee selection on firm size is controlled (for example, Idson and Feaster, 1990; Main and Reilly, 1993). Economists try to unveil the puzzle, but usually they ignore another important aspect associated with firm size and wages: larger firms are more likely to adopt more technologies and there are complementarities between technology adoption and human capital, which though has been largely documented (Stoneman and Kwon, 1994; Colombo and Mosconi, 1995; Idson and Oi, 1999; Troske, 1999; Huffman, 2001). For example, in agricultural settings, more educated farmers tend to be the first to attempt new tillage practices, plant new varieties, adopt site-specific technologies or implement new technological advances.

In addition to self-sorting of workers into different sizes of firms, workers with different observed characteristics and unobserved preference or abilities can be self-selected into different firms with different technological characteristics as well. In addition to complementarity between technologies and their observed human capital, workers may opt to technologically advanced firms due to other unobserved attributes. For instance, workers may want to obtain specific training pertaining to higher level of technologies and expect an increased return to the accumulated human capital in the long run. Alternatively, firms adopting certain technologies that value worker's cooperation would like to hire workers with less aggressive characteristics. Apparently, these econometrically unobservables may not be orthogonal to their earnings. It is not surprising that workers and employers have heterogeneous preference and attitudes toward types of firms that differ in wage structure, fringe benefits, company culture, working environment and long-run goals. Match of workers and employees will reflect both labor supply and labor demand decisions, characterizing the equilibrium in the labor market. When there is such a nonrandom assignment of workers across firms, endogeneities in earning's function from size and technology adoption intensity will bias estimation of size treatment effect, technology adoption effect on wages and other coefficients in earning's function.

In this study, we put both size and technology adoption in a double selection framework and decompose wages components across firm types, using a sample from workers in US hog farms. Earning's function in the US hog farms using the same data set has been examined by Hurley, *et al* (1999) and Yu *et al* (2008). Yu and Orazem (2008) further find positive relationship between hog farm size, production complexity and wage, simultaneously controlling for both observed and unobserved employer-employee characteristics. However, these studies either do not take into account potential selection bias on estimation of wage equations or are muted on the wage differentials for different types of farms.

This paper aims at improving understanding of size wage premium and earning's function in literature. We find that after control for individual's selectivity on both firm size and firm technology complexity, size wage premium and technology adoption premium still exist. However, the premiums are not as high as without controlling selection. Reduced wage premium due to selection on firm size and technologies can be justified from perspectives of both labor supply and labor demand.

At the same time, these findings shed light on the importance of labor supply and wage policies in the agriculture industry. Risk of occupational death is particularly important issue in the agriculture industry, which is the second to mining. According to the report in 2008 in Labor Bureau of Statistics, fatality rate in agricultural industry is 672 out of 100 thousands[1]. In particular, hog farmers are found markedly tend to have higher risk in reduced hand strength and respiratory symptoms than non farmers (Hurley, *et al*, 2000).

In addition to monetary returns, individuals also opt to better fringe benefits, working environment and health security which are heterogeneous across different firms. In this study, we also provide some complementary evidence on work environment and health of employees on the US hog farms, which can explain the shrunk wage gap between different types of farms. To the extent workers on a small hog farm which usually do not adopt many advanced technologies are believed to face greater health risks, they require a compensating differential in the form of higher salaries in exchange for accepting the relative more risks.

The remainder of the paper is organized as follows. The next section presents the double-selection corrected earning's function. The third section described the database. The fourth section reports the empirical findings from applying the double-selection techniques and offers some explanations. Wage differentials between different types of farms are decomposed such that we can specifically know how much of wage gap can be attributed to worker characteristics, coefficient responses and selectivity. Finally, the last section concludes the paper and discusses the potential improvement from further research.

II. Wage equations with double selection correction

[1] http://www.bls.gov/iif/oshwc/cfoi/cftb0232.pdf

As discussed above, neglecting of selections faced by workers will bias wage equation estimation. There are two choices that a worker makes need to be explicitly considered, the decision to work at a small or large firm and the decision to work at a firm with a large number of adopted technologies or with barely any advance technologies. Following the modeling strategy suggested by Tunali (1986), we use a bivariate selection to analyze a typical worker's choices.

We assume the decision will be made according the following unobservable utility indices.

$$(1) \quad \begin{cases} U_{1i}^{*} = Z_{1i}\alpha_1 + \epsilon_{1i} \\ U_{2i}^{*} = Z_{2i}\alpha_2 + \epsilon_{2i} \end{cases},$$

where the U_{ji}^{*}s represent the latent utility variables that a worker i could get when he make decision (j=1, 2). j=1 means the decision to work in small/large firms and j=2 means the decision to work in high technology/low technology firms. The Z_{ji}s are vectors of exogenous variables which affect these utilities. α_{ji}s are associated unknown coefficients. ϵ_{1i} and ϵ_{2i} are random errors and are assumed to jointly have bivariate normal distribution with their correlation coefficient ρ, $Cov(\epsilon_{1i}, \epsilon_{2i}) = \rho$. If ρ is significantly different from zero, ϵ_{1i} and ϵ_{2i} are not independent.

Although U_{ji}^{*}'s are not directly observed, two dummy variables can be defined as follows:

$$(2) \quad D_{1i} = 1 \text{ if } U_{1i}^{*} > 0 \text{ and } D_{1i} = 0 \text{ otherwise;}$$

$$(3) \quad D_{2i} = 1 \text{ if } U_{2i}^{*} > 0 \text{ and } D_{2i} = 0 \text{ otherwise.}$$

Based on the observed value of D_1 and D_2, workers can be put into four different groups S_j, $j = 1, 2, 3, 4$. S_1 includes firms that are small and use small number of technologies. S_2 includes small firms which uses a large number of technologies instead. S_3 includes large firms that lack advanced technologies. S_4 includes large and technologically advanced firms. The probabilities of being selected into each group are:

$$(4)\ P(S_{1i}=1)=\ P(D_{1i}=0,D_{2i}=0)=\Phi_2(-C_{1i},-C_{2i},\rho)$$

$$(5)\ P(S_{1i}=2)=\ P(D_{1i}=0,D_{2i}=1)=\Phi_2(-C_{1i},C_{2i},-\rho)$$

$$(6)\ P(S_{1i}=3)=\ P(D_{1i}=1,D_{2i}=0)=\Phi_2(C_{1i},-C_{2i},-\rho)$$

$$(7)\qquad P(S_{1i}=4)=\ P(D_{1i}=1,D_{2i}=1)=\Phi_2(C_{1i},C_{2i},\rho),$$

where Φ_2 is the cumulative density function for bivariate normal distribution. $C_{1i}=Z_{1i}\alpha_1$, $C_{2i}=Z_{2i}\alpha_2$. If the workers are randomly assigned to these four groups, the wage equation will be

$$(8)\quad lnw_{i1}=\ X_{i1}\beta_1+\mu_{1i}\ if\ i\in S_1$$

$$(9)\quad lnw_{i2}=X_{i2}\beta_2+\mu_{2i}\ if\ i\in S_2$$

$$(10)\quad lnw_{i3}=\ X_{i3}\beta_3+\mu_{3i}\ if\ i\in S_3$$

$$(11)\quad lnw_{i4}=\ X_{i4}\beta_4+\mu_{4i}\ if\ i\in S_4,$$

where lnw_{ij} denotes the logarithm of worker *i*'s wage in group $j=1,2,3,4$. X is a vector of explanatory variables which explain the worker's wage. $\beta's$ are vectors of unknown parameters associated with X. $\mu's$ are random terms. If common factors for both $\mu's$ and $\epsilon's$ exist, OLS estimation directly applied into these groups will lead to possible selection bias (Heckman, 1979).

In our case, we assume $\mu's$ and $\epsilon's$ are multivariate normally distributed with mean zero and covariance matrix,

$$(12)\qquad cov(\epsilon_{1i},\epsilon_{2i},\mu_{1i},\mu_{2i},\mu_{3i},\mu_{4i})=$$

$$\begin{pmatrix} 1 & \rho & \sigma_1^1 & \sigma_2^1 & \sigma_3^1 & \sigma_4^1 \\ \rho & 1 & \sigma_1^2 & \sigma_2^2 & \sigma_3^2 & \sigma_4^2 \\ \sigma_1^1 & \sigma_1^2 & \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_2^1 & \sigma_2^2 & \sigma_{12} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ \sigma_3^1 & \sigma_3^2 & \sigma_{13} & \sigma_{23} & \sigma_{33} & \sigma_{34} \\ \sigma_4^1 & \sigma_4^2 & \sigma_{14} & \sigma_{24} & \sigma_{34} & \sigma_{44} \end{pmatrix}$$

If σ_j^1 or σ_j^2 are not equal to zero, the expectation of random errors in (8) - (11) will not generally be zero, conditional on the fact that we only observe workers' group. Namely,

$$(13)\ E(lnw_{i1}) = \quad X_{i1}\beta_1 + E(\mu_{1i}|X_{i1}, D_{1i} = 0, D_{2i} = 0)$$

$$(14)\ E(lnw_{i2}) = \quad X_{i2}\beta_2 + E(\mu_{2i}|X_{i2}, D_{1i} = 0, D_{2i} = 1)$$

$$(15)\ E(lnw_{i3}) = \quad X_{i3}\beta_3 + E(\mu_{3i}|X_{i3}, D_{1i} = 1, D_{2i} = 0)$$

$$(16)\ E(lnw_{i4}) = \quad X_{i4}\beta_4 + E(\mu_{4i}|X_{i4}, D_{1i} = 1, D_{2i} = 1)$$

Tunali (1986) shows that if the error terms are normally distributed with covariance matrix (12), the above conditional wage equations turn out to be

$$(17)\ lnw_{i1} = X_{i1}\beta_1 + \sigma_1^1\lambda_{1i}^1 + \sigma_1^2\lambda_{1i}^2 + \xi_{1i}\ if\ D_{1i} = 0, D_{2i} = 0$$

$$(18)\ lnw_{i2} = X_{i2}\beta_2 + \sigma_2^1\lambda_{2i}^1 + \sigma_2^2\lambda_{2i}^2 + \xi_{2i}\ if\ D_{1i} = 0, D_{2i} = 1$$

$$(19)\ lnw_{i3} = X_{i3}\beta_3 + \sigma_3^1\lambda_{3i}^1 + \sigma_3^2\lambda_{3i}^2 + \xi_{3i}\ if\ D_{1i} = 1, D_{2i} = 0$$

$$(20)\ lnw_{i4} = X_{i4}\beta_4 + \sigma_4^1\lambda_{4i}^1 + \sigma_4^2\lambda_{4i}^2 + \xi_{4i}\ if\ D_{1i} = 1, D_{2i} = 1,$$

where $\xi_{1i}, \xi_{2i}, \xi_{3i}, and\ \xi_{4i}$ are random terms with mean zero because $\xi_{ji} = \mu_{1i} - \sigma_j^1\lambda_{ji}^1 - \sigma_j^2\lambda_{ji}^2,\ j = 1, 2, 3, 4.$ $\lambda's$ are the counterpart of inverse Mill's ratio in a double selection framework and derived in Tunali (1986) as:

$$(21)\quad \begin{matrix} \lambda_{1i}^1 = -P(S_i = 1)^{-1}\phi(C_{1i})\Phi(-C_{2i}^*) & \lambda_{1i}^2 = -P(S_i = 1)^{-1}\phi(C_{2i})\Phi(-C_{1i}^*) \\ \lambda_{2i}^1 = -P(S_i = 2)^{-1}\phi(C_{1i})\Phi(C_{2i}^*) & \lambda_{2i}^2 = P(S_i = 2)^{-1}\phi(C_{2i})\Phi(-C_{1i}^*) \\ \lambda_{1i}^1 = P(S_i = 3)^{-1}\phi(C_{1i})\Phi(-C_{2i}^*) & \lambda_{3i}^2 = -P(S_i = 3)^{-1}\phi(C_{2i})\Phi(C_{1i}^*) \\ \lambda_{4i}^1 = P(S_i = 4)^{-1}\phi(C_{1i})\Phi(C_{2i}^*) & \lambda_{4i}^2 = P(S_i = 4)^{-1}\phi(C_{2i})\Phi(C_{1i}^*) \end{matrix},$$

where $C_{1i}^* = \frac{Z_{1i}\alpha_1 - \rho Z_{2i}\alpha_2}{sqrt(1-\rho^2)}, C_{2i}^* = \frac{Z_{2i}\alpha_2 - \rho Z_{1i}\alpha\_1}{sqrt(1-\rho^2)}$. $\phi()$ is the density function of a standard normal distribution, Φ() is the cumulative density function of a standard normal distribution. Tunali shows that the parameters in wage equation could be consistently estimated by two stage regressions. Namely, in the first stage, a bivariate probit model of equation (2) and (3) describes worker's choices based on the explanatory variables $Z's$. After the regression, the consistent estimator of $\lambda's$ are calculated and used to estimate wage equation (17) – (20) separately. Because of the nonlinearity nature of probit model, $Z^{'}s$ are not necessarily needed to be different from $X's$ for the identification concern, while in some cases, the identical variables used in both selection model and wage equation will cause severe multicollinearity problem in wage equation (Willis and Rosen, 1979). Therefore, we choose a different set of explanatory variables for selection and wage equations. Discussion of choice and definition of variables are in the next section. Tunali also points out the heteroscedastic nature of error terms in equation (17) – (20) and the least square standard errors of the coefficients are inconsistent essentially.

III. Data

We use a unique cross sectional survey data from employees on U.S. hog farms in 1995, 2000, and 2005. Questionnaires were mailed to the subscribers to the *National Hog Farmer Magazine* and we collected 2,266 useful surveys. Hog industry has been consolidated in recent decades. Small farms have been driven out of the market and the share of large farms has been increasing, which lead to the decline of the total number of farms. So the number of observations in the sample is not evenly distributed across years. There are 1,149 observations in 1995, 617 in 2000 and 500 in 2005.

Each individual responded the question of how many pigs were produced per year defined by a categorical variable ranging from 1 to 10. The smallest farm produced fewer than 500 pigs annually and the largest farm may produce more than 100,000 pigs. We further define a binary variable *Size*, which is equal to one if a farm could produce more than 10,000 pigs, 0 otherwise. Again, hog market consolidation makes the distribution of farm sizes shifted to the large farms in our sample. 46% of farms were large in 1995 while 74% were large in 2005.

The data base also includes questions about if any of specific technologies was used in individual worker's farm. Hog production in the U.S. has experienced tremendous technological innovations in advances in genetics, nutrition, housing and handling equipment, veterinary and medical services, and management practices, and the technology adoption contributes to productivity gain in recent decades (McBride and Key, 2007). The appendix shows the technologies used in the hog farms between 1995 and 2005[2]. The number of technologies adopted by the farm represents the technology adoption intensity and can approximate the production complexity. In the pork industry, large farms are found to favor technology adoption. 7.3 % of farms adopted at most one of the advanced technologies and 70% of them produced fewer than 5,000 pigs. In contrast, 8.8% of farms adopted all of technologies and more than three quarters of them produced more than 25,000 pigs annually. On average, 4.5 technologies were used on a farm. Similarly, *Technology* is defined as a binary variable, equal to one if more than five technologies were adopted, 0 otherwise.

Hog farms are categorized into four types according to production scale (D_1 in the notation in Section II) and technology adoption intensity (D_2). Hence, there are

[2] Two new technologies, Auto Sorting (AS) and Parity Based Management (PBM) are new technologies and were only available in the survey in 2005. Fewer than 30% of farms in 2005 adopted either of the two technologies. Because we control year fixed effect in our model and hog operators are exposed to the same technological shocks, different composition of technology across survey years will not significantly alter our results.

four combinations of farm types, (0, 0), (0, 1), (1, 0) and (1, 1), as shown in Table 1[3]. Farms of type (0, 0) are small and use no more than five technologies. Farms of type (1, 1) are large and technologically intensive. The dataset enables us to estimate treatment effects from size and technology adoption on wages after correcting nonrandom assignment of workers into different types of firms. Finally, information about worker's social economic characteristics, wage level, work environment evaluation and their health conditions is also available[4]. In particular, there are several measures of worker skills or human capital: worker's formal education, previous working experience in the pork industry, tenure in the current farms and pork production related childhood background.

Summary of statistics is shown in Table 1. Log of wage is highest in farms of type (1, 1) and lowest in farms of type (0, 0). The wage differential in the two types of farms is 0.47. The other two types of farms also pay more than (0, 0) type of farms. Women are more likely to work in large farms but less likely to work in technologically intensive farms. Workers in large and small farms are nearly equally educated on average but more educated workers are more likely to work with more advanced technologies. There is a stronger complementarity of worker schooling with technology adoption than with farm size. Current work experience is

[3] Not all hog farms are farrow-to-finish ones. Some, though a smaller proportion, of farms specialize in farrow-to-feeder or feeder-to-finish operations. Farm size of feeder-to-finish operations is expected to be smaller than that of feeder-to-finish operations. At the same time, technology adoption scenarios may also be different. It may be expected that farms raising feeder pigs to the market tend to have fewer technology options than would farms that raise piglets to finish pigs. If selection process for this particular farm type is significantly different from general farrow-to-finish farms, estimation of earning's function and size wage premium will be biased. We replicated our analysis of model using a restricted sample that included only farrow-to-finish farms. We get qualitatively similar results and conclusions with those obtained with the full sample, and so our results are not driven by type of operations.

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

significantly skewed to small firms but not necessarily to high technology type of farms. In contrast, previous experience of working in the pork industry is positively related with both farm size and production complexity. Farm raised individuals tend to work in small farms and they are possibly still working for family farms which are generally small.

IV. Findings

We apply the methodology laid out in Section II to the sample of employees on the US hog operations from 1995 to 2005. The formulation of earnings function taking into account of selection on farm size and technology complexity enables us to address two major concerns of the literature. The first concern has to do with the importance of wage differentials in conditioning farm types. As shown in the estimated standard earning's function Table 2, even after controlling for worker's characteristics, firm's location and year fixed effect, dummy variables *Size* and *Technology* are significantly positively related with log of wage. Both size wage premium and technology wage premium are significantly positive. However, as noted above, potential endogeneity of *Size* and *Technology* may bias estimated coefficients for the whole sample and for subsample of farms with different types in particular. The second concern has to do with the treatment effect of the two important factors on realized wages. After controlling for differential responses and characteristics, treatment effect or impact of both *Size* and *Technology* may not be positive. In other words, if equivalent workers are randomly assigned to different types of farms, workers in large and technologically intensive farms may be paid less than their counterparts. Whether selection is positive or negative will lead to different conclusions about labor supply and labor demand in the pork industry. We present empirical findings regarding the implied wage premium and offer possible explanations by citing several theories and presenting complementary evidence from the survey questions. Then we make wage differentials decomposition.

A direct result from double selection: shrunk wage premium

Bi-variate probit model of double selection on *Size* and *Technology* is presented in Table 3. The results are not particularly surprising, consistent with general findings in the literature. Workers with higher education, workers with previous relevant working experience and workers with hog-raising background are more likely to work on large farms and on technologically advanced farms. The correlation coefficient is 0.57, indicating that unobserved attributes on farms and individuals significantly positively affect selection on farm size and technology adoption intensity.

Based on this double selection regression above, inverse mills ratios for four types of farms are obtained using equation (21) and added to the earnings function. Estimation of equations (17) – (20) is shown in the last four columns of Table 2. We find that earning's functions are different across different types of hog farms. And at least one of the coefficients of inverse mills ratios in each farm type is significantly different from zero. The null hypothesis of no selection is rejected at the 5 percent level of significance, indicating the existence of unobservables common to both the selection and wage determination process. Both farm size and technology complexity should be endogenously treated to remove the selection bias on wage premium estimation. Because truncated mean of inverse mill's ratios for farms with $D_1 = 0$ or $D_2 = 0$ are negative and positive for farms with $D_1 = 1$ or $D_2 = 1$, negative selection coefficients for both four types of farms indicate that estimated wage premiums on farm size and technology adoption intensity are reduced, compared to the wage gap when workers are randomly allocated to four types of farms (Idson and Feaster, 1990).

Several possibilities are proposed to account for the shrunk wage premiums. Since our results are based on samples from pork production and technology adoption is prevalent in today's agricultural production, specific theories pertaining to agricultural context are borrowed to justify the selection behaviors. However, we do not exclude other potential interpretations.

Firstly, pork industry and generally agricultural industry are quite competitive and small farms which do not benefit from economy of scale tend to easily exit the market. Therefore, job stability and job security are worker's big concerns. Workers who are risk averse to job instability would like not to work in small farms. Large farms attract workers because of higher profit margin and their dominant positions in the competitive agricultural market. However, agricultural production is consistent with the O-Ring theory where any mistake in a single stage from a series of production process may lead to catastrophic failure (Kremer, 1993; Yu *et al*, 2009). Infection of one pig may spread the diseases to the entire heard, driving profits to be negative. Farms of larger scale are at greater stake and they are assumed to bear more risks. Therefore, disease control is critically important for hog production. Large farms have greater incentives to adopt several advanced technologies to curb spread of diseases among pigs, such as Multiple Site Production, All-In-All-Out, Medicated Early Weaning and Parity Based Management. From the perspective of hog workers, farms that are less technologically intensive ensure a lower level of job security.

Secondly, workers in the agricultural industry are at increased risk for occupational injuries, illnesses and even death, and the pork industry is no exception. For example, hazardous gases released from decomposed manure and dust created primarily from feeding practices put workers at risk for respiratory illness. Hog farmers are found markedly tend to have higher risk in reduced hand strength and respiratory symptoms than non farmers (Hurley, *et al*, 2000). Workers, who are increasingly likely to be hired from varying backgrounds, have become more aware of existing occupational hazard than workers in the past. Farms with improved working conditions, especially for air quality will attract workers who care about health conditions.

We find that workers from either large farms or farms using complex technologies reported a low level of dust and gas in the workplace and their employer's provision of protection on ear, eye and feet. As shown in Table 4, farms that are large or technologically advanced, or both have better environment than (0, 0) type of farms. Dust and gas levels are lower in those farms. At the same time, nearly all of them provide dust masks or respirators and ear protection to their workers. They are about 50% more likely to provide protection on ears, eyes and feet.

However, it is noteworthy that as far as the consequences of employer supply of protection are concerned, not all of symptoms were reduced on large and technologically complex farms compared to the (0, 0) type of farms. Workers in high type farms are less likely to have throat irritation, chest tightness or wheezing chest, but they do not have significantly reduced occurrences of other symptoms such as phlegm, loess of hand strength or back pain. One of the reasons might be that workers do not always wear the masks or other protective devices even they are provided. Because working environment is believed to be better than other farms, workers have reduced incentives in wearing protective devices. Adverse selection problem occurs. The other reason is that some symptoms are hard to be avoided even if some protective devices are provided, such as loss of hand strength and back pain.

Last but not the least, the findings also shed light on the wage policies in the hog farms. The existence of positive size premium even after selection by workers is controlled can reflect wage policies by producers in multiple ways. Because large farms using more technologies benefit from economy of scale, they would like to share the productivity gain with employees. Alternatively, because the monitoring cost in the large firms tends to be higher than that in the small firms, large farms would rather set a wage premium as penalty for shirking, holding other characteristics constant. Similarly, farms could use the agency models where workers care about their pecuniary utility. It incurs monitoring cost to a less degree when evaluation of relative performance among workers is used. However, large farms are cautious in using relative performance to design wage structures. Highly skewed wage distribution may induce sabotage among workers (Lazear, 1989). Again, because agricultural production is consistent with the O-Ring theory, cooperation and coordination among workers are increasingly important with farm size and production complexity. Large farms tend to set average wages higher than those in small farms but reduce the wage gap among workers therefore reduce potential sabotage. A similar note has been made by Idson and Feaster (1990). Because large firms tend to have formal work environment and would more highly value workers who fit well into this environment, workers with "independence" and "individual drive" are less likely to offer themselves to such formal work environment.

At the same time, people usually prefer fairness to inequality (Agell, 2004). That is why pay is more compressed in large firms than in small firms. As shown in Table 1, variance of log of real salaries is smaller in large farms no matter to what extent advanced technologies are adopted. And in a reverse way, variance of log of real salaries is smaller in technologically advanced farms no matter how many pigs can be produced on those farms.

Decomposition of wage differentials

In this subsection, we decompose wage differences between different types of farms such that we can detect where the differentials are from and by how much they are attributed to different factors. Wage differentials are decomposed in a similar way of Idson and Feaster (1990) with a standard Oaxaca/Blinder method (Blinder 1973, Oaxaca 1973). For the difference of expected logarithm wage in group j and group 1, $j \neq 1,$ the wage differential is decomposed into several parts according to the following equation,

$$(22)\ \overline{lnw_j} - \overline{lnw_1} = 0.5\left(\beta_1 + \beta_j\right)^{'}\left(\overline{X_j} - \overline{X_1}\right) + 0.5\left(\beta_j - \beta_1\right)^{'}\left(\overline{X_j} + \overline{X_1}\right)$$

$$+(\sigma_j^1\overline{\lambda_j^1} + \sigma_j^2\overline{\lambda_j^2} - \sigma_1^1\overline{\lambda_1^1} - \sigma_1^1\overline{\lambda_1^2})$$

The left hand side term of (22) is the raw logarithm wage differential (R). The three terms in the right hand side are the endowment contribution to wage differential (E), the changing coefficients' contribution to wage differential, which could be further decomposed into the part explained by the explanatory variables other than the constant intercepts in wage equation (C) and the part absorbed in the intercepts (U), and wage differential caused by self-selection (S).

Table 5 shows bilateral wage differentials' decompositions among four types of farms. Wage differences mainly lie in individual's selectivity, responding coefficients and intercepts. Differences in worker endowments contribute to the smallest proportion of wage differentials. Furthermore, selection on size and technology adoption intensity is not uniform. Differentials from selectivity are all negative except for one case (S_3 vs S_2) and this is consistent with the selection effect of reducing wage premium.

We find that the effect of reducing wage gap is comparably stronger for selection on technology complexity than for selection on farm size. It can be seen from Table 5 that the magnitude of wage differentials from selectivity is larger than for technology selection, holding farm size constant. For example, more than 70% and 85% of the raw wage differences excluding selectivity for cases (S_2 vs S_1) and (S_4 vs S_3) are due to selection respectively. In contrast, no matter how many technologies farms adopted, i.e., holding technology complexity constant, selectivity bias from farm size is smaller. For example, only 44% and 79% of the raw wage differences excluding selectivity for cases (S_3 vs S_1) and (S_4 vs S_2) are due to selection respectively.

Therefore, it again justifies that technology adoption intensity be endogenous in wage equation and extending the selection dimension be required to reduce the estimation bias. As noted above, the majority of technologies used in the hog farms are used to prevent diseases that are extremely important to profits. Furthermore, as shown in Table 4, workers in high technology farms rated a better work environment than those in large farms. Workers self select themselves into high technology farms are more willing to compensate monetary income for working in a less hazardous workplace which has low job loss risks at the same time.

Holding the number of technologies used on the farms constant, difference in corresponding coefficients is the major component for wage differentials between large and small farms (case (S_3 vs S_1) and (S_4 vs S_2)). Large farms set higher coefficients responding to worker's characteristics and other firm attributes than small farms. As stated above, large farms find it hard to monitor workers, setting bigger coefficients could serve to prevent worker shirking. At the same time, knowing this, potential workers are attracted to large size farms.

We also calculate some conditional wage gaps across different groups, which could help us understand the potential wage benefit a worker could have by switching to different type of farms. The conditional wage gap for a worker who are observed in the group j is the wage difference between the expected wage he has obtained in group j and the expect wage he would have if he were selected into group k, where $j \neq k,\ j,k = 1,2,3\ and\ 4$. Explicitly,

$$(23)\quad \Delta lnw(k,j)|S_j = 1, X \equiv E\left(lnw_k \middle| S_j = 1\right) - E\left(lnw_j \middle| S_j = 1\right)$$

$$= (X\beta_k - X\beta_j) + (\sigma_k^1\lambda_j^1 + \sigma_k^2\lambda_j^2 - \sigma_j^1\lambda_j^1 - \sigma_j^2\lambda_j^2)$$

Table 6 shows the conditional wages for workers in (0, 0) farms and (1, 1) type of farms in the upper and lower panel respectively. Because of existence of dummy independent variables, worker characteristics are specified and evaluated at some values or status such that conditional wages can be calculated. As shown in the upper panel, a male worker in a typical type (0, 0) farm which was located in the west received wage 5.08 in 2005. If he was employed in (0, 1) type of farms, his total income will be 6.22, which comes from an increase in return to change in observables Xβ, 1.36, and a decrease due to selection, 0.22. Both male and female employees in farm of (0, 0) type experience wage increase from Xβ and wage decrease from selection. The lower panel of Table 6 shows the wage decrease experienced by female and male employees on farms of (1, 1) type if switching to other types of farms. Again, wage drop is mainly due to change in Xβ. Selection difference is very small. However, results from both panels indicate the same conclusion that selection on technologies is bigger in magnitude than selection on farm size in explaining wage differentials[5].

V. Conclusion and discussion

Size wage premium is voluminously documented in literature. However, the

[5] In the upper panel, selection differentials due to switch from S_1 to S_2 and S_4 are bigger in absolute value than those due to switch from S_1 to S_3. In the lower panel, selection differentials due to switch from S_4 to S_1 and S_3 are bigger in absolute value than those due to switch from S_4 to S_2.

current studies neglect the strong complementarity between firm size and technology adoption, which has been found to have significant treatment effects on wages. This study contributes to the literature by providing a better understanding of size wage premium, labor supply decisions and wage policies. We include both size and technology adoption in a double selection framework. We then apply the method to estimate the wage structure in the US hog farms. It is found that correction for selection on both size and technology adoption is required in wage equation and wage premium for large farms or for technologically advanced farms are reduced after this double selection is added into the earning's function. Workers would rather compensate pecuniary wages for better work environment and more secure job stability, which is particularly highlighted in the agricultural industry. The effect of reducing wage gap is comparably stronger for selection on technology complexity than for selection on farm size.

Technology adoption has been paid a lot of attention to in agricultural production because it can boost productivity and reduce cost. From this study we find that worker's belief on job stability and job itself induces them to self-select into technologically advanced farms. Agricultural production has been experiencing rapid technological innovation and farms become more and more specialized, which motives a future research direction: whether wage premium is stable over time. This study uses a cross sectional data base which provides a channel to the future research once a panel is available.

A limitation of the study is that because respondents of surveys are subscribers to the Magazine, they are not very representatives of all hog farm employees. And because the propensity to respond to surveys may be larger for employees in larger farms and lower for smaller farms, the sample under represents the small hog farms.

Therefore, this study is an attempt to better understand the wage structure in hog production based on a snapshot of hog farms. Availability of a new data base will facilitate the consistent estimation of size and technology treatment effects on wages of employee population in the US pork industry.

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Table 1 Characteristics of employees in the U.S. hog industry, 1995-2005

Variables	Description	(Small Size, Low Tech) (0,0)	(Small Size, High Tech) (0,1)	(Large Size, Low Tech) (1,0)	(Large Size, High Tech) (1,1)	Whole sample
lnw	Natural log of real salary	5.33 (.49)	5.65 (.45)	5.61 (.37)	5.80 (.34)	5.57 (.46)
Female	Gender, equal to 1 if the worker is a female	0.08 (.28)	0.07 (.26)	0.12 (.32)	0.10 (.31)	0.10 (.30)
Education	Years of schooling	13.80 (2.54)	15.19 (2.96)	13.78 (2.23)	14.60 (2.27)	14.10 (2.44)
Tenure	Working experience in the current farm	8.68 (8.00)	7.72 (7.15)	5.73 (5.79)	6.08 (6.24)	6.96 (6.94)
Prev Exp	1 if previously working in a hog farm, 0 otherwise	0.42 (.49)	0.56 (.50)	0.56 (.50)	0.62 (.49)	0.53 (.50)
Raised	1 if raised in a hog farm, 0 otherwise	0.55 (.50)	0.57 (.50)	0.44 (.50)	0.49 (.50)	0.50 (.50)
Northeast	1 if located in the northeast, 0 otherwise	0.07 (.25)	0.04 (.20)	0.05 (.23)	0.04 (.19)	0.05 (.23)
Southeast	1 if located in the southeast, 0 otherwise	0.08 (.27)	0.14 (.35)	0.14 (.34)	0.16 (.37)	0.12 (.33)
West	1 if located in the west, 0 otherwise	0.08 (.28)	0.06 (.23)	0.18 (.38)	0.13 (.34)	0.13 (.33)
2000	1 if survey was responded in 2000, 0 otherwise	0.17 (.37)	0.26 (.44)	0.38 (.49)	0.28 (.45)	0.27 (.45)
2005	1 if survey was responded in 2005, 0 otherwise	0.13 (.34)	0.22 (.41)	0.24 (.43)	0.31 (.46)	0.22 (.41)
Sized	Dummy, definition in the note	0	0	1	1	0.60 (.49)
Technology	Dummy, definition in the note	0	1	0	1	0.34 (.47)
λ_1	Inverse Mill's Ration on *Size*	-0.73(.29)	-1.54(0.43)	0.78(0.29)	0.34(0.19)	0.00(0.79)
λ_2	Inverse Mill's Ration on *Technology*	-0.30(.12)	1.62(0.29)	-0.77(0.21)	0.88(0.20)	0.00(0.79)
Obs	Number of observations	776	139	720	631	2266

Note: The number in the parenthesis is standard deviation. The education level in the survey is categorical. We define continuous variable *Edyears* as schooling years (SY) of a worker in the following way. SY = 9 if she is a high school dropout. SY = 12 if she is a high school graduate. SY = 14 if she attended the four year college but did not complete or had other equivalent diploma, such as completing vocational technical /school program or junior college program. SY = 16 if she is has a bachelor's degree. SY = 19 if she has master degree. SY = 23 if she is a Ph.D. degree holder or a Doctor of Veterinary Medicine. Salaries are discrete categories in the survey. We define the *salary* as a continuous variable by taking the mid-point of the range for each category, adjusted by the consumer price index from the Labor Statistics Bureau (CPI in 1995, 2000 and 2005 is 91.2177, 98.8768 , 110.4758 respectively). *lnW* is the natural log of the real *salary*. *Size* is defined as a dummy variable, equal to one if farms produce greater than or equal to 10,000 pigs each year, otherwise zero if farms produce fewer than 10,000 pigs. Technology is a dummy variable, equal to 1 if 6 or more technologies were used, 0 otherwise. Inverse Mill's Ratios are used in Table 2, 5 and 6.

Table 2 Earning's function

Variable	OLS	Farm type (D_1, D_2)			
		(0,0)	(0,1)	(1,0)	(1,1)
Constant	4.846	5.7215	9.0946	6.0648	8.1742
	(0.1695)***	(0.3649)***	(1.9330)***	(0.4582)***	(0.5533)***
Female	-0.2103	-0.2207	-0.2833	-0.1453	-0.2282
	(0.0277)***	(0.0702)***	(0.1525)*	(0.0439)***	(0.0446)***
Education	0.0144	-0.1894	-0.415	-0.1362	-0.2394
	(0.0228)	(0.0583)***	(0.1444)***	(0.0516)***	(0.0525)***
Education^2	0.0011	0.0085	0.0132	0.0047	0.008
	(0.0008)	(0.0022)***	(0.0042)***	(0.0019)**	(0.0016)***
Tenure	0.0135	0.0126	-0.023	0.0173	0.0271
	(0.0028)***	(0.0056)**	(0.0162)	(0.0047)***	(0.0040)***
Tenure^2	-0.0003	-0.0003	0.0014	-0.0003	-0.0005
	(0.0001)***	(0.0002)*	(0.0006)**	(0.0002)*	(0.0001)***
2000	0.075	-0.3177	-0.2782	0.047	-0.033
	(0.0201)***	(0.1066)***	(0.2264)	(0.0741)	(0.0633)
2005	0.016	-0.5218	-0.3246	-0.1453	-0.2119
	(0.0224)	(0.1006)***	(0.2113)	(0.0715)**	(0.0627)***
Northeast	0.0117	0.1285	-0.0661	0.0427	0.1493
	(0.0369)	(0.0750)*	(0.1985)	(0.0614)	(0.0672)**
West	-0.0399	-0.39	-0.2127	-0.1197	-0.0358
	(0.0257)	(0.0774)***	(0.1444)	(0.0466)**	(0.0428)
Southeast	0.0741	-0.2904	-0.1059	0.0924	0.1497
	(0.0258)***	(0.1381)**	(0.3393)	(0.0871)	(0.0723)**
Size	0.2651				
	(0.0191)***				
Technology	0.1832				
	(0.0188)***				
λ_1		-0.8694	-0.5849	-0.2054	-0.3598
		(0.1831)***	(0.2819)**	(0.1321)	(0.1904)*
λ_2		-0.1564	-0.6034	-0.8041	-0.6176
		(0.4714)	(0.4497)	(0.1908)***	(0.1677)***
Observations	2266	776	139	720	631
R-squared	0.27	0.138	0.237	0.213	0.242

Note: Standard errors are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
λ_1 and λ_2 are the selection terms corresponding to farm size decision and technology decision in wage equation.

Table 3 Probit model of farm size and bivariate model of farm size and technology adoption intensity

	Biprobit	
	Size	Technology
Constant	-3.2244	-3.762
	(0.5672)***	(0.6079)***
Female	0.0933	-0.0692
	(0.0949)	(0.0938)
Education	0.4097	0.3311
	(0.0761)***	(0.0803)***
Education^2	-0.0141	-0.008
	(0.0025)***	(0.0026)***
Raise	-0.1578	0.0275
	(0.0576)***	(0.0575)
Prev Exp	0.3375	0.2856
	(0.0562)***	(0.0566)***
2000	0.6736	0.1281
	(0.0666)***	(0.0662)*
2005	0.8302	0.4183
	(0.0745)***	(0.0712)***
Northeast	-0.139	-0.2198
	(0.1239)	(0.1326)*
West	0.4074	0.2256
	(0.0892)***	(0.0860)***
Southeast	0.6027	-0.0677
	(0.0906)***	(0.0877)
ρ	0.5709	
	(0.0409)***	
Observations	2,266	2,266

Table 4 Survey on work environment and health of employees by farm type, 2000

	Farm type			
	(0,0)	(0,1)	(1,0)	(1,1)
Working environment				
Rating of working environment (1 excellent to 4 poor)	2.15	1.82	1.93	1.79
Rating of dust levels (1 High, 2 Medium, 3 Low)	2.09	2.23	2.05	2.21
Rating of gas levels (1 High, 2 Medium, 3 Low)	2.48	2.60	2.44	2.53
Employer's supply of protection (1 Yes; 0 No)				
Dust masks or respirators	66.12%	86.96%	88.25%	94.94%
Ear protection	55.84%	72.92%	83.53%	93.88%
Eye protection	44.87%	55.10%	57.14%	68.82%
Footwear & protection	37.18%	58.33%	63.64%	60.15%
Lock-out or tag-out protection	32.89%	32.65%	43.53%	54.51%
Experience of Symptoms (1 Yes; 0 No)				
Dry cough	31.00%	33.80%	36.52%	31.48%
Throat irritation	33.33%	38.89%	33.03%	24.84%
Chest tightness	21.88%	12.31%	25.00%	20.52%
Wheezing chest	17.02%	18.46%	24.07%	13.58%
Cough with phlegm	34.95%	31.88%	37.93%	34.80%
Sinus problems	47.75%	50.00%	47.79%	44.44%
Loss of hand strength	20.00%	23.44%	23.64%	21.38%
Hands tingle or fall asleep	27.00%	26.87%	28.32%	30.03%
Back pain	45.71%	52.17%	47.37%	49.06%

Table 5 Decomposition of wage differentials

Comparison	Endowment(E)	Coefficient(C)	Selectivity(S)	
S_2 vs S_1	-0.0453	-2.2546	-0.7567	
S_3 vs S_1	-0.1292	0.2874	-0.2211	
S_4 vs S_1	-0.1350	-0.4997	-1.3451	
S_3 vs S_2	-0.0605	2.5186	0.5356	
S_4 vs S_2	-0.0876	1.7529	-0.5884	
S_4 vs S_3	-0.0194	-0.7733	-1.1239	
	Intercept(U)	Raw(R)	Raw net of Selectivity(N = R-S)	
S_2 vs S_1	3.3731	0.3165	1.0732	
S_3 vs S_1	0.3433	0.2803	0.5014	
S_4 vs S_1	2.4527	0.4730	1.8181	
S_3 vs S_2	-3.0298	-0.0362	-0.5718	
S_4 vs S_2	-0.9204	0.1565	0.7449	
S_4 vs S_3	2.1094	0.1927	1.3167	
	Endowment/Raw (E/R)	Coefficient/Raw (C/R)	Selectivity /Raw (S/N)	Intercept /Raw (U/R)
S_2 vs S_1	-0.0422	-2.1008	-0.7051	3.1430
S_3 vs S_1	-0.2577	0.5731	-0.4410	0.6846
S_4 vs S_1	-0.0742	-0.2748	-0.7398	1.3491
S_3 vs S_2	0.1059	-4.4047	-0.9367	5.2988
S_4 vs S_2	-0.1176	2.3533	-0.7899	-1.2357
S_4 vs S_3	-0.0148	-0.5873	-0.8536	1.6021

Note: S_1=(D_1=0, D_2=0); S_2=(D_1=0, D_2=1); S_3=(D_1=1, D_2=0); S_4=(D_1=1, D_2=1).

Table 6 Conditional wage gap for typical western workers in 2005

	S_1: (Small Size, Low Tech)			
	Male		Female	
S_1: (Small Size, Low Tech)	**5.08**		**4.96**	
Δ in $X\beta$		1.36		1.24
Δ in selection		-0.22		-0.27
S_2: (Small Size, High Tech)	6.22		5.93	
Δ in $X\beta$		1.06		1.08
Δ in selection		-0.65		-0.74
S_3: (Large Size, Low Tech)	5.49		5.29	
Δ in $X\beta$		2.45		2.37
Δ in selection		-0.51		-0.58
S_4: (Large Size, High Tech)	7.02		6.74	
	S_4: (Large Size, High Tech)			
	Male		Female	
S_4: (Large Size, High Tech)	**5.75**		**5.53**	
Δ in $X\beta$		-2.36		-2.35
Δ in selection		0.27		0.31
S_1: (Small Size, Low Tech)	3.66		3.50	
Δ in $X\beta$		-1.05		-1.16
Δ in selection		-0.02		-0.02
S_2: (Small Size, High Tech)	4.67		4.36	
Δ in $X\beta$		-1.37		-1.29
Δ in selection		-0.12		-0.13
S_3: (Large Size, Low Tech)	4.27		4.10	

Note: Δ represent "change". workers are defined with observable attributes/variables. Specifically, for a male worker,edyears=14.9, edsq=222.0, ycurjob=6.4,ycurjobsq=40.96. For a female worker, edyears=14.5, edsq=210.3, ycurjob=5.5, ycurjobsq=30.25.They represent typical hog workers of survey year 2005 in western states.

Similar wage gap patterns are found for workers in other areas and in other survey years.

Appendix

Table A1 Description of technologies in the hog production

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

Note: 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/.