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# Firm Size, Technical Change And Wages In The Pork Sector, 1990 -2005

Li Yu
*Iowa State University*

Terry M. Hurley
*University of Minnesota*

James B. Kliebenstein
*Iowa State University*, jklieben@iastate.edu

Peter F. Orazem
*Iowa State University*, pfo@iastate.edu

# IOWA STATE UNIVERSITY

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

Li Yu[a], Terry M. Hurley[b], James B. Kliebenstein[a] and Peter F. Orazem[a]

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

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a Iowa State University
b University of Minnesota
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## I. Introduction

A long-standing puzzle in labor economics has been the positive relationship between wages and firm size first discovered by Moore (1911).[1] Large firms pay 15 % more than small firms for observationally equivalent workers in the United States (Lluis 2003). Even after controlling for worker's observed characteristics such as education, work experience, gender, and geographic location and further correcting for wage differences due to unobserved abilities, a significant size-wage effect remains. Having exhausted supply-side explanations, various labor demand-side explanations have been advanced to explain the size-wage premium (Brown and Medoff 1989; Troske 1999). These include that larger firms use more capital-intensive technologies, more skilled managers, more skilled workers, and more sophisticated technologies. Larger firms may also pay efficiency wages to limit monitoring costs or to share rents from returns to scale. All of these demand-side explanations have been found to hold in cross-sectional studies, but none alone or in aggregate have been able to fully explain why larger firms pay more than smaller firms.

Past empirical work examining the size wage premium has focused on data that spans industries. That leads to a confusion of possible sources of large firm wage advantage: is it worker output or is it the price? If larger firms have more power, then the positive correlation between firm size and worker marginal product may be due to higher prices rather than higher productivity. Distinguishing between the two sources tells us whether the wage differential is due to atypical productive efficiencies or to inefficient monopolistic pricing.

Of other explanations for the size-wage premium, three involve the interaction between technology and workers' skills. Large firms tend to adopt new technologies before their smaller competitors (Rose and Jaskow, 1990). This suggests that the size wage advantage may reflect a temporary productive advantage that will dissipate as the smaller firms adopt. Cross sectional evidence from manufacturing firms shows that workers in plants that used more capital per worker, used research and development more intensively, and that adopted more information technologies were paid more than comparable workers in firms lacking those investments (Krueger 1993; Reily 1995; Dunne and Schmitz 1995; Troske 1999; Dunne *et al* 2004). Less clear is whether these technological advantages are due instead to firm size and whether they persist or diminish over time.

This study aims to address whether the size wage premium is due to price rather than productivity by evaluating wages by firm sizes in a single competitive market. Variation in wages should only reflect differential productivity. All firms are exposed to the same technology choices, and so we can assess whether the size wage correlation is making technology choice. Finally, we follow an industry over 15 years, long enough to see if the size wage premium persists as more firms adopt technologies.

Our context is the US hog industry. The study relies on four surveys of employees on hog farms conducted in 1990, 1995, 2000, and 2005. The industry is characterized by a large number of producers selling a virtually homogeneous output. Farms vary dramatically in size and in technology adoption intensity with the heaviest technology adopters being the largest farms (McBride and Key 2003). The largest farms also use more educated labor. Hurley, Kliebenstein and Orazem (1999) reported a substantial size-wage premium in a single cross section of hog farms. This paper explores whether that size-wage premium can be explained by the observed differences in skill levels and technology usage between the large and small farms and whether it dissipates or persists with time. We also investigate whether the pay differential can be explained by the matching process which sorts employees into farms of different size and technology use.

The next section lays out the stylized facts regarding hog farm size and wages and describes the data. Section three reviews the baseline empirical strategy, providing traditional least-squares estimates of the size-wage premium. Section four reviews an alternative statistical matching method to correct for selection bias due to observable differences in workers across farm sizes. It also applies the same strategy to correct selection bias due to differences in intensity of technology adoption. Regardless of methodology, the estimates show that the wage premia paid by large and more technologically advanced farms are persistent and pervasive, going to workers of all skill levels in all time periods and all regions of the country. Workers are rewarded for their higher productivity due to working on bigger farms and with superior technologies than their observationally equivalent counterparts elsewhere in the same market. Section five concludes the paper.

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

Our dataset is a series of surveys from a random sample of subscribers to *National Hog Farmer Magazine*. The surveys were conducted in years 1990, 1995, 2000 and 2005. Because subscribers to *National Hog Farmer Magazine* are not a representative sample of all hog farm employees and because propensity to respond to surveys may also differ by farm size, the survey data are weighted to conform to the size distribution of employees on U.S. hog farms. We base our sample weights on the Agricultural Census Data of the US Department of Agriculture (USDA). To be consistent with USDA classifications, each hog farms in our survey samples is categorized into one of eight regions and one of the three size levels. The number of employees who have either full time or part time jobs on hog farms is taken as the population universe.[2] The weights are computed as follows: Let $N$ be the total number of employees on U.S. hog farms and let $n_j$ of them be in region-size cell $j$. The proportion of employees in the $j^{th}$ cell is $n_j/N$. The corresponding number of employees in the $j^{th}$ cell in our sample is $s_j$. Each worker in our sample is then assigned a probability weight $\frac{n_j}{s_j}$.[3]

The U.S. hog industry has a large range of farm sizes, from farms producing fewer than 500 hogs to farms producing more than 100,000 hogs per year. The employment share by farm size category is presented in table 1. The size categories varied across surveys, but it is nevertheless apparent that the employment share of the largest farms is rising dramatically. The employment share on farms producing more than 10,000 hogs rose from 8% in 1990 to 23% in 2005. In contrast, the employment share on farms producing fewer than 5,000 pigs fell from 79% to 47%.[4]

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

The rapid change in employment share on large farms since 1990 corresponds to a period of rapid technology adoption in the industry. The technology adoption measures summarized in table 2 are only available for three years, 1995, 2000, 2005. Descriptions of technologies are included in the Appendix. Technology choices differed across survey years. Questions regarding Medicated Early Weaning and Modified Medicated Early Weaning technologies were only reported in 1995 and 2002. Auto Sorting Systems and Parity Based Management were only reported for 2005. Of the other technologies, the strongest growth is in Artificial Insemination, Formal Management Practices and Computer Usage. Phase Feeding or Split Sex Feeding, Multiple Site Production and All In All Out methods have been utilized by a nearly constant proportion of employees in the industry.

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

**III. Earnings Functions**

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

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

where *lnW* is the natural log of the worker's annual salary; $X$ is a vector of individual productive and demographic attributes including gender, education, tenure, prior farm experience, and having been raised on a farm; and $\varepsilon$ is a disturbance term. We augment the earnings function by adding aspects of the farm. Technology $T$ is measured as a vector of dummy variables indicating the intensive usage of advanced technologies. Farm size $S$ is measured alternatively by the number of pigs produced or by a dummy variable indicating production exceeding 10,000 pigs per year. The vector $Z$ includes remaining farm characteristics including location and year of interview.

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

Workers' average age is 36.6 years. Tenure on the current hog farm averages 8.9 years with 41% of the workers having experience working on other hog farms. In addition, 53% of workers were raised on a hog farm. Farm location is categorized by four regions in the survey: Midwest, Northeast, Southeast and West.[5] These are captured by three dummy variables with the Midwest region serving as the base.

Some notable differences between large and small farms are apparent in addition to the wage and technology differences already discussed. Large farms in the sample pay workers 38% (or 0.32 log points)[6] more than the average US hog farms. Small farms employ a relatively higher proportion of high school graduates, while large farms employ relatively more workers with at least a four-year college degree. Workers on large farms have three fewer years of job tenure but are more likely to have prior experience on other hog farms. Employees on small farms are more likely to have been raised on a farm. Small farms are atypically located in the Midwest, while large farms are more likely to be in the Southeast and the West.

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

Model (2) presents the size augmented earnings function. It is apparent that some worker attributes are correlated with farm size. With farm size held constant, the implied wage advantage decreases for males, for high school and college graduates, and for those with prior work experience. Instead, workers benefit from employment on larger farms. Although the marginal gains decrease with farm size, the effect is always positive across the range of farm sizes in the data. Evaluated at sample means, the wage elasticity with respect to farm size is 0.11, consistent with findings for the labor market as a whole (Lluis, 2003).

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

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

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

In table 5, we replicate the earnings function allowing for separate wage effects for individual technologies listed in table 2.[7] We estimate the equation separately by year and then pool the data across years. Although most technologies have positive estimated effects on wages, only Artificial Insemination (AI); Phase Feeding (PF); and Formal Management (FM) have significant positive effects on wages. The only significant outlier is a negative estimated effect of computer usage in 2005. Joint tests of the equality of the coefficients across survey years reject the null hypothesis for many of the coefficients including several of the technologies, but the signs rarely change. The parsimonious pooled regression seems to yield adequate inferences about the effects of farm size and technology over the sample period. Farmers using more advanced technologies and larger operations pay a premium for their workers above that paid to similarly educated and experienced workers on small farms and farms not using those technologies. Both farm size and technology have independent effects on wages.

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

## IV. Worker Returns Measured Using Propensity Score Matching

The inference from figure 1 and tables 4 and 5 is that workers on larger farms are paid higher wages. However, that analysis treats farm size as exogenous. Those inferences may be misleading if workers sort non-randomly across firms based on unobserved worker attributes that are correlated with farm size. For example, if more ambitious workers are attracted to larger farms, the wage premium on large farms may reflect this differential ambition and not farm size *per se.*

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

***The Assumptions Underlying Propensity Score Matching***

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

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

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

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

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

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

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

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

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

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

***Matching***

We define the binary outcome $D$ as follows: $D = 0$ when farms producing 10,000 or fewer pigs are defined as small farms; $D = 1$ when those producing more than 10,000 pigs are large farms. The size break is chosen to have sufficient numbers of incumbents in both groups —selecting smaller farm sizes would result in too few workers in the later years. We estimate the propensity scores as the fitted values of a probit model[10] that predicts the probability that each individual works on a large hog farm. The regression results are shown in the first model of table A2 in the Appendix. The characteristics of the workers include gender, the education level, age, tenure, agricultural background, geographical location and time. Workers with higher education, more previous experience and those in the Southeast or the West will be more likely to work on a large farm. These findings are consistent with those reported by McBride and Key (2003). Persons raised on a hog farm are also less likely to be employed on a large farm.

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

Applying Smith and Todd (2005) to our application, the size impact estimator takes the form:

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

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

where $n_1$ is the number of individuals in the treated group, $I_1$ denotes the set of observations with $D_i = 1$, $I_0$ is the set of control group with $D_i = 0$, $S_P$ is the region with common support, and $\hat{w}(i, j)$ are weights depending upon the distance between the propensity scores for individual *i* in the treatment group and individual *j* in the control group. For robustness, we used three matching strategies summarized in the Appendix: Nearest neighbor, Caliper and Kernel matching. Results are not sensitive to the choice of matching method. Matching is with replacement in the control group in order to reduce the bias and avoid the deterioration in quality of matches (Dehejia and Wahba 2002). We utilize the bootstrap method, re-sampling the data with replacement *m* times, to approximate the standard errors (Becker and Ichino 2002).

***Estimated Size and Technology Effects using Matching Estimators***

Using the full sample, we calculated the size-wage effect using the matching methods above. The results are very consistent across methods. The mean effects using Methods 1-3 respectively are 0.307, 0.329, and 0.293. All three estimates have one standard deviation bounds that contain the least-squares estimate of 0.33 from Model (3) in table 4. Estimated effects of about 0.3 imply that the salary paid on the largest farms is 35% higher than that on small farms.

We can use the matching methods to explore the size-wage effect for subsamples of interest. Table 6 reports the size-wage premium for different education, region, and technology groups as well as for groups employed in different years. The size-wage difference is largest for the least educated and smallest (and imprecisely estimated in some cases) for the most educated. Nevertheless, all size-wage premia are large, ranging from 20% for the four year college degree holders to 53% for high school dropouts using the nearest neighbor and Kernel matching methods. The Caliper matching method finds the same pattern of estimates but with higher returns for more educated workers: ranging from 31% for the worker who has at least a master degree to 46% for the high school dropouts.

The size-wage premium is large in all parts of the country, but largest in the West at about 55%. The premium is smallest and sometimes insignificant in the Northeast. There is no consistent pattern of the size-wage effect over time, but it is large and significant in every time period, ranging from 25% to 50% depending on the year and matching methods.

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

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

***Model of Employment on Farms by Number of Technologies***

If workers are rewarded for their added productivity on large farms, they must be rewarded from other sources of productive advantages, such as the use of more advanced technologies. We expect that if technologies raise farm productivity, some of the inframarginal rents earned by adopting technologies in the early stages of diffusion may be shared with the workers. Again, we need to control for individual attributes that sort workers into high and low technology farms that could confound our estimate of the return to technology use.

In this application, the binary outcome *D* indicates that a worker is on a technology-intensive farm, defined as using at least six advanced technologies. Since 1995, farms have employed more and more workers who operate on technology intensive farms. As shown in the last row of table 2, 12% of workers are employed on farms using at least six technologies in 1995 and the proportion increased to 30% in 2005. A probit model is again used to predict the propensity score for each observation. The regression results are shown in the second model of table A2 in the Appendix. Farms employing workers with more education, more previous work experience and that are located in the West are the most likely to be heavy adopters of technologies. Figure 4 reports histograms of the estimated propensity scores $\hat{P}(x_i)$ for workers in the two technology groups. Again, there is substantial overlap in the propensity score distributions, and so we have good comparisons for workers employed on the technologically intensive farms.

Using the same matching methods yields a technology wage effect of 0.225, 0.280, and 0.231. The implied salary differential paid on the technology intensive farms varies between 25% and 32%.

Table 7 reports the detailed outcomes of the matched comparisons for technology wage premiums. Again, it is the least educated workers who benefit the most from working on farms using more complex technologies, and the technology-wage premium decreases with years of schooling. The wage returns to more intensive technology use exceed 19% in all regions. The ranking of returns varies by estimation method, with marginally lower returns in the Midwest and marginally higher in the Northeast. However, the general conclusion is that workers consistently earn substantial returns to technological intensity in every part of the country. The technology-wage premium has trended modestly downward over time. In 2000, the premium decreased by nearly a half of that in 1995. But it rebounded again in 2005.

While large farms are more likely to adopt multiple technologies than are small farms, returns to technology use are not masking a farm size effect. The small farms that adopt technologies more intensively pay an even larger premium to attract workers than do larger, technology intensive farms. Regardless of how we cut the sample, workers earn substantial rents from the use of more technologies on hog farms. The higher wages are paid whether the worker is educated or not, regardless of where the farm is located, and whether the farm is large or small. These returns have persisted over 15 years with only modest evidence that the returns have fallen over time.

## V. Conclusion

This study examined evidence of the size-wage premium within a single narrowly defined industry with a competitive priced output and a commonly available mix of technologies. Even in this narrowly defined market, there are large and persistent wage differentials favoring workers on large firms. The higher wage is clearly due to increased productive efficiency and not market power. The premium is paid to all workers regardless of individual productive attributes, with the largest rewards going to the least skilled.

We also find substantial returns to workers in firms using more advanced technologies. These returns also go to all workers regardless of skill and the premium remains large over time. Clearly, workers are rewarded for their higher productivity on larger and more technologically advanced farms, even though it is the farmer that undertook the investment in the farm size and technologies. How workers are able to extract these rents from the farmer's capital investment remains a puzzle.

## References

Becker, S., and A. Ichino. 2002. "Estimation of Average Treatment Effects Based on Propensity Scores." *The Stata Journal* 2 (4): 358-377.

Brown, C., and J. Medoff. 1989. "The Employer Size-Wage Effect." *Journal of Political Economy* 97(5): 1027-59.

Dehejia, R., and S. Wahba. 2002. "Propensity Score Matching Methods for Nonexperimental Causal Studies." *The Review of Economics and Statistics* 84(1): 151-161.

Dunne, T., L. Foster, J. Haltiwanger, and K. Troske. 2004. "Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment." *Journal of Labor Economics* 22(2): 397–429.

Dunne, T., and J. Schmitz. 1995. "Wage, Employment Structure and Employer Size-Wage Premia: Their Relationship to Advanced Technology Usage at US Manufacturing Eestablishment." *Economica 62:* 89-107.

Heckman, J., S. Ichimura, and P. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *The Review of Economic Studies* 64(4): 605-654.

—.1998. "Characterizing Selection Bias Using Experimental Data." *Econometrica* 66(5): 1017-1098.

Hurley, T., J. Kliebenstein and P.F. Orazem. 1999. "The Structure of Wages and Benefits in the U.S. Pork Industry**."** *American Journal of Agricultural Economics* 81(1): 144-163.

Krueger, A. 1993. "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989." *Quarterly Journal of Economics* 108: 33-60.

Lawrence, J., and G. Grimes. 2001. “Production and Marketing Characteristics of U.S. Pork Producers, 2000." Ames, IA: Iowa State University Staff Paper No. 343.

Lluis, S. 2003. “Endogenous Choice of Farm Size and the Structure of Wages: A Comparison of Canada and the United States.” Working Paper 0203, Industrial Relations Center, University of Minnesota.

McBride, W., and N. Key. 2003. *Economic and Structural Relationship in U.S. Hog Production.* Washington DC: Economic Research Service, U.S. Department of Agricultural Economic Report No. 818.

Moore, H. 1911. *Laws of Wages: An Essay in Statistical Economics*. New York: Augustus. M. Kelley.

Oi, W.Y., and T.L. Idson. 1999. “Firm Size and Wages.” In Ashenfelter, O. and D. Card ,ed. *The Handbook of Labor Economics*. Elsevier. pp. 2165-2214.

Reily, K.T. 1995. “Human Capital and Information: The Employer Size Wage Effect.” *Journal of Human Resource* 30(1): 1-18.

Rose, Nancy and Paul Joskow. 1990. “The Diffusion of New Technologies: Evidence of the Electric Utility Industry.” *The Rand Journal of Economics* 21(3); 354 – 373.

Rosenbaum, P., and D. Rubin. 1983. “The Central Role of Propensity Score in Observational Studies for Causal Effects.” *Biometrika* 70(1): 41-55.

Smith, J., and P. Todd. 2005. “Does Matching Overcome LaLonde’s Critique of Non-Experimental Estimators?” *Journal of Econometrics* 125: 305-353.

Troske, K.R. 1999. “The Worker-Establishment Characteristics Database.” In J. Haltiwanger and M. Manser, eds. *Labor Statistics Measurement Issues.* Chicago, IL: University of Chicago Press.

**Table1. Frequency Distribution of Employees and Technology Adoption Intensity on Hog Farms by Size of Farm**

| Code | Size Class ( pigs per year) | Weighted Frequencies (%) | | | | Number of Technologies | |
|---|---|---|---|---|---|---|---|
| | | 1990 | 1995 | 2000 | 2005 | Mean | Std Dev |
| 1 | Less than 500 | 14.87 | 8.86 | 4.41 | . | 2.760 | 1.886 |
| 2 | 500 to 999 / less than 1000 in 2005 | 16.48 | 11.75 | 3.05 | 16.53 | 2.986 | 1.589 |
| 3 | 1,000 to 1,999 | 23.51 | 26.04 | 6.47 | 8.64 | 2.768 | 1.781 |
| 4 | 2,000 to 2,999 | 15.06 | 23.28 | 16.80 | 7.99 | 3.477 | 1.824 |
| 5 | 3,000 to 4,999 | 9.05 | 8.86 | 16.70 | 13.78 | 4.088 | 1.844 |
| 6 | 5,000 to 9,999 | 13.09 | 13.28 | 26.94 | 27.43 | 3.818 | 1.872 |
| 7 | 10,000 or more (1990) /10,000 to 14,999 (1995) | 7.94 | 2.09 | 4.55 | 3.08 | 4.628 | 1.663 |
| 8 | 15,000 to 24,999 | . | 1.83 | 3.50 | 2.65 | 4.907 | 1.812 |
| 9 | 25,000 or more / 25,000 to 49,999 (2005) | . | 4.02 | 17.58 | 4.63 | 5.301 | 1.838 |
| 10 | 50,000 to 99,999(2005) | . | . | . | 3.3 | 4.844 | 2.044 |
| 11 | 100,000 or more (2005) | . | . | . | 11.96 | 6.322 | 2.080 |

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

**Figure1. Size wage effect: Log of salary distribution in different size categories**

**Table2. Fraction of Employees on Hog Farms Using Various Technologies**

| Number | Name | Notation | 1995 Mean | 1995 Std Dev | 2000 Mean | 2000 Std Dev | 2005 Mean | 2005 Std Dev |
|---|---|---|---|---|---|---|---|---|
| 1 | Artificial Insemination | AI | 0.407 | 0.492 | 0.606 | 0.489 | 0.687 | 0.464 |
| 2 | Split Sex Feeding | SSF | 0.321 | 0.467 | 0.450 | 0.498 | 0.345 | 0.476 |
| 3 | Phase Feeding | PF | 0.479 | 0.500 | 0.535 | 0.499 | 0.492 | 0.500 |
| 4 | Multiple Site Production | MSP | 0.220 | 0.414 | 0.329 | 0.470 | 0.287 | 0.453 |
| 5 | Segregated Early Weaning | SEW | 0.089 | 0.285 | 0.222 | 0.416 | 0.234 | 0.424 |
| 6 | Medicated Early Weaning | MEW | 0.065 | 0.247 | 0.024 | 0.152 | . | . |
| 7 | Modified Medicated Early Weaning | MMEW | 0.004 | 0.061 | 0.004 | 0.066 | . | . |
| 8 | All in / All out | AIAO | 0.572 | 0.495 | 0.638 | 0.481 | 0.568 | 0.496 |
| 9 | Auto Sorting Systems | AS | . | . | . | . | 0.025 | 0.158 |
| 10 | Parity Based Management | PBM | . | . | . | . | 0.186 | 0.389 |
| 11 | Formal Management | FM | 0.479 | 0.500 | 0.582 | 0.494 | 0.688 | 0.464 |
| 12 | Computer Use | CU | 0.589 | 0.492 | 0.686 | 0.464 | 0.721 | 0.449 |
| - | Number of Technologies | - | 3.214 | 1.839 | 4.072 | 1.978 | 4.233 | 2.085 |
| - | Proportion of employment on farms using at least six technologies | | 12.4% | | 25.6% | | 30.2% | |

Note: Statistics are weighted. Dot (.) represents that the category is not asked in the survey. Technology definitions and descriptions are presented in Table A.1 in the Appendix.

**Figure 2. Workers on farms adopting more technologies earn more**

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

| Variables | Description | Full sample | | Large Farms | | Small Farms | |
|---|---|---|---|---|---|---|---|
| *lnW* | Log of salary | 5.407 | (0.540) | 5.726 | (0.380) | 5.350 | (0.545) |
| *lnW*[a] | Log of salary | 5.437 | (0.550) | 5.732 | (0.386) | 5.372 | (0.560) |
| *Female* | Gender of workers | 0.088 | (0.284) | 0.110 | (0.313) | 0.084 | (0.278) |
| *Edu12* | High school graduate | 0.299 | (0.458) | 0.259 | (0.438) | 0.307 | (0.461) |
| *Edu14* | 2 year college diploma or equivalent | 0.206 | (0.404) | 0.206 | (0.405) | 0.206 | (0.404) |
| *Edu16* | 4 year university degree or equivalent | 0.342 | (0.474) | 0.427 | (0.495) | 0.327 | (0.469) |
| *Edu18+* | Higher degree education level | 0.086 | (0.280) | 0.057 | (0.232) | 0.091 | (0.288) |
| *Age* | Age of workers | 36.639 | (10.845) | 36.627 | (10.089) | 36.641 | (10.975) |
| *Tenure* | Experience in the current farm | 8.942 | (8.175) | 6.286 | (5.950) | 9.413 | (8.423) |
| *PrevExp* | Dummy variable, equal to one if previously working in a hog farm | 0.413 | (0.492) | 0.565 | (0.496) | 0.386 | (0.487) |
| *Raise* | Dummy variable, equal to one if raised in a hog farm | 0.534 | (0.499) | 0.451 | (0.498) | 0.548 | (0.498) |
| *Northeast* | Dummy variable, equal to one if located in the northeast | 0.087 | (0.282) | 0.055 | (0.228) | 0.092 | (0.290) |
| *Southeast* | Dummy variable, equal to one if located in the southeast | 0.140 | (0.347) | 0.208 | (0.406) | 0.128 | (0.334) |
| *West* | Dummy variable, equal to one if located in the west | 0.143 | (0.350) | 0.195 | (0.397) | 0.134 | (0.341) |
| *Farm Size* | Number of pigs produced ( unit: 10,000 heads) | 0.765 | (1.407) | 3.318 | (2.260) | 0.312 | (0.257) |
| *Farm Size*[a] | Number of pigs produced ( unit: 10,000 heads) | 0 .953 | (1.629) | 3.705 | (2.261) | 0.346 | (0.262) |
| *Number of technologies*[a] | Number of technologies used | 3.758 | (2.016) | 5.301 | (1.944) | 3.417 | (1.867) |

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

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

**Table 4. Traditional Wage Regression for U.S. Hog Industry Employees (1990-2005)**

| | Model (1) | Model (2) | Model (3) | Model (4) |
|---|---|---|---|---|
| *Female* | -0.203 | -0.193 | -0.201 | -0.173 |
| | (3.84)** | (3.59)** | (3.75)** | (2.68)** |
| *Edu12* | 0.211 | 0.200 | 0.204 | 0.225 |
| | (2.71)** | (2.63)** | (2.71)** | (2.36)* |
| *Edu14* | 0.353 | 0.332 | 0.334 | 0.350 |
| | (4.51)** | (4.35)** | (4.41)** | (3.62)** |
| *Edu16* | 0.439 | 0.423 | 0.418 | 0.419 |
| | (5.62)** | (5.57)** | (5.56)** | (4.40)** |
| *Edu18+* | 0.745 | 0.784 | 0.764 | 0.709 |
| | (7.31)** | (7.75)** | (7.62)** | (5.61)** |
| *Age* | 0.044 | 0.042 | 0.042 | 0.044 |
| | (5.23)** | (5.08)** | (5.09)** | (4.08)** |
| *$Age^2$* | -0.000 | -0.000 | -0.000 | -0.0005 |
| | (4.35)** | (4.22)** | (4.24)** | (3.41)** |
| *Tenure* | 0.003 | 0.007 | 0.007 | 0.005 |
| | (0.63) | (1.58) | (1.51) | (0.96) |
| *$Tenure^2$* | -0.000 | -0.000 | -0.000 | -0.0002 |
| | (0.64) | (1.05) | (1.10) | (0.89) |
| *PrevExp* | 0.170 | 0.153 | 0.157 | 0.136 |
| | (6.03)** | (5.56)** | (5.71)** | (3.83)** |
| *Raise* | -0.067 | -0.064 | -0.062 | -0.103 |
| | (2.50)* | (2.42)* | (2.36)* | (3.00)** |
| *Northeast* | 0.053 | 0.071 | 0.062 | 0.077 |
| | (0.99) | (1.32) | (1.17) | (1.07) |
| *Southeast* | 0.071 | 0.041 | 0.033 | 0.047 |
| | (1.89) | (1.10) | (0.89) | (0.98) |
| *West* | -0.068 | -0.092 | -0.088 | -0.140 |
| | (1.49) | (2.04)* | (1.97)* | (2.41)* |
| *Year 1995* | -0.032 | -0.041 | -0.027 | |
| | (1.17) | (1.49) | (0.98) | |
| *Year 2000* | 0.101 | 0.024 | 0.052 | 0.063 |
| | (2.88)** | (0.66) | (1.44) | (1.54) |
| *Year 2005* | 0.074 | -0.041 | 0.011 | 0.020 |
| | (1.79) | (0.87) | (0.27) | (0.45) |
| *Farm Size* | | 0.145 | | |
| | | (12.28)** | | |
| *Farm $Size^2$* | | -0.004 | | |
| | | (8.03)** | | |
| *Size[a]>10,000* | | | 0.330 | 0.257 |
| | | | (14.25)** | (8.76)** |
| *Technologies[b] >5* | | | | 0.240 |
| | | | | (5.84)** |
| *Constant* | 4.051 | 4.057 | 4.063 | 4.001 |
| | (25.86)** | (26.69)** | (26.27)** | (19.28)** |
| Observations | 3934 | 3934 | 3934 | 2266 |
| R-squared | 0.21 | 0.25 | 0.25 | 0.29 |

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

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

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

**Table 5. Technology Augmented Wage Equation and Joint Test for Technology Effect (1995-2005)**

| | 1995 | 2000 | 2005 | Pooled | Pooled | $\beta_T^{1995} = \beta_T^{2000}$ | $\beta_T^{2000} = \beta_T^{2005}$ | $\beta_T^{1995} = \beta_T^{2000} = \beta_T^{2005}$ |
|---|---|---|---|---|---|---|---|---|
| *Female* | -0.104 | -0.209 | -0.003 | -0.145 | -0.150 | 0.683 | 2.308 | 1.169 |
| | (1.11) | (2.39)* | (0.03) | (2.30)* | (2.40)* | (0.409) | (0.129) | (0.311) |
| *Edu12* | 0.033 | 0.457 | 0.013 | 0.189 | 0.193 | 3.370 | 3.548 | 2.126 |
| | (0.24) | (2.47)* | (0.09) | (1.93) | (1.98)* | (0.067) | (0.060) | (0.120) |
| *Edu14* | 0.125 | 0.519 | 0.211 | 0.299 | 0.303 | 2.878 | 1.611 | 1.475 |
| | (0.91) | (2.77)** | (1.37) | (3.02)** | (3.06)** | (0.090) | (0.205) | (0.229) |
| *Edu16* | 0.137 | 0.607 | 0.166 | 0.334 | 0.334 | 4.183 | 3.304 | 2.333 |
| | (1.02) | (3.26)** | (1.07) | (3.39)** | (3.40)** | (0.041)* | (0.069) | (0.097) |
| *Edu18+* | 0.145 | 0.940 | 0.737 | 0.627 | 0.616 | 8.647 | 0.538 | 5.045 |
| | (0.84) | (4.50)** | (4.06)** | (5.05)** | (4.98)** | (0.003)** | (0.463) | (0.007)** |
| *Age* | 0.047 | 0.003 | 0.081 | 0.043 | 0.044 | 4.423 | 10.561 | 5.333 |
| | (3.81)** | (0.19) | (4.72)** | (3.98)** | (4.02)** | (0.036)* | (0.001)** | (0.005)** |
| *Age²* | -0.000 | 0.000 | -0.001 | -0.000 | -0.000 | 4.950 | 11.793 | 5.908 |
| | (3.36)** | (0.37) | (4.70)** | (3.31)** | (3.33)** | (0.026)* | (0.001)** | (0.003)** |
| *Tenure* | 0.013 | -0.010 | 0.031 | 0.008 | 0.007 | 0.090 | 0.520 | 0.517 |
| | (2.13)* | (0.89) | (2.59)** | (1.45) | (1.42) | (0.764) | (0.471) | (0.597) |
| *Tenure²* | -0.000 | 0.000 | -0.001 | -0.000 | -0.000 | 2.060 | 0.489 | 2.614 |
| | (1.87) | (0.95) | (2.34)* | (1.00) | (1.04) | (0.151) | (0.485) | (0.074) |
| *PrevExp* | 0.039 | 0.144 | 0.202 | 0.108 | 0.109 | 0.022 | 0.008 | 0.012 |
| | (0.88) | (2.49)* | (3.36)** | (3.13)** | (3.17)** | (0.881) | (0.930) | (0.989) |
| *Raise* | -0.091 | -0.071 | -0.015 | -0.089 | -0.089 | 0.005 | 0.961 | 0.560 |
| | (2.07)* | (1.45) | (0.24) | (2.71)** | (2.71)** | (0.946) | (0.327) | (0.571) |
| *Northeast* | 0.033 | 0.007 | 0.023 | 0.031 | 0.030 | 0.151 | 7.689 | 3.960 |
| | (0.36) | (0.04) | (0.22) | (0.46) | (0.44) | (0.698) | (0.006)** | (0.019)* |
| *Southeast* | 0.049 | 0.055 | -0.057 | 0.012 | 0.013 | 0.363 | 0.303 | 2.100 |
| | (0.72) | (0.79) | (0.63) | (0.26) | (0.26) | (0.547) | (0.582) | (0.123) |
| *West* | -0.078 | -0.034 | -0.357 | -0.154 | -0.147 | 0.500 | 0.121 | 1.898 |
| | (0.84) | (0.54) | (3.66)** | (2.82)** | (2.71)** | (0.480) | (0.728) | (0.150) |
| *AI* | 0.132 | 0.170 | 0.435 | 0.217 | 0.213 | 0.241 | 4.560 | 3.368 |
| | (2.89)** | (2.74)** | (4.05)** | (5.11)** | (5.00)** | (0.624) | (0.033)* | (0.035)* |
| *SSF* | -0.001 | 0.084 | -0.094 | 0.001 | -0.000 | 1.174 | 3.303 | 1.652 |
| | (0.03) | (1.26) | (1.31) | (0.02) | (0.00) | (0.279) | (0.069) | (0.192) |
| *PF* | 0.075 | -0.063 | 0.149 | 0.052 | 0.055 | 3.251 | 5.559 | 2.908 |
| | (1.78) | (0.98) | (2.35)* | (1.43) | (1.53) | (0.072) | (0.019)* | (0.055) |
| *MSP* | 0.020 | -0.061 | -0.092 | -0.023 | -0.020 | 1.073 | 0.081 | 0.827 |
| | (0.38) | (1.05) | (1.01) | (0.60) | (0.53) | (0.301) | (0.777) | (0.438) |
| *EW* | 0.095 | 0.061 | 0.073 | 0.077 | 0.081 | 0.179 | 0.016 | 0.091 |
| | (1.63) | (1.16) | (0.99) | (1.92) | (2.03)* | (0.672) | (0.901) | (0.913) |
| *AIAO* | 0.055 | 0.010 | 0.122 | 0.074 | 0.075 | 0.328 | 1.352 | 0.676 |
| | (1.15) | (0.17) | (1.67) | (1.97)* | (2.02)* | (0.567) | (0.245) | (0.509) |
| *FM* | 0.182 | 0.136 | 0.031 | 0.137 | 0.133 | 0.319 | 1.109 | 1.493 |
| | (3.87)** | (2.02)* | (0.41) | (3.68)** | (3.55)** | (0.572) | (0.293) | (0.225) |
| *CU* | 0.078 | 0.027 | -0.180 | -0.016 | -0.015 | 0.419 | 3.996 | 3.714 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1.65) | (0.43) | (2.19)* | (0.42) | (0.39) | (0.518) | (0.046)* | (0.025)* |
| *Year 2000* | | | | 0.032 | 0.036 | | | |
| | | | | (0.79) | (0.88) | | | |
| *Year 2005* | | | | -0.047 | -0.023 | | | |
| | | | | (0.98) | (0.52) | | | |
| *Farm Size* | 0.237 | 0.136 | 0.056 | 0.082 | | 3.213 | 6.162 | 3.138 |
| | (2.66)** | (0.95) | (3.06)** | (6.35)** | | (0.073) | (0.013)* | (0.044)* |
| *Farm Size$^2$* | -0.050 | -0.015 | -0.001 | -0.002 | | 2.605 | 5.414 | 2.715 |
| | (1.95) | (0.37) | (1.16) | (4.01)** | | (0.107) | (0.020)* | (0.066) |
| *Size >10,000* | | | | | 0.210 | | | |
| | | | | | (6.72)** | | | |
| *Constant* | 3.888 | 4.449 | 3.069 | 3.867 | 3.863 | | | |
| | (17.70)** | (12.43)** | (8.46)** | (18.71)** | (18.54)** | | | |
| *Observations* | 1149 | 617 | 500 | 2266 | 2266 | | | |
| *R-squared* | 0.29 | 0.34 | 0.52 | 0.33 | 0.33 | | | |
| *Joint test of technology adoptions*[a] | 1.65 (0.117) | 1.87 (0.073) | 3.96* (0.00)** | 4.22* (0.00)** | 3.98** (0.00)** | | | |

Note: Dependent variable is natural log of adjusted real annual salary. Numbers in parentheses for the column two to column six are absolute values of t statistics. Column seven to nine reports the joint F test for each variable, along with the P-value in the parenthesis. Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1% respectively. Early Weaning (EW) technology is a dummy variable, equal to one if at least one of the three technologies, SEW, MEW, MMEW was adopted.

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

**Figure 3. Propensity score distribution in large and small hog farms**

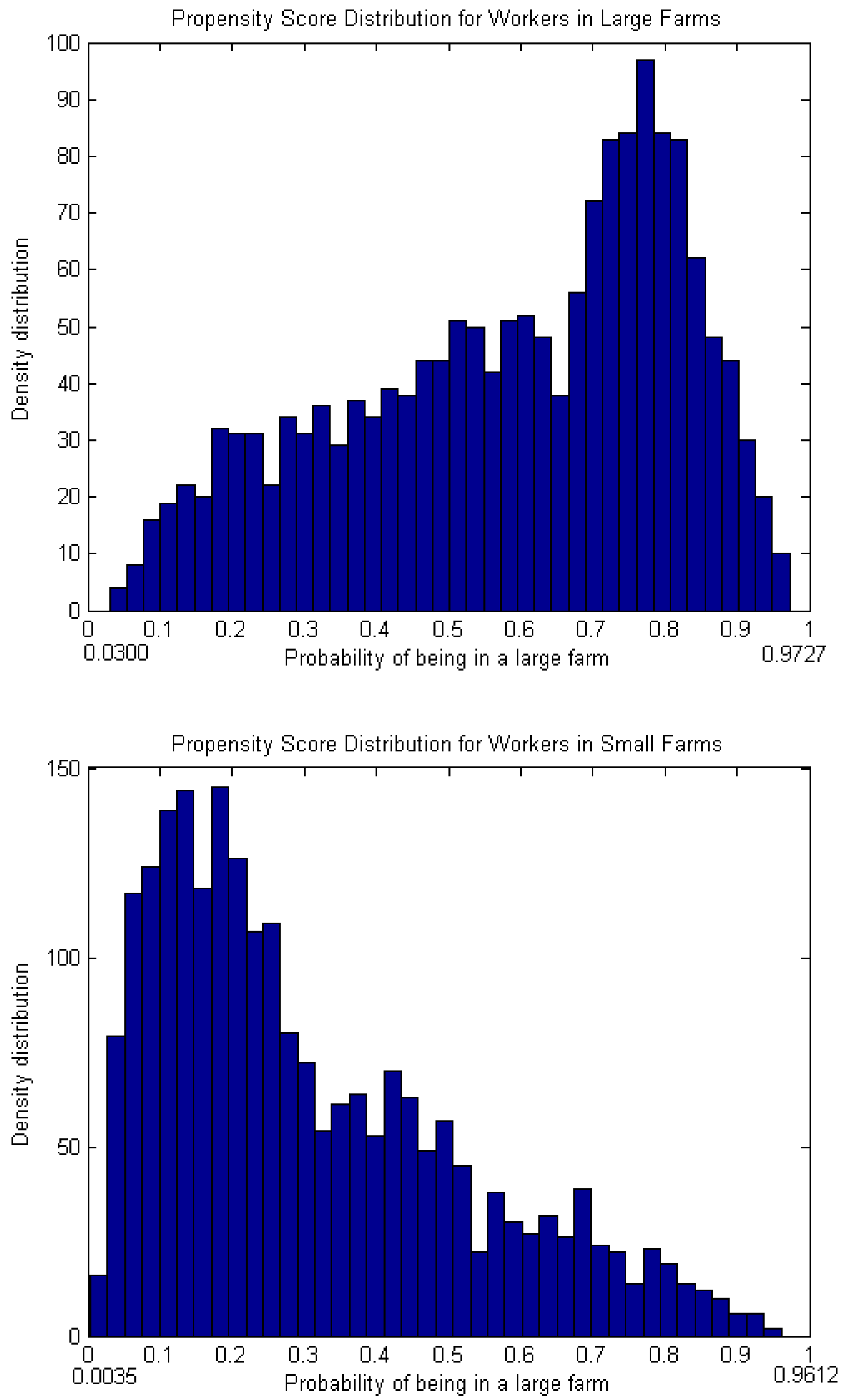


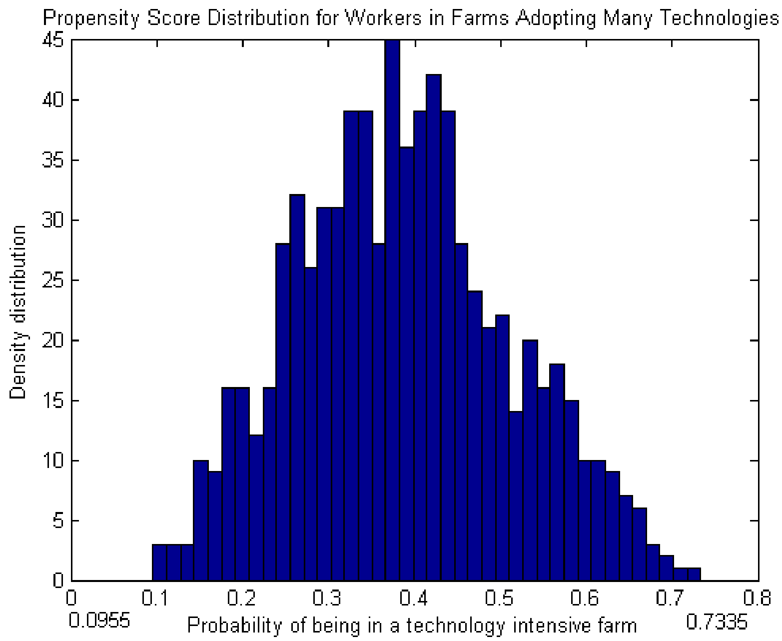
**Table 6. Estimated Wage Premium on Hog Farms Producing 10,000 or More Hogs, by Worker and Farm Attributes**

| | Nearest Neighboring | | | Caliper | | | Kernel | | | Mean *lnW*[a] | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Premium (*lnW*) | Std Err | Premium (%) | Premium (*lnW*) | Std Err | Premium (%) | Premium (*lnW*) | Std Err | Premium (%) | D=1 | D=0 |
| | | | | 6a. Estimation by education group | | | | | | | |
| *Edu9* | 0.422 | 0.164 | 52.5% | 0.377 | 0.099 | 45.8% | 0.416 | 0.129 | 51.6% | 5.533 | 4.960 |
| *Edu12* | 0.312 | 0.042 | 36.6% | 0.331 | 0.022 | 39.2% | 0.315 | 0.026 | 37.0% | 5.607 | 5.232 |
| *Edu14* | 0.175 | 0.052 | 19.1% | 0.319 | 0.027 | 37.6% | 0.201 | 0.048 | 22.3% | 5.691 | 5.327 |
| *Edu16* | 0.296 | 0.035 | 34.4% | 0.310 | 0.022 | 36.3% | 0.283 | 0.028 | 32.7% | 5.786 | 5.429 |
| *Edu18+* | 0.239 | 0.185 | 27.0% | 0.271 | 0.093 | 31.1% | 0.217 | 0.134 | 24.2% | 6.111 | 5.820 |
| | | | | 6b. Estimation by region group | | | | | | | |
| *Mid-west* | 0.265 | 0.030 | 30.3% | 0.327 | 0.017 | 38.7% | 0.264 | 0.022 | 30.2% | 5.712 | 5.332 |
| *Northeast* | 0.124 | 0.120 | 13.2% | 0.189 | 0.071 | 20.8% | 0.140 | 0.086 | 15.0% | 5.596 | 5.396 |
| *Southeast* | 0.298 | 0.044 | 34.7% | 0.316 | 0.033 | 37.2% | 0.294 | 0.044 | 34.2% | 5.775 | 5.465 |
| *West* | 0.427 | 0.093 | 53.3% | 0.431 | 0.066 | 53.9% | 0.446 | 0.084 | 56.2% | 5.749 | 5.298 |
| | | | | 6c. Estimation by year | | | | | | | |
| *1990* | 0.381 | 0.043 | 46.4% | 0.361 | 0.025 | 43.5% | 0.353 | 0.024 | 42.3% | 5.694 | 5.304 |
| *1995* | 0.222 | 0.038 | 24.9% | 0.299 | 0.023 | 34.9% | 0.249 | 0.024 | 28.3% | 5.673 | 5.320 |
| *2000* | 0.246 | 0.048 | 27.9% | 0.253 | 0.050 | 28.8% | 0.247 | 0.043 | 28.0% | 5.727 | 5.427 |
| *2005* | 0.422 | 0.072 | 52.5% | 0.364 | 0.067 | 43.9% | 0.336 | 0.072 | 39.9% | 5.763 | 5.415 |
| | | | | 6d. Estimation by the often used individual technologies | | | | | | | |
| *AI* | 0.204 | 0.032 | 22.6% | 0.180 | 0.025 | 19.7% | 0.173 | 0.026 | 18.9% | 5.748 | 5.568 |
| *PF* | 0.302 | 0.040 | 35.3% | 0.310 | 0.027 | 36.3% | 0.293 | 0.030 | 34.0% | 5.811 | 5.445 |
| *AIAO* | 0.303 | 0.036 | 35.4% | 0.305 | 0.025 | 35.7% | 0.288 | 0.036 | 33.4% | 5.792 | 5.432 |
| *FM* | 0.249 | 0.041 | 28.3% | 0.250 | 0.022 | 28.4% | 0.229 | 0.030 | 25.7% | 5.745 | 5.491 |
| *CU* | 0.328 | 0.033 | 38.8% | 0.291 | 0.020 | 33.8% | 0.285 | 0.026 | 33.0% | 5.757 | 5.429 |

Note: The estimated mean is the difference of log of salary between large farms and small farms. Standard error is obtained by bootstrapping 100 times. Table 6a, 6b and 6c use the data set in all of four survey years. All results about technologies in table 6d uses the data in 1995, 2000 and 2005 except Formal Management, which uses all of the four survey data sets.

[a] Weighted mean log of the annual wage.

**Figure 4. Propensity score distribution of hog farms adopting either many or few technologies**



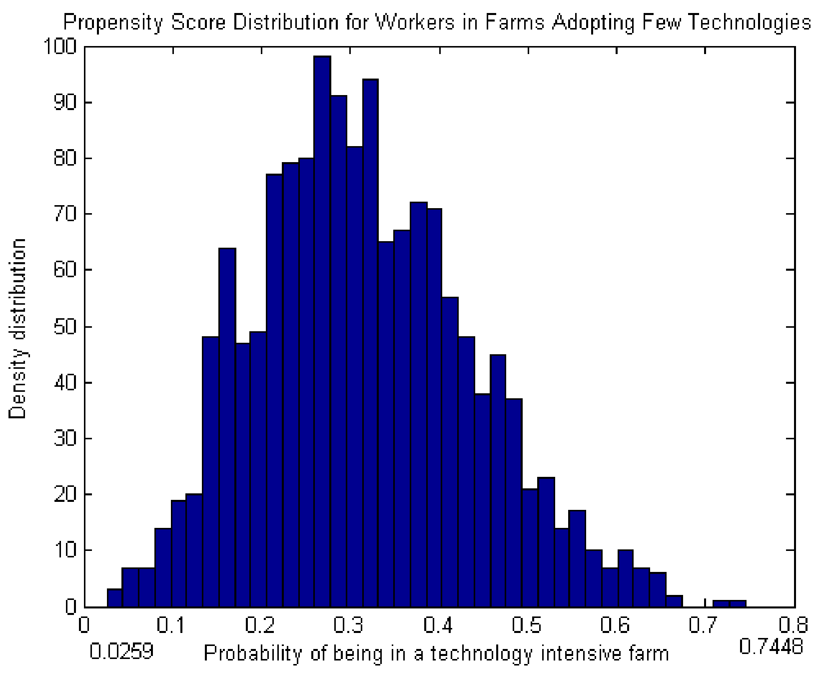



**Table 7. Estimated Wage Premium on Hog Farms Using 6 or More Technologies, by Worker and Farm Attributes**

| | *Nearest Neighboring* | | | *Caliper* | | | *Kernel* | | | Mean $lnW$[a] | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Premium ($lnW$) | Std Err | Premium (%) | Premium ($lnW$) | Std Err | Premium (%) | Premium ($lnW$) | Std Err | Premium (%) | D=1 | D=0 |
| | | | | 7a. Estimation by education group | | | | | | | |
| *Edu9* | 0.312 | 0.222 | 37% | 0.467 | 0.109 | 60% | 0.517 | 0.135 | 68% | 6.002 | 4.902 |
| *Edu12* | 0.239 | 0.059 | 27% | 0.306 | 0.033 | 36% | 0.284 | 0.034 | 33% | 5.629 | 5.319 |
| *Edu14* | 0.230 | 0.052 | 26% | 0.262 | 0.037 | 30% | 0.231 | 0.035 | 26% | 5.743 | 5.423 |
| *Edu16* | 0.192 | 0.032 | 21% | 0.206 | 0.027 | 23% | 0.183 | 0.022 | 20% | 5.736 | 5.507 |
| *Edu18+* | 0.179 | 0.139 | 20% | 0.267 | 0.097 | 31% | 0.166 | 0.091 | 18% | 6.039 | 5.863 |
| | | | | 7b. Estimation by region group | | | | | | | |
| *Mid-west* | 0.222 | 0.029 | 25% | 0.260 | 0.020 | 30% | 0.215 | 0.020 | 24% | 5.744 | 5.394 |
| *Northeast* | 0.448 | 0.149 | 57% | 0.321 | 0.088 | 38% | 0.237 | 0.090 | 27% | 5.659 | 5.478 |
| *Southeast* | 0.234 | 0.061 | 26% | 0.296 | 0.043 | 34% | 0.268 | 0.042 | 31% | 5.925 | 5.537 |
| *West* | 0.171 | 0.071 | 19% | 0.299 | 0.061 | 35% | 0.253 | 0.053 | 29% | 5.765 | 5.258 |
| | | | | 7c. Estimation by year | | | | | | | |
| *1995* | 0.279 | 0.040 | 32% | 0.292 | 0.020 | 34% | 0.272 | 0.023 | 31% | 5.727 | 5.419 |
| *2000* | 0.115 | 0.041 | 12% | 0.196 | 0.032 | 22% | 0.169 | 0.030 | 18% | 5.711 | 5.433 |
| *2005* | 0.261 | 0.058 | 30% | 0.237 | 0.042 | 27% | 0.221 | 0.044 | 25% | 5.853 | 5.353 |
| | | | | 7d. Estimation by farm size | | | | | | | |
| *Large* | 0.145 | 0.024 | 16% | 0.167 | 0.017 | 18% | 0.152 | 0.018 | 16% | 5.793 | 5.598 |
| *Small* | 0.243 | 0.071 | 28% | 0.299 | 0.044 | 35% | 0.230 | 0.042 | 26% | 5.726 | 5.329 |

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

## Appendix A

Table A.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 A.2. Probit Model of Employment on Large and Small Hog Farms / on Farm by Adoption of Many or Few Technologies

| | Model (A1) Probit model of farm size | | Model (A2) Probit model of technology adoption intensity | |
|---|---|---|---|---|
| *Variables* | Coefficient | t-Statistic | Coefficient | t-Statistic |
| *Female* | 0.040 | 0.49 | -0.081 | -0.86 |
| *Edu12* | 0.186 | 1.73 | 0.364 | 2.35* |
| *Edu14* | 0.255 | 2.29* | 0.620 | 3.96** |
| *Edu16* | 0.386 | 3.61** | 0.814 | 5.36** |
| *Edu18+* | -0.218 | -1.53 | 0.950 | 5.11** |
| *Age* | 0.051 | 3.69** | 0.044 | 2.51* |
| $Age^2$ | -0.001 | -3.33** | -0.001 | -2.57** |
| *Tenure* | -0.052 | -6.18** | -0.025 | -2.47** |
| $Tenure^2$ | 0.001 | 2.42* | 0.001 | 1.63 |
| *PrevExp* | 0.205 | 4.30** | 0.227 | 3.84** |
| *Raise* | -0.109 | -2.31* | 0.062 | 1.06 |
| *Northeast* | -0.017 | -0.17 | -0.227 | -1.70 |
| *Southeast* | 0.696 | 9.83** | -0.056 | -0.63 |
| *West* | 0.415 | 5.74** | 0.217 | 2.50* |
| *Year 1995* | 0.689 | 12.88** | -0.451 | -6.13** |
| *Year 2000* | 1.376 | 20.33** | -0.340 | -4.20** |
| *Year 2005* | 1.571 | 20.69** | | |
| *Constant* | -1.984 | -7.24** | -1.550 | 4.31** |
| Observations | 3934 | | 2266 | |
| LR $\chi^2(17)$ | 1200.84 | | LR $\chi^2(16)$=164.3 | |

Note: The dependent variable in the model (A1) is a dummy variable indicating employment on a farm producing 10000 or more hogs. The data are year 1990 – 2005 surveys. The dependent variable in the model (A2) is a dummy variable indicating employment on a farm using 6 or more technologies. The data are year 1995 – 2005 surveys. Asterisk (*) and double asterisk (**) denote variables significant at 5% and 1% respectively.

**Appendix B: Three Matching Strategies**

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

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

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

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

## Endnotes

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

[2] USDA accounts originally include 18 regions and four size classifications. Since some region-size cells included very few observations in our samples, we aggregated some of the cells. The eight regions are 1. IL 2. IN 3. IA 4. MN 5. MO, TX, OK and AR 6. OH, WI and MI 7. NE 8 other states (including ND, SD, PA, CT, ME, MD, MA, VT, NJ, NH, NY, RI, DE, NC ,KY, WV, VA, GA, SC, FL, AL, TN, MS, LA, WA, ID, OR, NV, CA, AZ, UT, HI, AK, KS, MT, WY, CO and NM). Farm sizes have three levels for the 1990 and 1995 surveys: small if fewer than 3,000 pigs produced per year, medium if 3000 to 9,999 pigs produced per year and large if more than 10,000 pigs produced per year. For the 2000 and 2005 year surveys. Farm size is further aggregated into two levels: small if fewer than 10,000 pigs produced per year and large if more than 10,000 pigs produced per year.

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

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

[5] States included in the Midwest: IA, IL, IN, MN, MO, ND, NE, OH, SD, WI; in the Northeast: CT,DC, DE, MA, MD, ME, MI, NH, NJ, NY, PA, RI, VT; in the Southeast:

AL,FL, GA, KY, LA, MS, NC, SC, TN, VA, WV; and in the West: AK, AR, AZ, CA,CO, HI, ID, KS, MT, NM, NV, OK, OR, TX, UT, WA, WY.

[6] Exp(0.32) - 1 = 0.38.

[7] In order to compare the returns to individual technologies, the set of included technologies into the equations should be consistent. A dummy variable Early Weaning (EW) is used to indicate if any of the three technologies, SEW, MEW, MMEW was adopted. Since Auto Sorting System (AS) and Parity-based Management (PM) is only available in the survey in 2005, they are not considered in models in table 5. Plus, estimated coefficients on AS and PM are not significant in the single wage equation in 2005.

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

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

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

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