FIRM SIZE, TECHNICAL CHANGE AND WAGES:

EVIDENCE FROM THE PORK SECTOR FROM 1990-2005

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Abstract: A long-standing puzzle in labor economics has been the positive relationship between wages and firm size. Even after controlling for worker's observed characteristics such as education, work experience, gender, and geographic location, a significant firm size wage effect averaging 15 percent remains. This paper investigates whether the size-wage premium on hog farms persists over time and whether the magnitude is growing or shrinking. The paper pays particular attention to the matching process by which workers are allocated 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. The survey was conducted across the United States. The data allow us to evaluate how farm size and technology adoption have changed over time and how employee pay has changed in response to these changes.

Detailed investigations of these pay differences between small and large hog farms and between farms using few and many technologies show that the differences cannot be explained away by differences in the education, work experience, or geographic location of the farm. 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 remain large and statistically significant when differences in observable worker attributes are controlled. Furthermore, these effects are reinforcing in that large hog farms also adopt more technologies, and so the firm size effect persists even after differences in the number of technologies are held constant. The size-wage and technology-wage prema have persisted over time, and we cannot reject the null hypothesis that the premia are constant over the sample period.

I. Introduction

A long-standing puzzle in labor economics has been the positive relationship between wages and farm size. The estimated size-wage premium is 15 percent in the United States (Lluis, 2003), holding measures of worker skill fixed. Many hypotheses have been advanced to explain the size-wage premium (Brown and Medoff , 1989; Troske, 1999), including : 1) Larger farms employ more capital which is complementary with labor; 2) Larger farms have more skilled managers; 3) Larger farms have more skilled workers who are complementary with one another; 4) Larger farms use more sophisticated technologies; 5) Larger farms pay higher wages to limit monitoring costs; and 6) Larger farms share rents from returns to scale.

All of these hypotheses are true at least in certain settings, but none alone or in aggregate have been able to fully explain why large farms pay more than small farms. 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 productivity, a significant size wage effect remains.

Three out of the six explanations relate to the role of technology on the size wage puzzle. On average, large farms employ more capital per worker and use more advanced technologies, paying their workers a premium for using these technologies. Evidence from manufacturing firms shows that operators who used information technologies more intensively were paid more than comparable workers in firms lacking those investments (for example, Raily, 1995, Krueger, 1993, Dunne and Schmitz, 1995, Dunne *et al*, 2004).

A similar phenomenon is apparently at work in the US hog industry: The market share of large hog farms has been increasing steadily. At the same time, farms have been adopting new technologies in increasing numbers with the heaviest adopters being the largest farms (McBride and Key, 2003). Finally, there appears to be increased use of more educated labor on hog farms with evidence of rising average farm wages.

Previous work by Hurley, Kliebenstein and Orazem (1999) used cross-sectional data on employees on hog farms in 1995 to show that there was a substantial wage premium paid to employees on larger hog farms compared to employees on smaller farms. Their results suggest that the same size-wage premium that has persisted for decades in the non-farm sector may hold also in the farm sector. This paper extends that work to investigate whether the size-wage premium on hog farms persists over time and whether the magnitude is growing or shrinking. The paper pays particular attention to the matching process by which workers are allocated 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. The data allow us to evaluate how farm size and technology adoption have changed over time and how employee pay has changed in response to these changes.

We use alternative estimation strategies to control for observed and unobserved productivity across workers. Regardless of methodology employed, we find large and persistent effects of farm size and technology adoption on worker's wages. The farm size effect remains large, even after controlling for differential technology adoption across large and small farms, suggesting that workers are earning rents from returns to scale on large hog farms. Workers of all types receive the wage premia, regardless of education level, experience or region of the country. While there is some evidence of modest declines in the wage-size and wage-technology premia over time, the premia are still very large.

The paper is organized as follows. Section two looks at the trends of employer size and wages on US hog farms. Section three reviews the baseline empirical strategy and describes the data while section four provides estimates of the size-wage effect using traditional least squares estimates of earnings functions augmented by farm size. Because of possible nonrandom sorting of more able workers into large farms, section five reviews alternative statistical matching methods to correct for selection bias in the wage comparison across farm sizes. Section six presents the comparable strategy applied to difference in intensity of technology adoption. Both sections provide evidence that the wage premia paid by large and more technologically advanced farms are due to the technologies adopted and not to unmeasured worker productivity. The final section summarizes the paper's findings.

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

The U.S. hog industry has a large range of farm sizes, from farms producing fewer than 500 hogs to farms producing more than 100,000. The employment share by farm size category is presented in Table 1. The size categories varied across surveys so that in 2005, the smallest farm is defined as producing fewer than 1000 pigs rather than 500 as in the other three survey years 1990, 1995 and 2000. On the other hand, the top category in 2005 involves producing more than 100,000 pigs as opposed to producing 10,000 or more in 1990 and 25,000 or more in 1995 and 2000. It is apparent that the employment share of the largest farms is rising dramatically. In 1990, 42 percent of hog farm workers were on farms that produced 10, 000 or more pigs. By 2005, the proportion of employment on farms producing 10,000 or more pigs had risen to 82 percent. In contrast, farms producing fewer than 5,000 pigs employed 16% of hog farm workers in 1990, but employed only 6 percent of hog farm employment by 2005. Very large farms are becoming the norm. They are accounting for a larger share of employers and number of pits while the smallest farms are losing market share.

The move toward larger farms appears to be correlated with rising farm wages. A size-wage pattern similar to that found in other labor markets is apparent in the relationship between salaries and size of operation on hog farms. Figure 1 shows the log salary distribution on hog farms from smallest to largest. It is apparent that wages in the hog industry in the U.S. are positively correlated with the farm size. The wage profile for the smallest farms (fewer than 500 pigs – size 1) is heavily weighted toward the lower tail of the distribution. The majority of workers are in the lower half of the salary range. As the size categories rise, the median log salary moves to the right and the lower tail of the salary distribution eventually disappears. In the largest farms, virtually all workers are in the upper half of the salary range.

The rapid change in employment share on large farms since 1990 corresponds to a period of rapid technology advance and adoption. Various technologies and their frequency of use by employees are reported in Table 2. The technology adoption measures are only available for three years 1995, 2000, 2005. Additionally, questions regarding Auto Sorting Systems and Parity Based Management were not asked in 1995 or 2000, and so adoption rates for those technologies are only reported for 2005.[1]

Of the other technologies, the strongest growth is in Artificial Insemination and Early

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

Weaning. There has also been growth in exposure to Formal Management practices. Fewer employees have been using Phase Feeding or Split-Sex Feeding. The remaining technologies (All In All Out, Multiple Site Production, and Computer Usage) have been utilized by a nearly constant proportion of employees in the industry.

There is *prima facie* evidence that the wage distribution may reflect differences in the number of technologies employed on large versus small farms. Farms with fewer than 500 hogs use an average of 1.1 technologies while those producing over 50,000 hogs use an average of 4.4 technologies. Figure 2 presents the log salary distribution by the number of technologies employed on the farm. Farms using at most one of the technologies listed in Figure 2 have log salary distributions weighted toward the lower tail of the observed range. As the number of technologies used increases, the salary distribution shifts to the right. Farms using 9 or more technologies had salary distribution entirely in the upper-half of the observed wage range.

III. Empirical strategy and data

We are interested in examining the role of changing farm size and technology utilization on the distribution of wages for hog farm employees. The standard Mincerian earnings function is defined as

$$\ln W_{ijt} = \alpha_0 + \alpha_1 Female_i + \alpha_2 Edu_i + \alpha_3 Exp_{it} + \alpha_4 Exp_{it}^2 + \alpha_5 Z_{jt} + \varepsilon_{ijt} \tag{1}$$

where *i* indexes the worker, *j* indexes the farm, and *t* indexes the time period. *lnW* is the natural log of the worker's annul salary; *Female* is a self-defining dummy variable; *Edu* is a vector of dummy variables indicating the worker's education level; *Exp* is the worker's years of work experience; *Z* is a vector of farm characteristics; and *ε* is a disturbance term we assume initially to be *i.i.d.* normal. The coefficients are interpretable as follows: α_1 is a measure of the proportional gap in pay between women and men; α_2 measures the proportional gap in pay between the worker's education level and the base pay for a high school dropout; and α_3 and α_4 allow a potentially concave relationship that is often observed in the time path of salaries over the work career.

To augment the earnings function to capture the returns to farm size and technology and to capture the shift in the pay structure over time, we can insert additional measures of technology T_{jt}, farm size F_{jt} , and time period t_t so that

$$\ln W_{ijt} = \alpha_0 + \alpha_1 Female_i + \alpha_2 Edu_i + \alpha_3 Exp_{it} + \alpha_4 Exp_{it}^2 + \alpha_5 Z_{jt} + \beta_T T_{jt} + \beta_{F1} F_{jt} + \beta_{F2} F_{jt}^2 + \beta_t t_t + \varepsilon_{ijt}' \tag{2}$$

where T is alternatively measured as the number of technologies employed or as a vector of dummy variables that indicate the presence or absence of specific technologies on farm j in year t; and F is a measure of the number of pigs on the farm in year t. Farm size F is defined in two ways, one as a continuous variable indicating how many pigs are produced by farm j in year t, and again by a dummy variable that distinguishes between farms producing more or less than 10,000 pigs per year. The coefficient β_T measures workers' return from the farm's use of technologies and the β_F will measure workers' return from potential farm returns to scale. The last coefficient β_t will tell us if real salaries on the farm are rising or falling over time, holding worker and farm attributes fixed.

This paper uses the survey data from a random sample of subscribers to *National Hog Farmer Magazine*. The surveys were conducted in years 1990, 1995, 2000 and 2005. Because subscribers to *National Hog Farmer Magazine* are not a representative sample of all hog farms and because propensity to respond to surveys may also differ by farm size, the survey data are weighted to conform to the size distribution of hog farms in the USDA Agricultural Census Data (ACD). USDA counts of hog farms in 18 census regions and four farm size classifications were taken as the population universe.[2] USDA summaries of farm size range from fewer than 1000 pigs, 1000 to 1999, 2000 to 4999 and more than 5000 pigs. The weights are computed as follows: there are N hog farms in total in the US and n_j farms in region and size cell j. The proportion of all hog farms in the j^{th} cell is n_j/N. The comparable number of farms in the same region and size group in our sample is s_j. Each farm in sample is then assigned a probability weight by $\frac{s_j}{n_j / N}$.[3]

Characteristics of workers and farms are shown in Table 3. Workers' human capital is measured by four dummy variables indicating their educational attainment with high school dropouts being the comparison group: *Edu12* indicates a high school graduate; *Edu14* indicates completing two years post high school; *Edu16* indicates completing a four year college degree; and *Edu18+* indicates completing a post graduate degree such as master, Ph.D, or Doctor of Veterinary Medicine. 94 percent of workers have completed high school and 43 percent have a 4 year university degree. On average, workers have two years of education post high school.

Workers' experience is measured age minus schooling years minus six. The average

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

[3] Weights based on the 1987 Census were used for 1990 survey responses, 1992 Census were used for 1995 survey responses and the 1997 Census was used to construct weights for the 2000 and 2005 survey responses. 2002 Census data were not available at the time of the analysis.

worker has 13.9 years of working experience. Plus, tenure effect is also very important to differentiate the wages across workers. There are two variables, *Tenure* and *PrevExp* to indicate the working time in the current farm and whether working in previous hog farms before respectively. The tenure in the current hog farms is 6.3 years on average. And about 53 percent of workers have working experience from previous employment in other hog farms. Farm location is categorized by four regions: Midwest, Northeast, Southeast and West[4]. These are captured by three dummy variables with the Midwest region serving as the base.

There are some notable differences between large and small farms. Larger farms in the sample pay workers 10% more than average and 25% more than do the smaller farms. Workers on large farms are more educated and have more working experience. Small farms employ a relatively high proportion of high school graduates and two year college diploma holders, 58.4 % in total, compared to 49.5% in large farms. Large farms employ relatively more workers with at least four year university degree compared to small farms (45.6% vs. 33.2%). Workers in large farms have 1.2 less years experience than those in small farms. However, more proportions of workers in large farms have working experience in other hog farms before employed in the current farms. Small farms are mainly in the Midwest while large farms are more likely to be in the Southeast and the West. Farm size is positively related to technology adoption, with large farms using and average of 1.6 more technologies than the small farms.

IV. Earnings Functions

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

Regression results from the traditional earnings function are presented in Table 4. Model (1) serves as our base of comparison in that it excludes the effects of farm size and technology on wages. Female workers are paid 19 % less than male workers, other things equal. (Gender wage ratio is *exp(-0.206)*). Earnings rise with education and there is an increasing return to education. High school graduate earn 29 % more than the high school drop outs, while workers with a four year university degree earn 60% more than the high school drop outs, other characteristics equal. The earnings' profiles peak at thirteen years of working experience, which suggesting that younger workers may have different and more valued skill sets than older workers. Workers who have experience in previous employment in the hog sector earn 11% more than those lacking that experience. The longer the workers stay in the same farms, the higher wages they can earn, other things equal, though at a decreasing rate. Workers employed in the Southeast earn the most with an eleven percent wage premium over employees in the Midwest. 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 since 1990, although they declined modestly between 2000 and 2005.

Model (2) presents the size augmented earnings function of equation (2) with the technology parameters constrained to be zero. It is apparent that some worker attributes are correlated with farm size. When farm size is held constant, the implied wage advantage for males rises to 25% while the returns to high school (25%) and college (52%) remain significant but smaller compared to model (1). Earnings now peak at 26 years of working experience. The wage advantage for Southeast workers falls to 6% but workers in the West earn 6% less than their counterparts in the Midwest.

Workers benefit from the scale of farm operations in the hog industry. Though 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 0.22. 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 falling. 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. The estimates suggest that a worker employed for fifteen years on a hog farm that did not increase in size over the sample period would have experienced a 19% reduction in real wages, other things equal.

The fourth column replaces the continuous measure of farm size with a dummy variable indicating whether the farm has annual production exceeding 10,000 hogs per year. Coefficients are similar to those in the first two models. The discrete effect of the farm size dummy variable on the wage is 0.22.[5]

The last column results incorporate the effect from technology adoption in the hog production. A dummy variable is defined to indicate intensity technologies usage, which 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. Estimated coefficients of education are even smaller than model (3), indicating that technology usage is complementary with the worker's human capital level. The discrete effect of the farm size dummy variable on the wage is 0.20. Workers in farms intensively using technologies earn 27% more than those in farms using

[5] Exp (.201) – 1 = 0.223.

fewer technologies. The premium advantage from using technologies is higher than that from economy of scale.

In Table 5, we replicate the earnings function allowing for separate wage effects for individual technologies used on the farm. We estimate the equation separately by year and then pool the data across years. This allows us to test for changes in the earnings structure over time. Although we did not have strong priors about the likely changes in returns over time, it is apparent that the earnings structure with regard to human capital, farm size and technology adoption are remarkably stable. None of the null hypotheses of equality over time of returns to education, farm size, or individual technology adoption could be rejected at the 5% significance level.

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. Controlling for individual technology adoptions does not affect the conclusion about relative earnings by gender: the wage disadvantage for women remains large and significant at -14%. Returns to human capital are moderated, however. Returns to high school graduates are no longer significant. Returns to college graduates remain significant but are about one-third smaller in size. Returns to work experience decrease in magnitude as well. The marginal effect of farm size on wages decreases to 0.13 after controlling for the individual technology effects.

Of the individual technologies, only Artificial Insemination; Phase Feeding; Early Weaning; All In-All Out; And Formal Management are tied significantly to wages. All have positive estimated effects on wages. Joint test rejects the hypothesis that there is an equal effect on wages from individual technologies. Most of the other technologies also have positive, albeit imprecisely estimated impacts. It appears that farmers pay a premium to get workers who can use advanced technologies above what is paid to similarly educated and experienced workers in the absence of those technologies.

V. Worker Returns Measured Using Propensity Score Matching

From Figure 1 and Table 4, we know that workers on larger farms are paid higher wages. In that analysis farm size is treated as exogenous. However, workers may target farm size in their job search decisions, and those decisions may be due to unobservable worker attributes that are correlated with wages. For example, we know that large farms have more educated workers, but they may also have workers who have balanced skills in handling several things at the same time, a worker attribute that we cannot measure. Non-random sampling of these workers into larger farms may bias our interpretation of the farm size effect on wages downward. The wage premium on large farms may reflect this differential ambition and not farm size *per se.*

In this section, we quantify the workers benefit in terms of log of real salary using the Propensity Score Matching (PSM) method to see how benefits vary between workers who are equally likely to be found on large farms. PSM balances the distributions of observed covariates between the treatment group and a control group based on their propensity scores. It allows us to estimate the average causal effects of farm size on real salary gain without arbitrary assumptions about the functional forms and disturbance term distribution. The method is used to examine how the farm size effect differs by workers' education level, regional location, and technology used.

Assumption of Propensity Score Matching Method

The treated group is composed of workers who are employed in the large farms (denoted as $D_i = 1$) and the control group includes workers in 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 are observed workers' characteristics and V_U are unobservable factors. [6] Workers self select into the large farms $D = 1$ and receive the log wage $\ln W_1$ if $U > 0$, otherwise are employed in small farms, $D = 0$ and paid $\ln W_0$. Subscripts 1 and 0 denote large and small farms respectively.

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

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

where V_1 and V_0 are unobserved factors related to the wage variation in treatment group and 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 mean $E(\ln W_0 \mid D = 1, x)$ 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 this propensity score:

$$P(x_i) = \Pr(D_i = 1 \mid x_i); 0 < P(x_i) < 1 \text{ for individual } i. \quad (3)$$

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

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

[6] Model represents a given worker and the subscript i is suppressed for notational ease in the following analysis.

(ii) if outcomes (in this case the wage) 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 $P(x_i)$, $(\ln W_{1i}, \ln W_{0i}) \perp (D_i \mid P(x_i))$. 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 in a large farm can be viewed as being drawn from the same universe. Exact matching on $P(x_i)$ will eliminate the bias caused by unobserved individual heterogeneity across the samples of workers in large and small farms.

Matching

We define the binary outcome D as follows: farms producing fewer than or equal to 10,000 pigs are defined as small farms; those greater than or equal to 10,000 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 that, for each worker in the sample, predicts the probability that the employee works on a large hog farm. The regression results are shown in Table 6. The characteristics of the workers include gender, the education level, working experience, geographical location and time effect. Workers with higher education, more experience and those in the Southeast or the West will be more likely to work on a large farm.

Matching on fitted probabilities $\hat{P}(x_i)$ seems to work quite well. The estimated probability of ending up in a large farm for those who actually work on large farms is 0.585 on average. The average estimated probability for those who actually work on small farms is

0.303. Moreover, as seen in Figure 3, there is substantial overlap in the distributions of the estimated propensity scores $\hat{P}(x_i)$ for workers in large and small farms, and so for every employee on a large farm, we have a worker on a small farm with a similar propensity score.

When $\hat{P}(x_i)$ is available, we can employ several methods to get the PSM estimator. The size impact estimator takes the form:

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

$$\ln \hat{W}_{oi} = \sum_{j \in I_o} \hat{w}(i,j) \ln W_{0j} \qquad (4)$$

where n1 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 (Smith and Todd, 2005)and $\hat{w}(i,j)$ are weights depending upon the distance between the propensity scores for observation *i* and *j*. By choosing different weighting functions, we have the following three variations on matching which are commonly used in literature.

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

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

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

1997,1998), where *G(s)* is a kernel function, which 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. [7]

In order to measure the accuracy of this estimate, we must utilize the bootstrap method, re-sampling the data with replacement *m* times to approximate the standard error. The estimated standard error is $\sigma_\tau = \sqrt{\frac{1}{m-1}\sum_{q=1}^{m}(\hat{\tau}_q - \bar{\tau})^2}$ where $\bar{\tau} = \frac{1}{m}\sum_{q=1}^{m}\hat{\tau}_q$ (Efron and Tibshirani, 1993).

Estimated Size and Technology Effects using Matching Estimators

Using the full data sample, we calculated the size-wage effect using the matching methods above. The mean effect is estimated to be 0.248 (standard error of 0.026), 0.329 (0.015) and 0.290 (0.019) using Nearest matching, Caliper matching and Kernel matching methods respectively, and so results are a little sensitive to the choice of matching mechanism. The estimated effect of 0.3 implies that the salary paid on the largest farms is 35% higher than that on small farms. This is higher than the size-wage effect estimated by least squares regression. This result is similar to Idson and Feaster (1990) who argued that selection on unobservable characteristics of workers would bias downward the least squares estimate of the size-wage premium.

The matching method can also be used to explore the size-wage effect for sub samples of interest. Table 7 reports the size-wage premium for different education, region, and technology groups as well as for groups employed in different years. The size-wage premium is larger for the workers who are high school dropouts and smaller for the most educated.

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

Nevertheless, all size wage premia are large, ranging from 8% (though not significant) for the most educated to 62% for high school dropouts using the nearest neighbor method and 28% to 47% using the Caliper matching and 16% to 50% using Kernel matching methods.

There is also considerable heterogeneity in the size-wage premium by part of the country. The premium is larger in the West and Southeast, while the premium in the Northeast is the least and not significant.

The size-wage effect is large and significant in every time period but has decreased substantially from 38% in 1990 to 19% in 2000 but rebounded to 32% in 2005 using nearest neighbor matching and roughly 44% to 29% then to 37% using Caliper matching method and kernel matching method. One possible reason is that over time, labor markets adjust as technologies diffuse. Large farms make higher profits relative to small farms from technology adoption in the early stage of technology diffusion, and thus have rents to share with their workers. As the technologies mature, more workers invest in the skills that had earned large rents early in the adoption process, lowering the premium needed to attract workers to use the technologies. However, new technologies Auto-sorting System and Parity Based Management enter the hog market in 2005. Only large farms which have already used many technologies adopt them in this early stage of technology diffusion. This generates higher monopolized profits thereafter more rent to share with their employees.

The size wage premium also differs by technology employed on the farm. The often used technologies are Artificial Insemination (AI), Phase Feeding (PF), All-In-All-Out (AIAO), Computer Usage (CU), and Formal Management (FM). Workers on large farms using Phase Feeding (PF), All-In-All-Out (AIAO), Computer Usage, and Formal management practices, get the largest wage premium of roughly more than 30% over the pay on small farms employing the same technology. The smallest size-wage premium (about 19%) is associated with Artificial Insemination (AI) 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.

Model of Employment on Farms by Number of Technologies

We further expect that workers in the farms using multiple technologies earn more than their counterparts on less technologically advanced farms under the hypothesis of complementarity between technologies and human capitals. We employ a similar methodology to explore the wage premia associated with the intensity of technological adoption on the farm. We expect that if technologies raise farm productivity, some of the inframarginal; rents earned by the farm may be shared with the workers.

The binary outcome D indicates that a farm adopts at least six advanced technologies out of the ten possible. Those adopting fewer than four technologies are treated as the control group, while the farms with four or five technologies are excluded from the analysis. A *probit* model is used to predict the propensity score for each observation. The regression results are shown in Table 8. Farms employing workers with more education, more experience and that are located in the Midwest 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 about 0.317(0.029), 0.376(0.021) and 0.312(0.025) using three matching methods respectively, implying that salaries paid in the technology intensive farms are 37% to 46% higher than pay in farms using fewer technologies. The estimated return to technology adoption in model (4) of Table 4 is only 27%, suggesting substantial downward bias for at least 10 points in the least squares estimate of returns to technology adoption.

Table 9 reports the detailed outcomes of the matched comparisons. Again, it is the least educated that benefit the most from the presence of technologies. However, this largest treatment effect has also highest variations. The second largest premium goes to the workers with a two year college degree. Premium in returns to education is decreasing with the years of schooling received. Positive wage premium indicate that a worker with high education is complementary with advanced technologies. She is more productive in technology intensive farms thus is rewarded at a higher wage rate. For high school dropouts in farms adopting many technologies, they seem to earn highest premium. One reason is that though these farms employ smaller proportion of high school dropouts, these workers have many years of working experience. For example, for workers in the treatment group *(D=1),* an average high school dropout has 22 years of working experience while a college diploma holder has only 13.5 years of experience. Experienced workers are also highly rewarded due to their complementarity with the advanced technologies for farms using many technologies.

The wage returns to more intensive technology use on the farm exceeds 32% in all regions. Similar to the outcomes of the size-wage estimation but not quite the same, the largest premia are paid in the southeast.

Like the size-wage premium, there is no evidence of straight deterioration of the technology-wage premium over time. We can only make the comparison back to 1995 because of the lack of technology data in the 1990 survey, but the premium appears to have persisted over the last ten years. Specifically, the treatment effect is relatively higher in 1995 and 2005 but smaller in 2000.

We know that large farms are more likely to adopt multiple technologies than are small farms. Nevertheless, the small farms that adopt technologies more intensively pay a larger premium to attract workers than do larger, technology intensive farms. From Table 9d, the technology causal effect for small farms is at least 4% higher than that for large farms using Nearest Matching and Kernel Matching methods and 14% higher using Caliper Matching method.

VI. Conclusion

This study has examined workers' returns in the hog farms in the US. The sample consists of the 1990, 1995, 2000 and 2005 surveys of employees in the hog industry in the United States. Workers are rewarded from their schooling and working experiences. Farms in the Mid-west pay higher wages to their employees. In addition, salary of workers is declining along the time. The paper then focus on the size wage premium.

Simple cross-tabulations of the data indicate that large farms offer higher wages than small farms. Larger farms also hire more educated and experienced workers tend to use more technologies. Least squares regressions find that even after controlling for worker characteristics, there are substantial wage premia associated with working on larger farms and employing more technologies. However, these wage premia may be due to more able workers sorting into larger farms using multiple technologies. Propensity Score Matching methods find that even larger wage effects averaging 35%, suggesting that the usual OLS estimate is underestimated by about 12 percentage points.

Size wage premium differs in various samples. The premium is higher for the workers who are high school dropouts but smaller for workers with at least Master's degree. Patterns are different for the technology wage premium distribution across the differently educated groups. Technologies are more sensitive and complementary with the workers education and working experience than farm size.

Large farms located in the Mid-west and west pay higher wages than those in the northeast. The premium is declining along the time but still very significant. For farms using different technologies, there is also a significant size wage premium.

Due to the high correlation between farm size and the number of technologies employed, we can treat technology adoption as a treatment. Similar wage results to those found with respect to farm size are reported. There is a substantial technology adoption wage premium exceeding the OLS estimate that exists across farms regardless of location, size, and worker skill set. Farms in the southeast pay relatively higher wage premium both from economy of scale and technology usage intensity.

This empirical study supports the existence of size wage effect on U.S. hog farms. The results also can not reject the technology related size wage hypothesis in the current literature. The effect exists even after controlling for technology adoption. It is plausible that workers receive a share of the returns to scale on large farms, a possibility that will require additional research to confirm.

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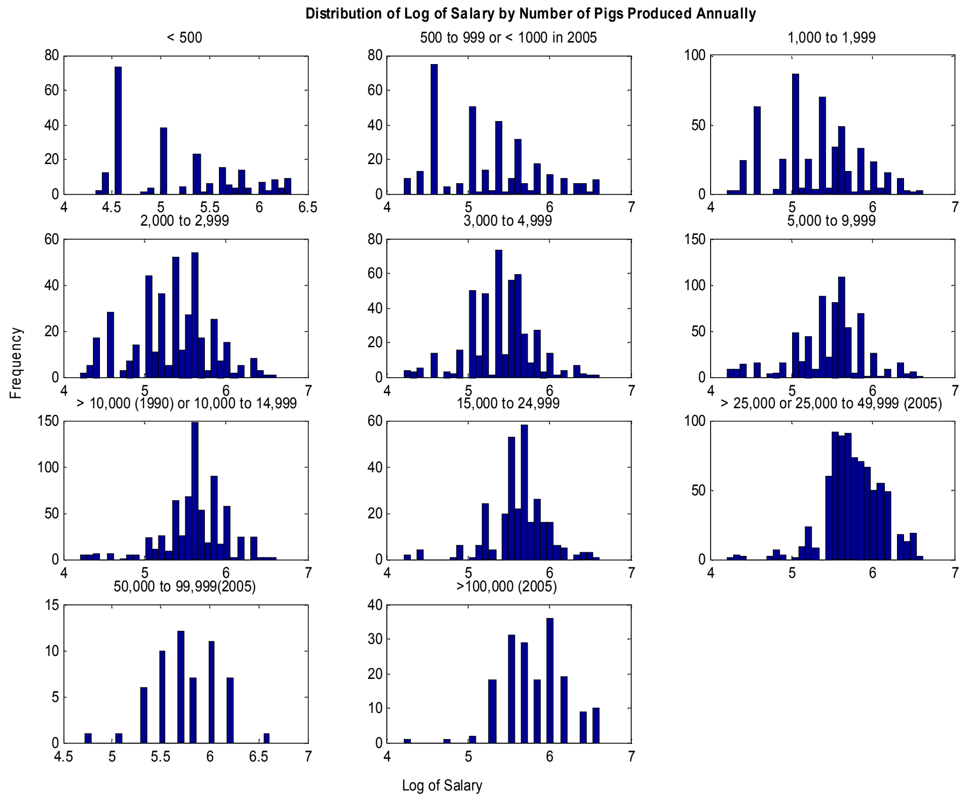
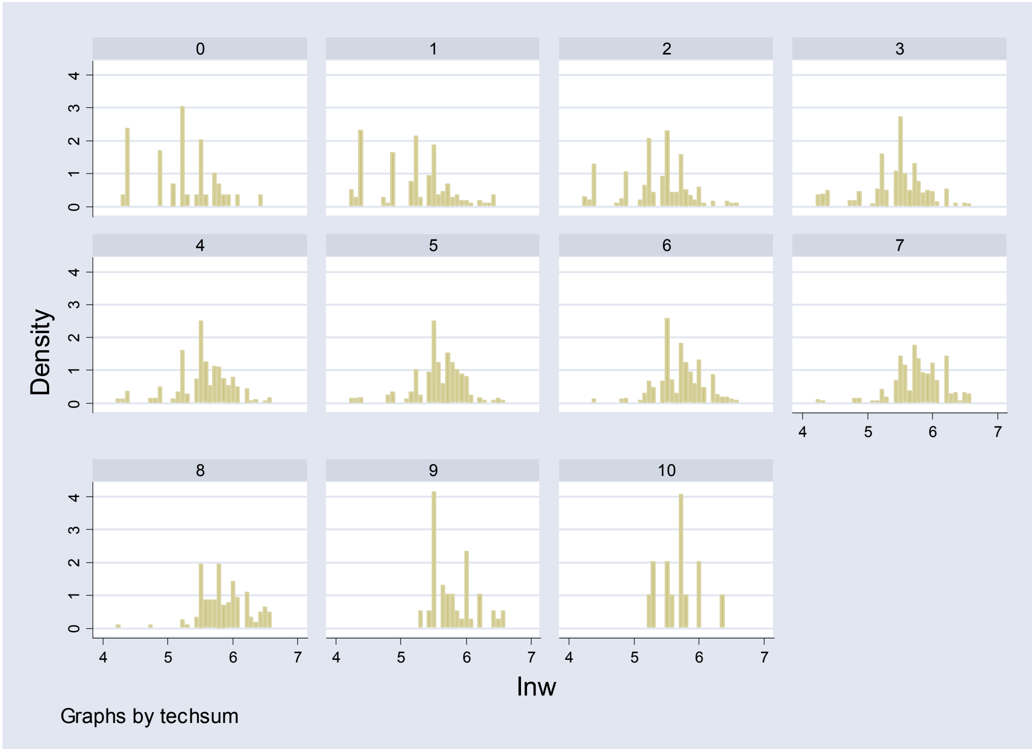
Figure1. Size Wage Effect: Log of Salary in Different Size Categories.



* Size categories refer to the Table1.

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



* Size categories refer to the Table1.

Table1. Frequency Distribution of Employees on Hog Farms by Size of Farm

Code	Size Class (pigs per year)	Weighted Frequencies (%)			
		1990	1995	2000	2005
1	Less than 500	0.07	0.01	0.64	.
2	500 to 999 / less than 1000 in 2005	0.09	0.01	0.58	2.76
3	1,000 to 1,999	3.18	0.86	1.23	0.69
4	2,000 to 2,999	6.21	3.24	3.27	1.04
5	3,000 to 4,999	6.45	3.83	3.24	1.31
6	5,000 to 9,999	41.64	24.55	13.07	12.32
7	10,000 or more（1990）/10,000 to 14,999	42.35	18.02	14.7	11.98
8	15,000 to 24,999		14.91	12.4	12.69
9	25,000 or more / 25,000 to 49,999 (2005)		34.58	50.87	15.79
10	50,000 to 99,999(2005)				10.43
11	100,000 or more (2005)		.	.	30.97

Employee responses are weighted to reflect the size distribution of hog farms as reported by the USDA.

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

Number	Name	Notation	1995		2000		2005	
			Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
1	Artificial Insemination	AI	0.656	0.475	0.779	0.415	0.824	0.380
2	Split Sex Feeding	SSF	0.576	0.494	0.480	0.500	0.456	0.498
3	Phase Feeding	PF	0.612	0.487	0.497	0.500	0.549	0.498
4	Multiple Site Production	MSP	0.480	0.500	0.507	0.500	0.500	0.500
5	Early Weaning	EW	0.276	0.447	0.337	0.473	0.340	0.474
6	All in / All out	AIAO	0.772	0.420	0.663	0.473	0.671	0.470
7	Auto Sorting Systems	AS	.	.	.	.	0.080	0.271
8	Parity Based Management	PBM	.	.	.	.	0.297	0.457
9	Formal Management	FM	0.694	0.461	0.718	0.450	0.790	0.407
10	Computer Use	CU	0.763	0.425	0.735	0.441	0.782	0.413

* Statistics are weighted.

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

Variables	Description	Full sample	Large Farms	Small Farms
lnW	Log of salary	5.578 (0.393)	5.674 (0.343)	5.449 (0.419)
Female	Gender of workers	0.080 (0.271)	0.086 (0.280)	0.071 (0.257)
Edu12	High school graduate	0.302 (0.459)	0.268 (0.443)	0.348 (0.476)
Edu14	2 year college diploma or equivalent	0.231 (0.421)	0.227 (0.429)	0.236 (0.424)
Edu16	4 year university degree or equivalent	0.369 (0.482)	0.418 (0.493)	0.304 (0.460)
Edu18+	Higher degree education level	0.034 (0.181)	0.038 (0.192)	0.028 (0.165)
Tenure	Experience in the current farm	6.301	5.799	6.985
PrevExp	Dummy variable, equal to one if previously working in a hog farm	0.531	0.551	0.504
Experience	Working experience	13.909 (9.250)	14.034 (9.028)	13.740 (9.515)
Farm Size	Number of pigs produced (unit: 10,000 heads)	1.457 (1.127)	2.083 (1.132)	0.627 (0.209)
Northeast	Dummy variable, equal to one if located in the northeast.	0.036 (0.187)	0.034 (0.180)	0.040 (0.196)
Southeast	Dummy variable, equal to one if located in the southeast.	0.095 (0.293)	0.132 (0.228)	0.046 (0.209)
West	Dummy variable, equal to one if located in the west.	0.134 (0.341)	0.159 (0.365)	0.101 (0.301)
Number of technologies	Number of technologies used	4.913 (1.999)	5.400 (1.919)	3.829 (1.732)

* The statistics of the variables are weighted. The number is the weighted mean. The number in the parenthesis is standard deviation.

* Salaries are discrete categories in the survey. We define the *salary* as a continuous variable by taking the mid-point of the range for each category, adjusted by the consumer price index. And the salary is adjusted by the consumer price index (CPI) from the Labor Statistics Bureau. CPI in 1990, 1995, 2000 and 2005 is 79.9975, 91.2177 98.8768 110.4758 respectively. *lnW* is the natural log of the real salaries.

* Experience is age minus the schooling years minus six.

*The education level reflected in the survey is categorical. The schooling years (SY) of worker is defined in the following way. SY = 9 if she is a high school drop out. SY = 12 if she is a high school graduate. SY = 14 if she attended the four year college but did not complete. SY = 16 if she is has a bachelor's degree. SY = 19 if she has master degree. SY = 23 if she a Ph.D. degree hold or a Doctor of Veterinary Medicine.

* 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.

* Education variables are dummies based on high school dropout.

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

	(1)	(2)	(3)	(4)
Female	-0.206	-0.222	-0.210	-0.149
	(6.57)**	(7.64)**	(6.97)**	(4.00)**
Edu12	0.253	0.225	0.228	0.051
	(4.70)**	(4.30)**	(4.35)**	(0.70)
Edu14	0.362	0.313	0.329	0.141
	(6.7)**	(5.92)**	(6.21)**	(1.96)*
Edu16	0.469	0.416	0.423	0.193
	(8.80)**	(7.98)**	(8.12)**	(2.66)**
Edu18+	0.694	0.647	0.656	0.353
	(9.82)**	(9.28)**	(9.32)**	(3.27)**
Experience	0.025	0.021	0.022	0.018
	(9.47)**	(8.22)**	(8.56)**	(4.77)**
Experience^2	-0.001	-0.0004	-0.0004	-0.0004
	(7.37)**	(6.27)**	(6.60)**	(3.93)**
Tenure	0.010	0.016	0.013	0.012
	(3.24)**	(5.17)**	(4.14)**	(2.45)*
Tenure^2	-0.0002	-0.0002	-0.0002	-0.0001
	(1.53)	(2.54)*	(1.91)	(0.94)
PrevExp	0.102	0.101	0.100	0.109
	(6.01)**	(6.29)**	(6.08)**	(4.05)**
Northeast	0.017	0.015	0.007	0.062
	(0.45)	(0.40)	(0.20)	(1.23)
Southeast	0.108	0.059	0.055	0.116
	(5.50)**	(3.05)**	(2.79)**	(3.50)**
West	-0.020	-0.060	-0.051	-0.021
	(0.71)	(2.26)*	(1.89)	(0.52)
Year 1995	0.016	-0.097	-0.029	
	(0.96)	(5.27)**	(1.74)	
Year 2000	0.085	-0.082	0.014	0.045
	(4.02)**	(3.53)**	(0.67)	(1.70)
Year 2005	0.074	-0.205	-0.010	0.008
	(2.60)**	(4.84)**	(0.36)	(0.23)
Farm Size		0.156		
		(15.85)**		
Farm Size^2		-0.004		
		(9.48)**		
Size[a]*>10,000*			0.201	0.180
			(11.81)**	(6.00)**
Technologies[b] *>5*				0.239
				(9.67)**
Constant	4.8933	4.815	4.862	4.928
	(88.27)**	(88.04)**	(88.80)**	(64.70)**
Observations	4049	4045	4045	1606
R-squared	0.21	0.28	0.27	0.32

Absolute value of t statistics in parentheses

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

a. Size dummy variable is defined later, which is 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.

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.

Model (4) use year 1995, 2000 and 2005 data and the other three models use four year survey data.

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	-0.152	-0.197	-0.270	-0.164	-0.155	0.47	0.93	1.68
	(4.21)**	(3.65)**	(5.06)**	(5.20)**	(4.74)**			
Edu12	0.097	0.182	-0.001	0.093	0.095	0.22	0.91	0.51
	(1.14)	(1.14)	(0.01)	(1.31)	(1.34)			
Edu14	0.191	0.218	0.135	0.186	0.200	0.02	0.18	0.12
	(2.23)*	(1.33)	(1.25)	(2.60)**	(2.80)**			
Edu16	0.255	0.314	0.176	0.251	0.265	0.10	0.50	0.29
	(2.94)**	(1.92)	(1.60)	(3.48)**	(3.67)**			
Edu18+	0.256	0.554	0.717	0.373	0.388	1.89	0.46	3.05*
	(2.20)**	(3.02)**	(4.65)**	(3.89)**	(4.00)**			
Experience	0.019	0.004	0.026	0.018	0.020	4.29*	4.83*	3.05*
	(4.85)**	(0.65)	(3.21)**	(5.56)**	(5.95)**			
Experience^2	-0.0004	-0.000	-0.001	-0.0004	-0.0004	2.91	4.49*	2.52
	(3.34)**	(0.25)	(2.88)**	(4.15)**	(4.55)**			
Tenure	0.014	0.019	0.021	0.014	0.012	0.31	0.06	0.34
	(3.02)**	(3.00)**	(2.80)**	(3.87)**	(3.17)**			
Tenure^2	-0.0002	-0.0003	-0.0003	-0.0002	-0.0002	0.16	0.04	0.04
	(1.18)	(1.77)	(1.41)	(1.67)	(1.31)			
PrevExp	0.102	0.169	0.156	0.108	0.104	2.21	0.04	1.35
	(4.30)**	(4.37)**	(3.21)**	(5.14)**	(4.86)**			
Northeast	0.013	-0.028	0.012	0.009	0.011	0.15	0.07	0.08
	(0.26)	(0.30)	(0.10)	(0.21)	(0.25)			
Southeast	0.084	0.078	-0.039	0.080	0.094	0.01	2.10	1.92
	(2.95)**	(1.35)	(0.69)	(3.08)**	(3.55)**			
West	-0.043	-0.037	-0.252	-0.049	-0.038	0.01	4.59*	2.51
	(1.06)	(0.81)	(2.81)**	(1.41)	(1.10)			
AI	0.076	0.113	0.227	0.087	0.100	0.36	1.19	1.39
	(2.85)**	(2.05)*	(2.53)*	(3.56)**	(3.90)**			
SSF	0.031	0.027	0.032	0.030	0.022	0.01	0.00	0.00
	(1.27)	(0.62)	(0.64)	(1.37)	(0.99)			
PF	0.044	0.032	0.120	0.048	0.042	0.06	1.70	1.01
	(1.72)	(0.74)	(2.29)*	(2.12)*	(1.86)			
MSP	-0.001	0.003	-0.011	0.007	0.037	0.01	0.05	0.03
	(0.04)	(0.09)	(0.22)	(0.32)	(1.67)			
EW	0.028	0.060	-0.030	0.026	0.030	0.63	2.72	1.37
	(1.09)	(2.00)*	(0.66)	(1.16)	(1.32)			
AIAO	0.083	0.041	0.057	0.080	0.084	0.80	0.05	0.41
	(2.87)**	(1.11)	(0.91)	(3.26)**	(3.42)**			
FM	0.112	0.066	0.055	0.107	0.125	0.78	0.02	0.62
	(4.05)**	(1.54)	(0.89)	(4.33)**	(5.10)**			
CU	0.036	0.014	-0.039	0.028	0.032	0.21	0.65	0.77
	(1.30)	(0.38)	(0.72)	(1.16)	(1.29)			
AS					-0.013			
					(0.25)			

PM					-0.034			
					(0.72)			
Year 2000				0.036	0.050			
				(1.79)	(2.47)*			
Year 2005				-0.072	0.025			
				(1.83)	(0.73)			
Farm Size	0.054	0.268	0.052	0.094		2.98	3.64	1.82
	(1.01)	(2.38)*	(3.42)**	(9.16)**				
Farm Size^2	0.011	-0.044	-0.001	-0.002		2.91	2.29	1.46
	(0.73)	(1.54)	(1.45)	(5.34)**				
Size>10,000					0.124			
					(5.16)**			
Constant	4.712	4.646	4.636	4.697	4.722			
	(50.17)**	(23.40)**	(30.42)**	(58.97)**	(59.07)**			
Observations	1172	624	505	2301	2301			
R-squared	0.34	0.31	0.42	0.33	0.31			
Joint test of technologies	2.14*	0.71	1.99*	2.55*	2.75**			

Absolute value of t statistics in parentheses

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

a. Joint F-test. The numbers in the last three columns are F-values of joint test.

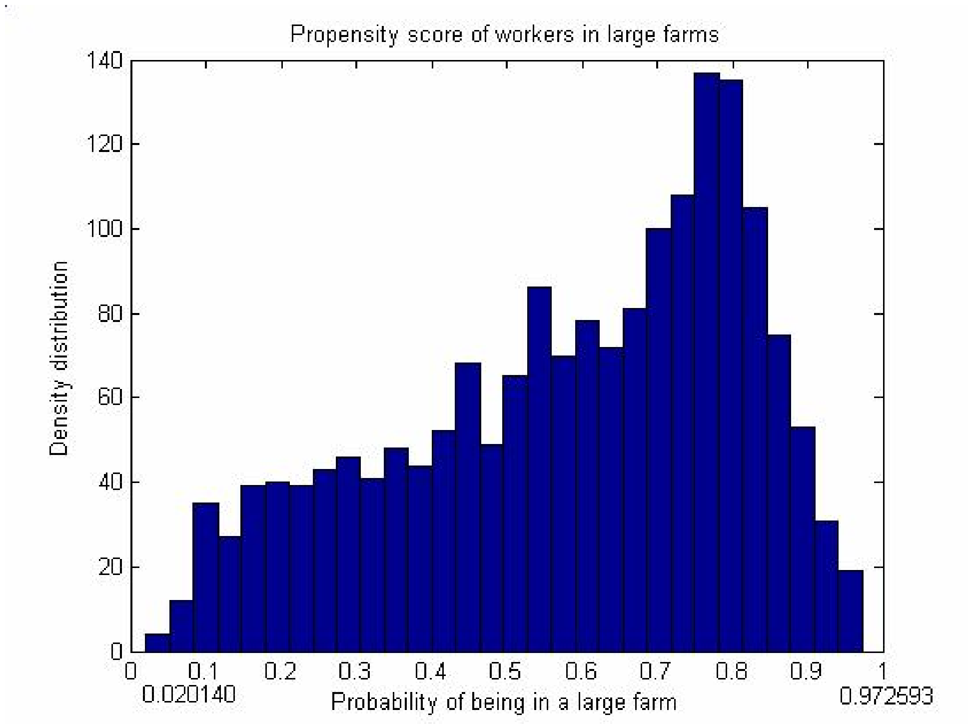
Table 6: Probit Model of Employment on Large and Small Hog Farms

Variables	Coefficient	t-Statistic
Female	0.067	0.84
Edu12	0.179	1.82
Edu14	0.250	2.44*
Edu16	0.413	4.19**
Edu18+	-0.093	-0.72
Experience	0.027	4.12**
Experience^2	-0.001	-3.60**
Tenure	-0.049	-6.54**
Tenure^2	0.001	2.27*
PrevExp	0.232	5.08**
Northeast	-0.031	-0.32
Southeast	0.739	10.98**
West	0.403	5.94**
Year 1995	0.743	14.45**
Year 2000	1.401	21.43**
Year 2005	1.593	21.87**
Constant	-1.296	-11.31**
Observations	4267	
LR $\chi^2(13)$	1324.33	

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

The data are year 1990 – 2005 surveys.

Figure 3. Propensity Score Distribution in Large and Small Hog Farms.



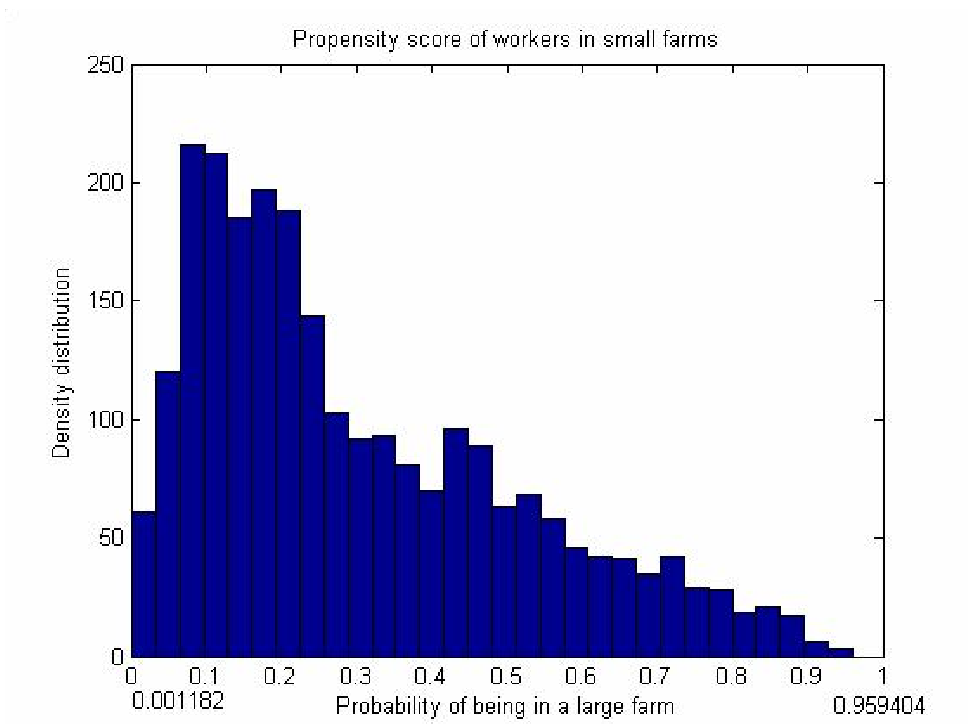


Table 7. Large Hog Farm Premium Estimated Wage[8]

	Nearest		*Caliper*		*Kernel*		Mean Log of Wage [a]	
	Mean	Std	Mean	Std	Mean	Std	D=1	D=0
	7a. Estimation by education group							
Edu9	0.480	0.154	0.386	0.089	0.405	0.131	5.39	5.16
Edu12	0.315	0.039	0.335	0.024	0.318	0.029	5.60	5.40
Edu14	0.176	0.042	0.317	0.024	0.191	0.048	5.66	5.45
Edu16	0.259	0.036	0.306	0.021	0.279	0.033	5.74	5.53
Edu18+	0.073	0.144	0.247	0.081	0.146	0.088	5.96	5.87
	7b. Estimation by region group							
Mid-west	0.216	0.025	0.330	0.015	0.266	0.024	5.66	5.46
Northeast	0.126	0.103	0.197	0.086	0.142	0.095	5.55	5.49
Southeast	0.293	0.047	0.301	0.040	0.281	0.051	5.74	5.47
West	0.386	0.075	0.418	0.060	0.439	0.070	5.71	5.32
	7c. Estimation by year							
1990	0.320	0.042	0.365	0.021	0.351	0.028	5.68	5.47
1995	0.236	0.031	0.304	0.022	0.254	0.024	5.66	5.41
2000	0.170	0.049	0.258	0.040	0.248	0.040	5.72	5.41
2005	0.275	0.069	0.340	0.064	0.318	0.063	5.73	5.35
	7d. Estimation by the often used individual technologies							
AI	0.173	0.028	0.173	0.024	0.166	0.024	5.70	5.49
PF	0.254	0.036	0.299	0.030	0.279	0.029	5.73	5.44
AIAO	0.280	0.037	0.300	0.025	0.278	0.031	5.71	5.45
FM	0.262	0.032	0.242	0.021	0.215	0.028	5.69	5.50
CU	0.308	0.029	0.284	0.023	0.254	0.040	5.70	5.48

Standard error is obtained by bootstrapping 100 times.

a: weighted mean of log of salary.

[8] Table 7a, 7b and 7c use the data set in whole four survey years. All results about technologies in Table 7d uses the data in 1995, 2000 and 2005 except Formal Management, which uses four survey data sets.

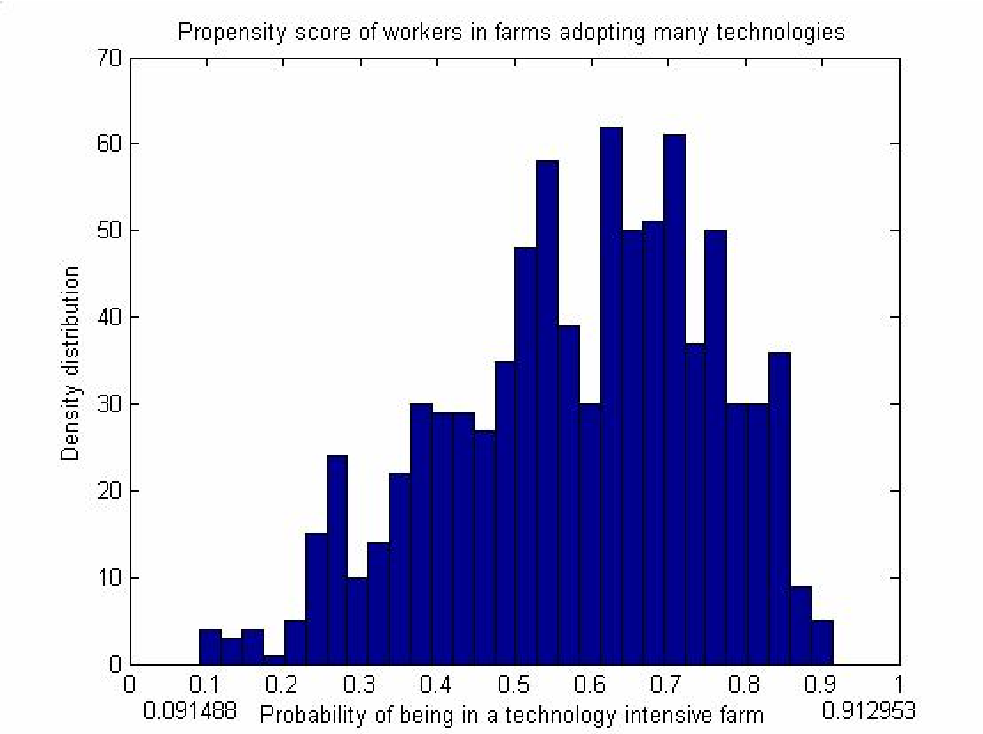
Table8 Probit Model of Employment on Farm by Adoption of Many or Few Technologies

Variables	Coefficient	t-Statistic
Female	-0.126	-1.17
Edu12	0.397	2.54*
Edu14	0.692	4.3**
Edu16	1.132	7.24**
Edu18+	1.101	5.67**
Experience	0.016	1.59
Experience^2	-0.001	-2.49*
Tenure	-0.020	-1.89
Tenure^2	0.0003	1.04
PrevExp	0.371	5.36**
Northeast	-0.316	-2.09*
Southeast	0.027	0.27
West	0.288	2.83**
Year 2000	0.220	2.77**
Year 2005	0.506	5.94**
Constant	-1.021	-5.73**
Observations	1655	
LR $\chi^2(15)$	258.58	

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

The data are year 1995 – 2005 surveys.

Figure 4. Propensity Score Distribution of Hog Farms Adopting Either Many or Few Technologies.



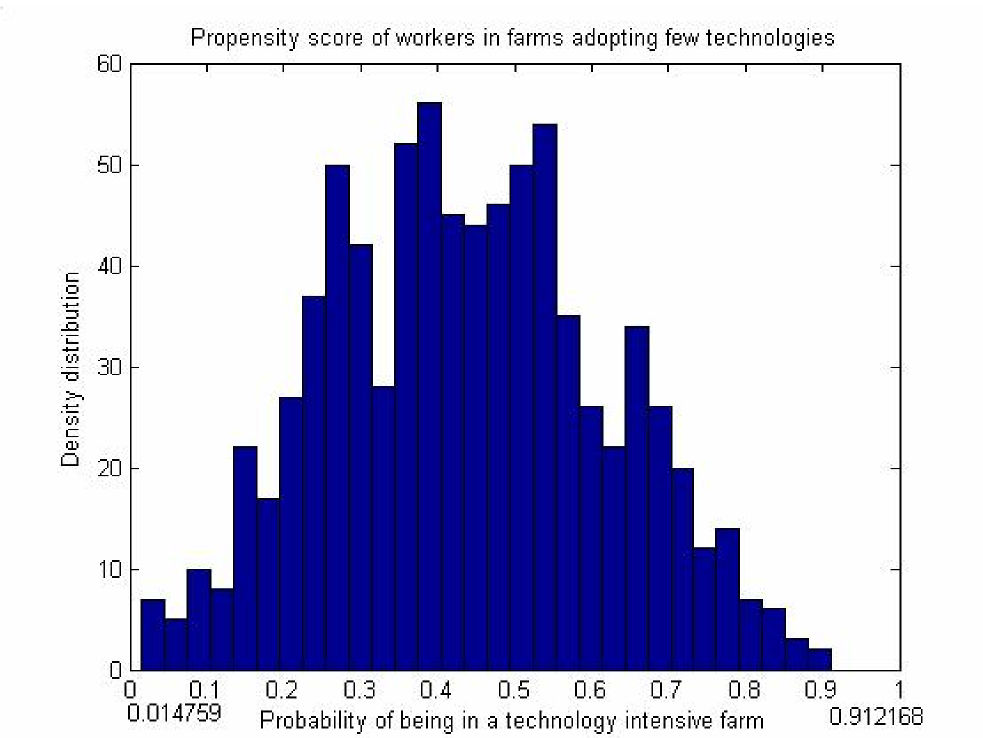


Table 9. Technology Wage Premium of Hog Farms

	Nearest		*Caliper*		*Kernel*		Mean Log of Wage [a]	
	Mean	Std	Mean	Std	Mean	Std	D=1	D=0
9a. Estimation by education group								
Edu9	0.691	0.128	0.583	0.111	0.615	0.106	5.95	5.14
Edu12	0.392	0.050	0.365	0.035	0.339	0.032	5.57	5.37
Edu14	0.349	0.054	0.354	0.047	0.306	0.040	5.72	5.44
Edu16	0.280	0.039	0.313	0.042	0.263	0.039	5.77	5.49
Edu18+	0.229	0.128	0.466	0.157	0.236	0.109	6.03	5.46
9b. Estimation by region group								
Mid-west	0.328	0.033	0.349	0.026	0.296	0.025	5.72	5.40
Northeast	0.438	0.153	0.375	0.123	0.375	0.116	5.68	5.50
Southeast	0.342	0.073	0.405	0.066	0.381	0.063	5.91	5.50
West	0.278	0.080	0.380	0.082	0.281	0.086	5.82	5.21
9c. Estimation by year								
1995	0.353	0.042	0.388	0.029	0.357	0.034	5.81	5.44
2000	0.291	0.047	0.291	0.048	0.270	0.050	5.74	5.39
2005	0.388	0.029	0.337	0.065	0.269	0.058	5.74	5.40
9d. Estimation by farm size								
Large	0.258	0.031	0.255	0.026	0.233	0.024	5.78	5.48
Small	0.300	0.073	0.359	0.048	0.265	0.048	5.59	5.31

Standard error is obtained by bootstrapping 100 times.

a: weighted mean of log of salary.

APPENDIX

An alternative way is to estimate the propensity score through a probit model by weighted data, which corrects the sample selection. We further apply these three matching methods using the estimated propensity scores. According to Becker and Ichino(2002), the standard error is obtained $Var(\hat{\tau}) = \frac{1}{N^T} Var(\ln w_{1i}) + \frac{1}{N^{2T}} \sum_{j \in I_0} \hat{w}(i,j)^2 Var(\ln w_{0j})$. However, the standard errors of kernel matching estimators can not be obtained by using this formula. Since we have already regarded the weighted data as a representative from the population, bootstrapping the data does not make any sense.

The following tables A1a and A1b list the probit estimation of propensity scores for the size treatment and technology treatments respectively. The size premium is 0.260(standard error of 0.025), 0.300(0.015) and 0.264 for Nearest Neighbor matching, Caliper matching and Kernel matching respectively .The technology premium is 0.350(0.034), 0.372(0.024) and 0.347 for Nearest Neighbor matching, Caliper matching and Kernel matching respectively.

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

Table A1a: Probit Model of Employment on Large and Small Hog Farms

Variables	Coefficient	Statistic
Female	0.064	(0.55)
Edu12	0.360	(2.27)*
Edu14	0.482	(2.97)**
Edu16	0.657	(4.15)**
Edu18+	0.551	(2.56)**
Experience	0.042	(4.01)**
Experience^2	-0.001	(-3.41)**
Tenure	-0.034	(-2.69)**
Tenure^2	0.001	(1.15)
PrevExp	0.027	(0.40)
Northeast	0.125	(0.84)
Southeast	0.780	(8.36)**
West	0.438	(4.49)**
Year 1995	0.611	(9.27)**
Year 2000	1.008	(12.34)**
Year 2005	1.585	(11.70)**
Constant	-0.964	(-5.30)**
Observations	4045	
Log likelihood	-2488.3	

t statistics in parentheses

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

The data are year 1990 – 2005 weighted survives.

TableA1b Probit Model of Employment on Hog Farms which Adopt Many and Few Technologies

Variables	Coefficient	Statistic
Female	0.118	(0.68)
Edu12	0.794	(3.41)**
Edu14	1.027	(4.28)**
Edu16	1.423	(6.02)**
Edu18+	1.593	(4.73)**
Experience	0.029	(1.89)
Experience^2	-0.001	(-2.10) **
Tenure	-0.052	(-2.58)**
Tenure^2	0.001	(1.69)
PrevExp	0.345	(3.21)**
Northeast	-0.309	(-1.52)
Southeast	-0.260	(-1.80)
West	0.266	(1.71)
Year 2000	-0.085	(-0.89)
Year 2005	0.290	(2.42)*
Constant	-0.939	(-3.50)**
Observations	1545	
Log Likelihood	-928.8	

t statistics in parentheses

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

The data are year 1995 – 2005 weighted surveys.

Table A2a. Large Hog Farm Premium Estimated Wage[9]

	Nearest		*Caliper*		*Kernel*		Mean Log of	Wage [a]
	Mean	Std	Mean	Std	Mean	Std	D=1	D=0
7a. Estimation by education group								
Edu9	0.342	0.133	0.291	0.090	0.319	.	5.36	5.18
Edu12	0.309	0.041	0.328	0.025	0.325	.	5.6	5.4
Edu14	0.187	0.055	0.300	0.029	0.207	.	5.66	5.45
Edu16	0.291	0.037	0.291	0.024	0.274	.	5.74	5.53
Edu18+	0.240	0.120	0.212	0.084	0.177	.	5.96	5.87
7b. Estimation by region group								
Mid-west	0.242	0.029	0.304	0.017	0.261	.	5.66	5.46
Northeast	0.082	0.097	0.169	0.076	0.129	.	5.56	5.48
Southeast	0.325	0.065	0.259	0.048	0.251	.	5.74	5.49
West	0.238	0.080	0.322	0.061	0.320	.	5.69	5.31
7c. Estimation by year								
1990	0.341	0.036	0.342	0.023	0.319	.	5.68	5.47
1995	0.251	0.035	0.289	0.024	0.243	.	6.66	5.41
2000	0.287	0.054	0.257	0.045	0.254	.	5.72	5.42
2005	0.208	0.089	0.248	0.067	0.238	.	5.73	5.35
7d. Estimation by the often used individual technologies								
AI	0.124	0.036	0.151	0.028	0.144	.	5.7	5.48
PF	0.261	0.038	0.292	0.027	0.269	.	5.72	5.43
AIAO	0.262	0.037	0.291	0.025	0.266	.	5.71	5.45
FM	0.246	0.033	0.201	0.023	0.180	.	5.69	5.51
CU	0.253	0.029	0.261	0.020	0.247	.	5.7	5.48

a: weighted mean of log of salary.

[9] Table 7a, 7b and 7c use the data set in whole four survey years. All results about technologies in Table 7d uses the data in 1995, 2000 and 2005 except Formal Management, which uses four survey data sets.

Table A2b. Technology Wage Effect Estimation of Hog Farms

	Nearest		*Caliper*		*Kernel*		Mean Log of Wage [a]	
	Mean	Std	Mean	Std	Mean	Std	D=1	D=0
9a. Estimation by education group								
Edu9	0.585	0.135	0.675	0.113	0.661	.	5.36	5.18
Edu12	0.344	0.055	0.369	0.038	0.363	.	5.6	5.4
Edu14	0.327	0.059	0.358	0.044	0.350	.	5.66	5.45
Edu16	0.268	0.049	0.303	0.043	0.282	.	5.74	5.53
Edu18+	0.861	0.238	0.561	0.161	0.545	.	5.96	5.87
9b. Estimation by region group								
Mid-west	0.351	0.039	0.342	0.028	0.335	.	5.66	5.46
Northeast	0.478	0.155	0.348	0.112	0.441	.	5.56	5.48
Southeast	0.426	0.100	0.410	0.062	0.438	.	5.74	5.49
West	0.419	0.122	0.325	0.096	0.307	.	5.69	5.31
9c. Estimation by year								
1995	0.378	0.046	0.380	0.030	0.382	.	5.68	5.47
2000	0.282	0.065	0.301	0.047	0.272	.	5.72	5.42
2005	0.298	0.080	0.296	0.065	0.286	.	5.73	5.35
9d. Estimation by farm size								
Large	0.199	0.037	0.246	0.030	0.233	.	5.7	5.48
Small	0.317	0.070	0.344	0.046	0.317	.	5.72	5.43

a: weighted mean of log of salary.