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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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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.

One concern has been that firm size may itself be correlated with differences across firms in the nature of the products produced. If, for example, larger firms have more power to set price, firm size may be positively correlated with worker marginal products for reasons that are not controlled in the analyses. We believe that the size-wage premium would be more convincingly supported if the pattern were found within a single competitive product market.

Of other explanations for the size-wage premium, three involve the interaction between technology and workers' skills. Evidence from manufacturing firms shows that workers in plants that used more capital per worker, used research and development more intensively,

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

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). Such evidence would be even stronger if the variation in technologies occurs within a single product market, eliminating the chance that variation in capital is correlated with different input, product or regional markets.

We examine evidence of the size-wage premium in the context of the US hog industry. 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) found evidence of a substantial size-wage premium in a single cross section of hog farms. This paper explores whether that size-wage premium persists over time and whether it can be explained by the observed differences in skill levels and technology usage between large and small farms. 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 study relies on four surveys of employees on hog farms conducted in 1990, 1995, 2000, and 2005. Regardless of the 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 all types of farms, suggesting that workers on large hog farms are earning rents from returns to scale. Workers of all types on large hog farms receive the wage premia, regardless of education level, related experience or region of the country.

The paper is organized as follows. Section two reviews the stylized facts regarding hog farm size and wages. Section three reviews the baseline empirical strategy and describes the data while section four provides traditional least-squares estimates of the size-wage premium. Section five reviews an alternative statistical matching method to correct for selection bias due to observable differences across farm sizes. Section six presents results from application of the same strategy applied to differences in intensity of technology adoption. Both sets of estimates suggest that the wage premia paid by large and more technologically advanced farms are due to the technologies adopted and not to unmeasured worker productivity.

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 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% in 1990 to 47% in 2005.[2]

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 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

[2] 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.

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. Questions regarding Auto Sorting Systems and Parity Based Management were only reported for 2005 and so we do not incorporate them in our statistical analysis.[3] 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. Empirical strategy and data

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

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

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

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 ε is a disturbance term.

We augment the earnings function by adding aspects of the farm. Technology T is measured alternatively as a vector of dummy variables indicating the use of specific technologies or else indicating the number of technologies used. 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.

This study uses 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 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.[4]

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 $\frac{n_j}{s_j}$.[5]

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.*

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[6]. These are captured by three dummy

[4] 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: 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.

[5] 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.

[6] 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.

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)[7] more than the average farms in the US. 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.

Comment [pfo1]: Why do we have two rows for log salary in table 3? We only need one

IV. Earnings Functions

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

[7] Exp(0.32) -1 = 0.38

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.

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 to 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 indicating farms that used 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 the Table 2. 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 from 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.

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.   Wage returns to farm size have declined, although the size-wage effect remains positive and significant in each period.

V. 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

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

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.

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

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

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:

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

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

[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.

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: farms producing 10,000 or fewer pigs are defined as small farms; 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 Table 6. 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 in large and small farms, and so for every employee on a large farm, we have a control group member that works on small farms 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

[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.

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.

Given $\hat{P}(x_i)$, we can employ several methods to get the PSM estimator. Applying Smith and Todd (2005) to our application, the size impact estimator takes the form:

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

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

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

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.[12]

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). In order to measure the accuracy of these estimates, we must 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 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 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.

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

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. It is large and significant in every time period, ranging from 28% in 2000 to returns exceeding 40% in both the earliest and latest periods.

We also estimate the size wage premium for large and small farm workers employing the most commonly employed technologies. 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

We can use the same methods to test for corroborating evidence that workers on farms using multiple technologies earn more than their counterparts on less technologically advanced farms. 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.

The binary outcome D now indicates that a farm adopts at least six advanced technologies out of the ten possible. A probit model is again used to predict the propensity score for each observation. The regression results are shown in Table 8. 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 0.248; 0.281; and 0.230 using matching methods 1-3, respectively. The implied salary differential paid on the technology intensive farms varies between 26% and 32%.

Table 9 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 23% 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 downward over time, although with only three years of data, we will characterize that conclusion as suggestive. Even the lowest returns are large at just under 20%.

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.

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.

VI. Conclusion

This study examined evidence of the size-wage premium on U.S. hog farms from 1990-2005. We examine whether the premium exists within narrowly defined industries, whether the premium persists over time, and whether it can be explained by correlation with other differences across farm size such as differences in technological adoption or differences in the sorting process of workers across large and small firms. We find that regardless of methodology employed, from simple least-squares analysis to various propensity score matching strategies, there are large and persistent wage differentials favoring workers on large hog farms. The magnitude of the premium differs across various groups. It is larger for the least skilled, for workers in the Western U.S. and for workers using technologies more intensively. However, the general finding is that regardless of worker attributes, they receive a premium for working on large hog farms.

We also find substantial returns to the use of technologies on hog farms. These positive returns are also found for all education levels, regions of the country and farm sizes.

Nevertheless, controlling for technology use has almost no impact on the magnitude of the size-wage effect. Additional research will be needed to determine why large farms persistently pay more to their employees regardless of worker attributes.

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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	2.763	1.772
4	2,000 to 2,999	15.06	23.28	16.80	7.99	3.472	1.815
5	3,000 to 4,999	9.05	8.86	16.70	13.78	4.083	1.847
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	4.618	1.638
8	15,000 to 24,999	.	1.83	3.50	2.65	4.898	1.807
9	25,000 or more / 25,000 to 49,999 (2005)	.	4.02	17.58	4.63	5.263	1.788
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

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.
"." represents that the category is not asked in the survey.

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

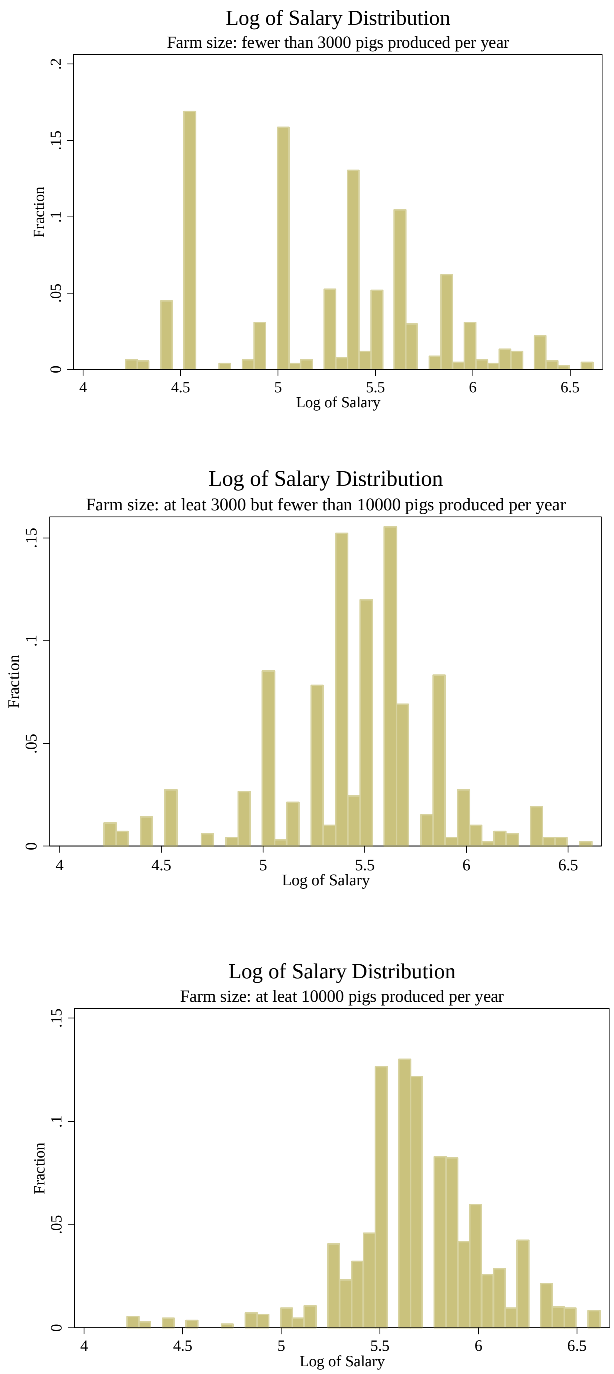


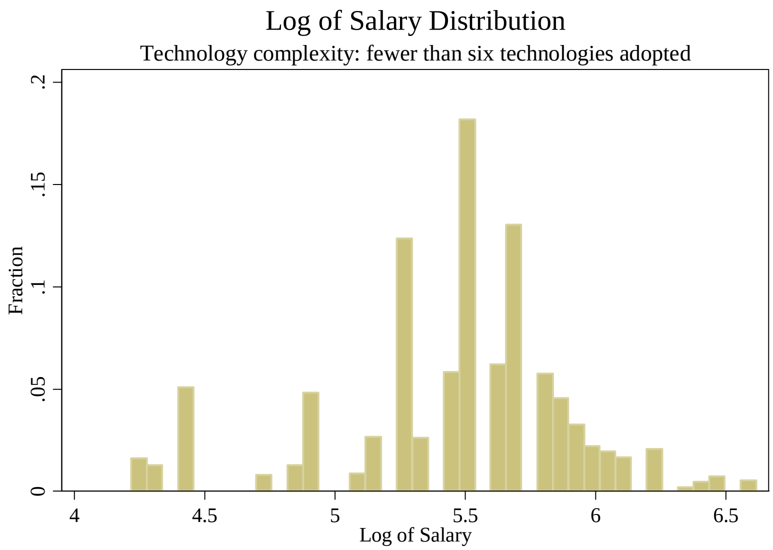
Table2. Fraction of Employees on Hog Farms Using Various Technologies.

Number	Name	Notation	1995		2000		2005	
			Mean	Std Dev	Mean	Std Dev	Mean	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	Early Weaning	EW	0.147	0.355	0.246	0.431	0.234	0.424
6	All in / All out	AIAO	0.572	0.495	0.638	0.481	0.568	0.496
7	Auto Sorting Systems	AS	.	.	.	.	0.025	0.158
8	Parity Based Management	PBM	.	.	.	.	0.186	0.389
9	Formal Management	FM	0.479	0.500	0.582	0.494	0.688	0.464
10	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

Statistics are weighted.

"." represents that the category is not asked in the survey.

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



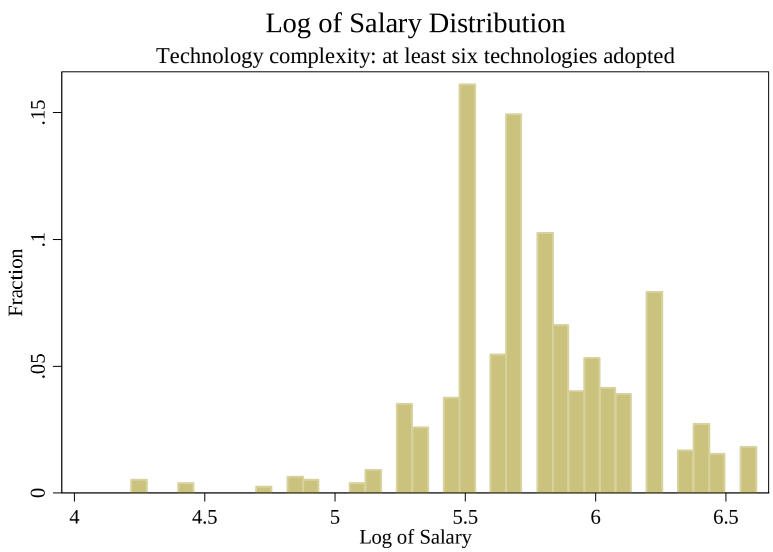


Table 3. Characteristics of Employees and farms in the U.S. Hog Industry.

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	3.752	(2.007)	5.281	(1.919)	3.415	(1.864)

* 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 110.4758 respectively. *lnW* is the natural log of the real 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)**	(2.69)**
Edu12	0.211	0.200	0.204	0.225
	(2.71)**	(2.63)**	(2.71)**	(2.37)*
Edu14	0.353	0.332	0.334	0.350
	(4.51)**	(4.35)**	(4.41)**	(3.64)**
Edu16	0.439	0.423	0.418	0.420
	(5.62)**	(5.57)**	(5.56)**	(4.42)**
Edu18+	0.745	0.784	0.764	0.710
	(7.31)**	(7.75)**	(7.62)**	(5.63)**
Age	0.044	0.042	0.042	0.044
	(5.23)**	(5.08)**	(5.09)**	(4.10)**
Age^2	-0.000	-0.000	-0.000	-0.000
	(4.35)**	(4.22)**	(4.24)**	(3.43)**
Tenure	0.003	0.007	0.007	0.005
	(0.63)	(1.58)	(1.51)	(0.97)
$Tenure^2$	-0.000	-0.000	-0.000	-0.000
	(0.64)	(1.05)	(1.10)	(0.89)
PrevExp	0.170	0.153	0.157	0.135
	(6.03)**	(5.56)**	(5.71)**	(3.84)**
Raise	-0.067	-0.064	-0.062	-0.103
	(2.50)*	(2.42)*	(2.36)*	(3.01)**
Northeast	0.053	0.071	0.062	0.077
	(0.99)	(1.32)	(1.17)	(1.08)
Southeast	0.071	0.041	0.033	0.048
	(1.89)	(1.10)	(0.89)	(0.99)
West	-0.068	-0.092	-0.088	-0.140
	(1.49)	(2.04)*	(1.97)*	(2.42)*
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)	(1.55)
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	0.258
			(14.25)**	(8.83)**
Technologies[b] >5				0.240
				(5.86)**
Constant	4.051	4.057	4.063	4.001
	(25.86)**	(26.69)**	(26.27)**	(19.36)**
Observations	3934	3934	3934	2266
R-squared	0.21	0.25	0.25	0.29

Dependent variable is natural log of salary.
Absolute value of *t* statistics in parentheses
* significant at 5%; ** significant at 1%
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.
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	-0.104	-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 (0.98)	-0.023 (0.52)			
Farm Size	0.237 (2.66)**	0.136 (0.95)	0.056 (3.06)**	0.082 (6.35)**		3.213 (0.073)	6.162 (0.013)*	3.138 (0.044)*
Farm Size^2	-0.050 (1.95)	-0.015 (0.37)	-0.001 (1.16)	-0.002 (4.01)**		2.605 (0.107)	5.414 (0.020)*	2.715 (0.066)
Size>10,000					0.210 (6.72)**			
Constant	3.888 (17.70)**	4.449 (12.43)**	3.069 (8.46)**	3.867 (18.71)**	3.863 (18.54)**			
Observations	1149	617	500	2266	2266			
R-squared	0.29	0.34	0.52	0.33	0.33			
Joint test of technologies adoptions [a]	1.65 (0.117)	1.87 (0.073)	3.96* (0.00)**	4.22* (0.00)**	3.98** (0.00)**			

Dependent variable is natural log of salary.
Absolute value of t statistics in parentheses for the column two to column six.
Column seven to nine reports the joint F test for each variable, along with the P-value in the parenthesis.
* significant at 5%; ** significant at 1%
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.

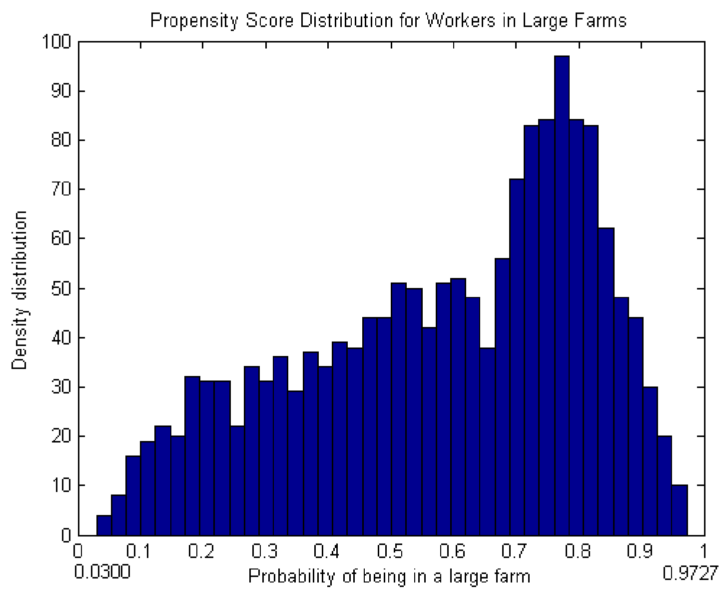
Table 6: Probit Model of Employment on Large and Small Hog Farms

Variables	Coefficient	t-Statistic
Female	0.040	0.49
Edu12	0.186	1.73
Edu14	0.255	2.29*
Edu16	0.386	3.61**
Edu18+	-0.218	-1.53
Age	0.051	3.69**
Age^2	-0.001	-3.33**
Tenure	-0.052	-6.18**
$Tenure^2$	0.001	2.42*
PrevExp	0.205	4.30**
Raise	-0.109	-2.31*
Northeast	-0.017	-0.17
Southeast	0.696	9.83**
West	0.415	5.74**
Year 1995	0.689	12.88**
Year 2000	1.376	20.33**
Year 2005	1.571	20.69**
Constant	-1.984	-7.24**
Observations	3934	
LR $\chi^2(17)$	1200.84	

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

The data are year 1990 – 2005 surveys.

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



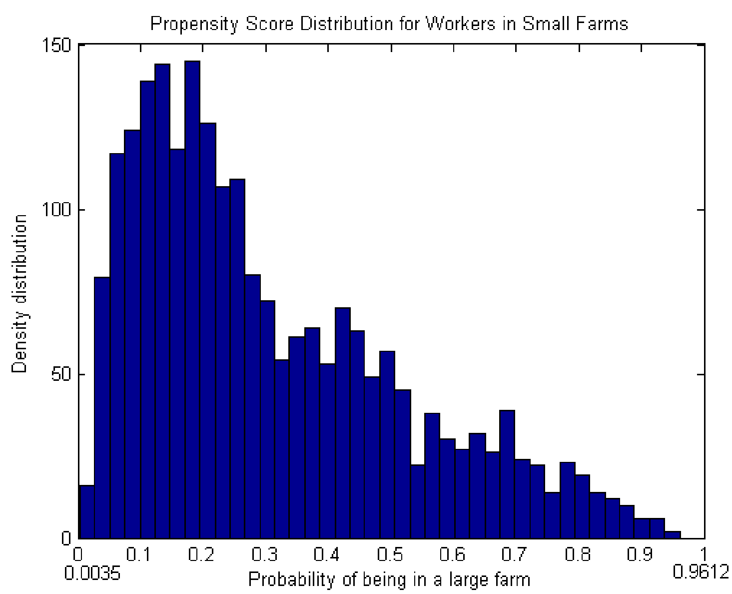


Table 7. Large Hog Farm Premium Estimated Wage[13]

	Nearest			*Caliper*			*Kernel*			Mean Log of Wage [a]	
	Premium (Log of wage)	Std Err	Premium (%)	Premium (Log of wage)	Std Err	Premium (%)	Premium (Log of wage)	Std Err	Premium (%)	D=1	D=0
7a. 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
7b. 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
7c. 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
7d. 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

The estimated mean is the difference of log of salary between large farms and small farms.

Standard error is obtained by bootstrapping 100 times.

a: weighted mean of log of wage.

[13] Table 7a, 7b and 7c use the data set in all of 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.

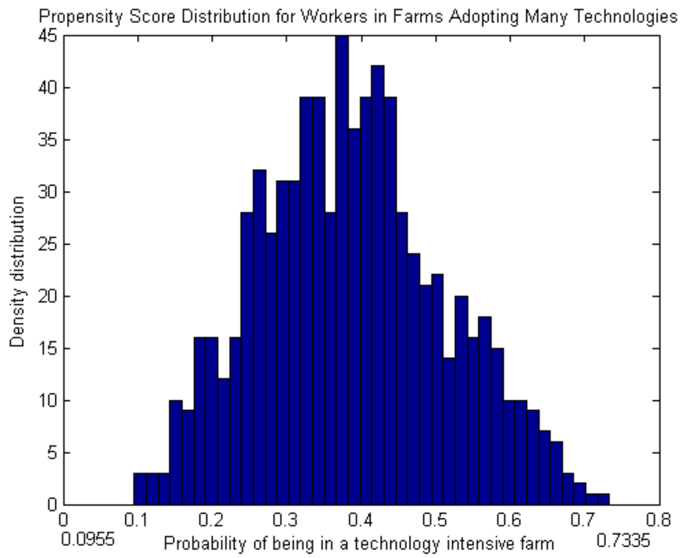
Table 8 Probit Model of Employment on Farm by Adoption of Many or Few Technologies

Variables	Coefficient	t-Statistic
Female	-0.092	-0.98
Edu12	0.352	2.27*
Edu14	0.621	3.97**
Edu16	0.810	5.33**
Edu18+	0.948	5.10**
Age	0.046	2.62**
Age^2	-0.001	-2.66**
Tenure	-0.025	-2.47**
$Tenure^2$	0.001	1.65
PrevExp	0.234	3.94**
Raise	0.054	0.93
Northeast	-0.224	-1.68
Southeast	-0.074	-0.84
West	0.220	2.53*
Year 1995	-0.456	-6.18**
Year 2000	-0.342	-4.23**
Constant	-1.588	-4.41**
Observations	2266	
LR $\chi^2(16)$	167.76	

* 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



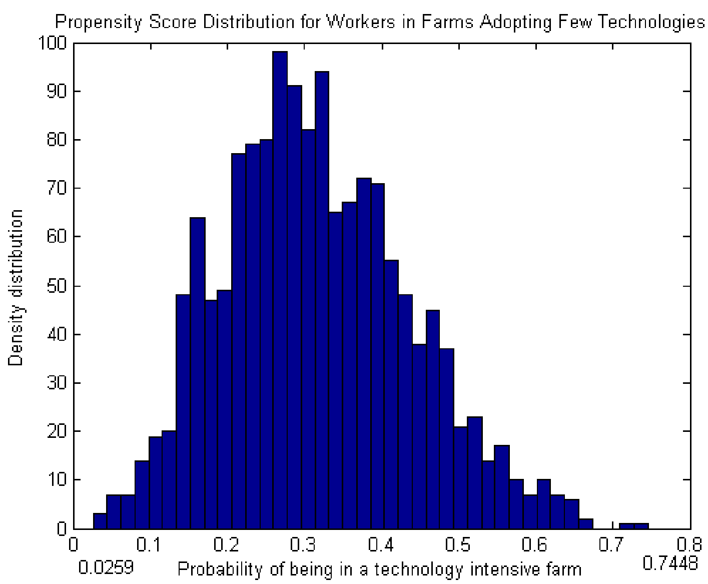


Table 9. Technology Wage Premium of Hog Farms

	Nearest			*Caliper*			*Kernel*			Mean Log of Wage [a]	
	Premium (log of wage)	Std Err	Premium (%)	Premium (log of wage)	Std Err	Premium (%)	Premium (log of wage)	Std Err	Premium (%)	D=1	D=0
9a. Estimation by education group											
Edu9	0.485	0.233	62.4%	0.470	0.089	60.0%	0.518	0.121	67.9%	6.005	4.934
Edu12	0.300	0.050	35.0%	0.308	0.026	36.1%	0.284	0.031	32.8%	5.628	5.266
Edu14	0.228	0.041	25.6%	0.263	0.033	30.1%	0.231	0.034	26.0%	5.698	5.349
Edu16	0.174	0.030	19.0%	0.204	0.026	22.6%	0.181	0.023	19.8%	5.712	5.457
Edu18+	0.251	0.137	28.5%	0.267	0.110	30.6%	0.164	0.085	17.8%	6.008	5.726
9b. Estimation by region group											
Mid-west	0.222	0.034	24.9%	0.260	0.022	29.7%	0.214	0.020	23.9%	5.740	5.334
Northeast	0.354	0.164	42.5%	0.318	0.098	37.4%	0.238	0.098	26.9%	5.625	5.438
Southeast	0.296	0.064	34.4%	0.295	0.046	34.3%	0.266	0.042	30.5%	5.890	5.484
West	0.206	0.062	22.9%	0.300	0.056	35.0%	0.253	0.056	28.8%	5.754	5.214
9c. Estimation by year											
1995	0.265	0.033	30.3%	0.293	0.024	34.0%	0.272	0.023	31.3%	5.668	5.303
2000	0.168	0.040	18.3%	0.193	0.027	21.3%	0.166	0.031	18.1%	5.710	5.433
2005	0.176	0.058	19.2%	0.237	0.039	26.7%	0.221	0.039	24.7%	5.853	5.353
9d. Estimation by farm size											
Large	0.162	0.024	17.6%	0.167	0.019	18.2%	0.151	0.017	16.3%	5.841	5.637
Small	0.217	0.062	24.2%	0.301	0.044	35.1%	0.229	0.038	25.7%	5.704	5.311

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.

a: weighted mean of log of wage.

Estimation is based on 1995, 2000 and 2005 surveys.

APPENDIX

An alternative way 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. The standard error is obtained by $Std \quad Err(\hat{\tau}) = \sqrt{\frac{\sum_{i \in I_1 \cap S_P} (\tau_i - \hat{\tau})^2 \tilde{w}(i)}{(n_1 - 1) \sum_{i \in I_1 \cap S_P} \tilde{w}(i)}}$ where $\tilde{w}(i)$ is the probability weight assigned to the individual i in the treatment group. 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 weighted probit estimation of propensity scores for the size treatment and technology treatments respectively. The size premium is 0.342(standard error of 0.015), 0.340(0.010) and 0.336 for Nearest Neighbor matching, Caliper matching and Kernel matching respectively .The technology premium is 0.119(0.021), 0.285(0.017) and 0.253 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: Weighted Probit Model of Employment on Large and Small Hog Farms

Variables	Coefficient	Statistic
Female	-0.047	-0.45
Edu12	0.077	0.59
Edu14	0.235	1.79
Edu16	0.269	2.11*
Edu18+	-0.296	-1.87
Age	0.028	1.80
Age^2	0.000	-1.54
Tenure	-0.051	-4.66**
$Tenure^2$	0.001	1.67
PrevExp	0.186	3.22**
Raise	-0.095	-1.63
Northeast	-0.161	-1.48
Southeast	0.504	5.59**
West	0.282	3.21**
Year 1995	-0.079	-1.45
Year 2000	0.682	9.38**
Year 2005	0.860	10.42**
Constant	-1.974	-6.26**
Observations	3934	
F(17, 3917)	16.98	

t statistics in parentheses

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

The data are year 1990 – 2005 weighted survives.

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

Variables	Coefficient	Statistic
Female	-0.277	-1.98*
Edu12	0.386	1.62
Edu14	0.769	3.14**
Edu16	0.911	3.90**
Edu18+	1.358	5.07**
Age	0.037	1.39
Age^2	-0.001	-1.65
Tenure	-0.003	-0.17
$Tenure^2$	0.000	-0.40
PrevExp	0.237	2.55**
Raise	0.181	2.00*
Northeast	-0.459	-2.60**
Southeast	0.031	0.21
West	0.362	2.73**
Year 2000	0.500	4.82**
Year 2005	0.688	5.91**
Constant	-2.666	-4.64**
Observations	2266	
F(16, 2250)	8.01**	

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[14]

	Nearest			*Caliper*			*Kernel*		Mean of Log Wage [a]	
	Premium (log of wage)	Std Err	Premium (%)	Premium (log of wage)	Std Err	Premium (%)	Premium (log of wage)	Std Err	D=1	D=0
			7a. Estimation by education group							
Edu9	0.441	0.119	55.4%	0.54	0.098	71.6%	0.623	.	5.533	4.96
Edu12	0.364	0.027	43.9%	0.354	0.019	42.5%	0.365	.	5.607	5.232
Edu14	0.244	0.035	27.6%	0.237	0.024	26.7%	0.201	.	5.691	5.327
Edu16	0.303	0.019	35.4%	0.332	0.014	39.4%	0.328	.	5.786	5.429
Edu18+	0.376	0.111	45.6%	0.422	0.103	52.5%	0.253	.	6.111	5.82
			7b. Estimation by region group							
Mid-west	0.301	0.018	35.1%	0.300	0.013	35.0%	0.301	.	5.712	5.332
Northeast	0.083	0.103	8.7%	0.074	0.086	7.7%	0.164	.	5.596	5.396
Southeast	0.327	0.031	38.7%	0.328	0.029	38.8%	0.311	.	5.775	5.465
West	0.636	0.044	88.9%	0.604	0.036	82.9%	0.496	.	5.749	5.298
			7c. Estimation by year							
1990	0.333	0.031	39.5%	0.395	0.02	48.4%	0.387	.	5.694	5.304
1995	0.234	0.023	26.4%	0.286	0.017	33.1%	0.302	.	5.673	5.32
2000	0.232	0.029	26.1%	0.254	0.02	28.9%	0.259	.	5.727	5.427
2005	0.351	0.038	42.0%	0.406	0.031	50.1%	0.369	.	5.763	5.415
			7d. Estimation by the often used individual technologies							
AI	0.221	0.017	24.7%	0.204	0.013	22.6%	0.203	.	5.748	5.568
PF	0.286	0.023	33.1%	0.329	0.016	39.0%	0.327	.	5.811	5.445
AIAO	0.319	0.02	37.6%	0.338	0.013	40.2%	0.339	.	5.792	5.432
FM	0.286	0.017	33.1%	0.260	0.012	29.7%	0.256	.	5.745	5.491
CU	0.333	0.017	39.5%	0.344	0.012	41.1%	0.334	.	5.757	5.429

a: weighted mean of log of salary.

[14] Table 7a, 7b and 7c use the data set in all of 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]	
	Premium (log of wage)	Std Err	Premium(%)	Premium (log of wage)	Std Err	Premium(%)	Premium (log of wage	Std Err	D=1	D=0
9a. Estimation by education group										
Edu9	0.635	0.163	88.7%	0.825	0.150	128.2%	1.009	.	6.005	4.934
Edu12	0.141	0.044	15.1%	0.378	0.031	45.9%	0.355	.	5.628	5.266
Edu14	0.091	0.034	9.5%	0.271	0.027	31.1%	0.301	.	5.698	5.349
Edu16	0.064	0.028	6.6%	0.208	0.024	23.1%	0.224	.	5.712	5.457
Edu18+	0.038	0.1	3.9%	0.030	0.096	3.0%	0.028	.	6.008	5.726
9b. Estimation by region group										
Mid-west	0.094	0.024	9.9%	0.269	0.019	30.9%	0.273	.	5.740	5.334
Northeast	-0.142	0.094	-13.2%	-0.095	0.094	-9.1%	-0.127	.	5.625	5.438
Southeast	0.246	0.06	27.9%	0.378	0.050	45.9%	0.386	.	5.890	5.484
West	0.103	0.055	10.8%	0.184	0.051	20.2%	0.139	.	5.754	5.214
9c. Estimation by year										
1995	0.162	0.029	17.6%	0.284	0.026	32.8%	0.308	.	5.668	5.303
2000	0.023	0.033	2.3%	0.159	0.030	17.2%	0.126	.	5.710	5.433
2005	0.159	0.045	17.2%	0.317	0.040	37.3%	0.306	.	5.853	5.353
9d. Estimation by farm size										
Large	0.135	0.019	14.5%	0.148	0.014	16.0%	0.155	.	5.841	5.637
Small	0.124	0.057	13.2%	0.297	0.043	34.6%	0.213	.	5.704	5.311