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

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This study investigates worker shares of the returns to scale and returns to technology adoption on U.S. hog farms. The wage analysis controls for a matching process by which workers are linked to farms of different sizes and technology uses. Using four surveys of employees on hog farms collected in 1990, 1995, 2000, and 2005, we find persistent large wage premiums are paid to workers on larger farms and on technologically advanced farms that remain large and statistically significant even after controlling for differences in observable worker attributes and in the observed sorting process of workers across farms.

Key words: economies of scale, firm size, hogs, propensity score matching, technology, wage premiums

Introduction

The positive relationship between wages and firm size first discovered by Moore (1911) is a long-standing puzzle in labor economics.[1] Large firms pay 15% more than small firms for observationally equivalent workers in the United States (Lluis, 2009). A significant size-wage effect remains even after controlling for workers' observed characteristics—such as education, work experience, gender, and geographic location—and further correcting for wage differences due to unobserved abilities. Hurley, Kliebenstein, and Orazem (1999) found a comparable wage premium related to operation size in a cross section of hog farms in 1995.

Having accounted for supply-side explanations, various labor demand-side explanations have been advanced to explain the size-wage premium. These include the hypothesis that larger firms employ more capital-intensive technologies, more skilled managers, more skilled workers, and more sophisticated technologies (Brown and Medoff, 1989; Troske, 1998). Larger firms may also pay efficiency wages to limit monitoring costs or to share rents from returns to scale. Each 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. More importantly, most previous empirical work has focused on data that spans industries, leading to confusion about possible sources of large firm wage advantage. If larger firms have more market power, then the positive correlation between firm size and worker marginal product may be attributable to higher product prices rather than higher productivity.

In this paper, we study the U.S. hog industry, which is characterized by a large number of producers selling virtually homogeneous output. Therefore, we can measure a size-wage premium

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

that is independent of variation in output price. Absent the confusion associated with price variation, wage differentials in this market must be attributable to measured or unmeasured productive efficiencies.

Several explanations for the size-wage premium involve the interaction between technology and workers' skills. Large firms tend to adopt new technologies before their smaller competitors (Rose and Joskow, 1990). This suggests that the size wage advantage may reflect a temporary productive advantage that will dissipate as smaller firms adopt those technologies. More persistent wage advantages may be paid from technological advantages. Cross sectional evidence from data on manufacturing firms shows that workers in plants using more capital per worker, more intensive research and development, and more information technologies were paid more than comparable workers in firms lacking those investments (Krueger, 1993; Reilly, 1995; Dunne and Schmitz, 1995; Troske, 1998; Dunne et al., 2004). The hog industry has experienced several technological shocks since 1990. Total factor productivity expanded steadily, with most of the growth due to technological advances and increases in scale of operation (Key and McBride, 2007). The largest farms were the heaviest technology adopters and employed the most educated labor (Key and McBride, 2007). They also paid the highest wages in 1995 (Hurley, Kliebenstein, and Orazem, 1999).

This paper explores whether size-wage and technology-wage premiums can be explained by the observed differences in skill levels among firms, whether they exist at all skill levels, and whether the premiums persist over time. We use a general equilibrium model based on Roback (1982) to show how equilibrium wages for identical workers can differ between farms of different scales or technology adoption intensities. The results indicate that workers are rewarded for their higher productivity from working on bigger farms with superior technologies compared to their observationally equivalent counterparts elsewhere in the same market.

Farm Size, Technology and Wages

We begin by illustrating the relationship between wages, farm size and technology adoption under a simple general equilibrium framework based on Roback (1982). Competitive equilibrium requires that all firms have zero economic profits, and so any productivity advantage enjoyed by large firms must be offset by cost disadvantages elsewhere, most plausibly in the form of higher labor and/or land costs. Adapting Roback's model to hog production, we assume that each farm can support a minimum efficient scale, s, which reflects a natural endowment related to local topography, water availability, weather, and land quality. As an example, areas most amenable to large farms will be more distant from populated areas and have flat topographies with nonporous soils that limit nutrient runoff. For simplicity, we let s vary continuously with support (s_1, s_2). There are two types of goods: hogs H and land L. Hogs are traded competitively on national markets so that hogs are priced equally. But land is a non-movable good and is traded locally.

In equilibrium, unit cost is equal to the hog market price, which is assumed to be unity.

$$C(w, r; s) = 1. \tag{1}$$

The unit price holds for all farms to reflect free entry and exit in a competitive market, even though larger farms (i.e., big s farms) may have higher levels of total factor productivity than smaller farms. That productivity advantage will increase the profitability of farm land with big s endowments, and land price r will be bid upward.

It is unlikely that land rents will capture all of the value of increased land productivity. If some workers have skills that complement farm size s, then farmers will have to bid to attract such workers to their farm. As the importance of these complementarities between farm size and worker skill increases, skilled workers will capture more of the productivity rents in higher wages, w.[2]

[2] These complementary skills may be observable (education, experience) or unobservable (ambition, reliability) to the econometrician. The key is that the productivity occurs because of the match between the worker and the farm size. An analogous argument holds for the complementarity between a worker's skills and technological complexity.

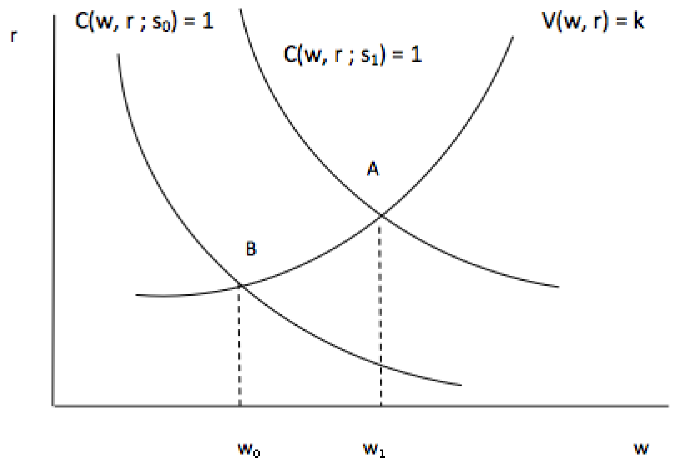

Figure 1: Equilibrium Wage and Rent on Large- and Small-Scale Farms

Workers obtain utility from consumption financed by higher wages, but higher land rents raise their costs of living. The workers' indirect utility function is:

(2) $$V(w,r;\boldsymbol{X}) = k$$

where $\boldsymbol{X}$ is a vector of observed workers' characteristics and utility rises in w and falls in r. In the initial formulation, we assume that workers have no preference for working on larger versus smaller farms, and so indirect utility does not vary with s.[3]

Figure 1 shows the resulting equilibrium. A farmer would be indifferent between locating in a place endowed with a large minimum efficient scale (s_1) but having to pay higher land prices and wages versus locating in a place with a smaller minimum efficient scale endowment (s_0) and paying lower wages and land rents. Note that in both areas, a negative tradeoff exists between wages and land rents from the farms' perspective so that if rents do not capture all land productivity, worker's wages will be bid higher. As illustrated in figure 1, equilibrium values for w and r, as determined by equations (1) and (2), both increase with a farm's scale of operation s. So farms with more efficient production, measured by endowed production scale or technology complexity, will pay higher wages w_1 and bid up local rents r_1.

In principle, we would want to estimate the effect of farm scale on wages by comparing how much the same worker would be paid at point A on the larger farm versus working at point B on the smaller farm. While we only observe workers on a single farm, we can approximate the ideal measure by comparing wages between observationally equivalent workers on large and small firms. If workers have no preference over the scaling parameter s, as our tests will confirm, the Roback model can be approximated by the Propensity Score Matching approach. Then, given a sample of workers on large farms locating at points such as A, we can generate a paired sample of workers with the same estimated probability of locating at A but that work at points such as B. The size-wage differential will be the difference in wages offered on the large and small farms.

Data and Trends

The dataset is a series of surveys conducted in 1990, 1995, 2000 and 2005 from a random sample of subscribers to *National Hog Farmer Magazine*. The surveys include hog farms with various

[3] We will relax the assumption that workers have no preferences over farm size later in the paper to illustrate how the assumption affects the empirical measurement of the size-wage premiums.

specializations that could affect their equilibrium wage premiums. For example, farrowing farms use artificial insemination technology to produce piglets, but finishing farms that purchase feeder pigs do not use artificial insemination. We restrict our sample to farrow-to-finish farms to insure a homogeneous set of observations.[4]

Subscribers to *National Hog Farmer Magazine* are not a representative sample of all hog farm employees, and the propensity to respond to surveys may also differ by farm size. Hence, the survey data are weighted to conform to the size distribution of employees on U.S. hog farms. Sample weights are based on the Agricultural Census Data of the U.S. Department of Agriculture (USDA). To be consistent with USDA classifications, each hog farm in the 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. 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 the sample is s_j. Each worker is then assigned a probability weight $\frac{n_j}{s_j}$.[5]

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. Size categories varied across surveys, but it is nevertheless clear that the employment share of the largest farms has risen dramatically. The employment share on farms producing more than 10,000 hogs rose from 6.5% in 1990 to 21.4% in 2005. In contrast, the employment share on farms producing fewer than 5,000 pigs fell from 81% to 46%.

A size-wage pattern similar to that found in other labor markets is apparent in the relationship between salaries and size of operation.[6] Figure 2 shows the log salary distribution on small, medium, and large hog farms. The log salary distribution is skewed to the right for farms producing fewer than 10,000 pigs per year. In contrast, the wage profile for farms producing more than 10,000 pigs a year is heavily weighted toward the upper tail of the distribution. As size increases, the median log salary moves to the right while wages disappear from the lower tail of the salary distribution.

The rapid increase in market share for large farms coincides with rapid technology adoption in the industry. The information about technology adoption measures and description summarized in appendix table A1 is only available for 1995, 2000, and 2005. The list of relevant technologies was developed in consultation with the National Pork Producers Council who helped fund the survey. The last two columns of table 1 indicate that farms with fewer than 500 hogs use an average of three technologies while those producing over 10,000 hogs use at least five technologies. Farms over 25,000 head use an even larger numbers of technologies. Farm wages are correlated with the number of technologies employed on the farm. As shown in the lower panel of figure 2, farms using at most five of the technologies have log salary distributions weighted toward the lower tail of the observed range. Farms using six or more technologies had salary distributions 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 by smaller and larger farms.

Characteristics of workers and farms are presented in table 2. Hog farm workers are more educated than average for the U.S. labor market as a whole: 85% have completed at least high

[4] As it turns out, we get substantially similar results when we use the full sample of firms, presumably because firms have the choice of farm type. As a result, even finishing operations that do not have a farrowing operation have the option of adding that to their production mix. If true, then they are in the same market as farrow-to-finish operations and do not need to be excluded.

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

[6] Most studies in the literature use employment to measure employer size. However, we only have information about the number of full time employees on farms, with many missing observations. Furthermore, farms tend to differ in employing full-time and part-time workers in a different proportion, which will generate inconsistent measures of employer size. We adopt output to measure farm size, which is an alternative way to measure firm size, as noted by Oi and Idson (1999).

Table 1: Distribution of Hog Farm Employees and Technology Adoption Intensities on by Year and Farm Size

		Weighted Frequencies (%)				Number of Technologies	
Code	**Size Class (pigs/year)**	**1990**	**1995**	**2000**	**2005**	**Mean**	**Std. Dev.**
1	Less than 500	12.8%	6.2%	2.9%	.	3.01	2.26
2	500 to 999 / less than 1000 in 2005	15.8%	13.1%	3.5%	13.4%	2.92	1.60
3	1,000 to 1,999	26.5%	23.9%	7.2%	10.6%	2.70	1.81
4	2,000 to 2,999	15.6%	28.8%	23.1%	8.8%	3.54	1.79
5	3,000 to 4,999	10.7%	10.2%	17.1%	13.3%	4.27	1.84
6	5,000 to 9,999	12.1%	11.6%	28.0%	32.5%	4.15	1.72
7	10,000 or more (1990) /10,000 to 14,999 (1995)	6.5%	1.7%	4.4%	2.9%	4.88	1.55
8	15,000 to 24,999	·	1.4%	3.1%	2.2%	5.31	1.70
9	25,000 or more / 25,000 to 49,999 (2005)	·	3.1%	10.9%	3.5%	5.94	1.54
10	50,000 to 99,999(2005)	·	·	·	2.0%	5.82	1.65
11	100,000 or more (2005)	·	·	·	10.8%	6.11	1.73

Notes: Dot (·) represents categories not asked in the survey.

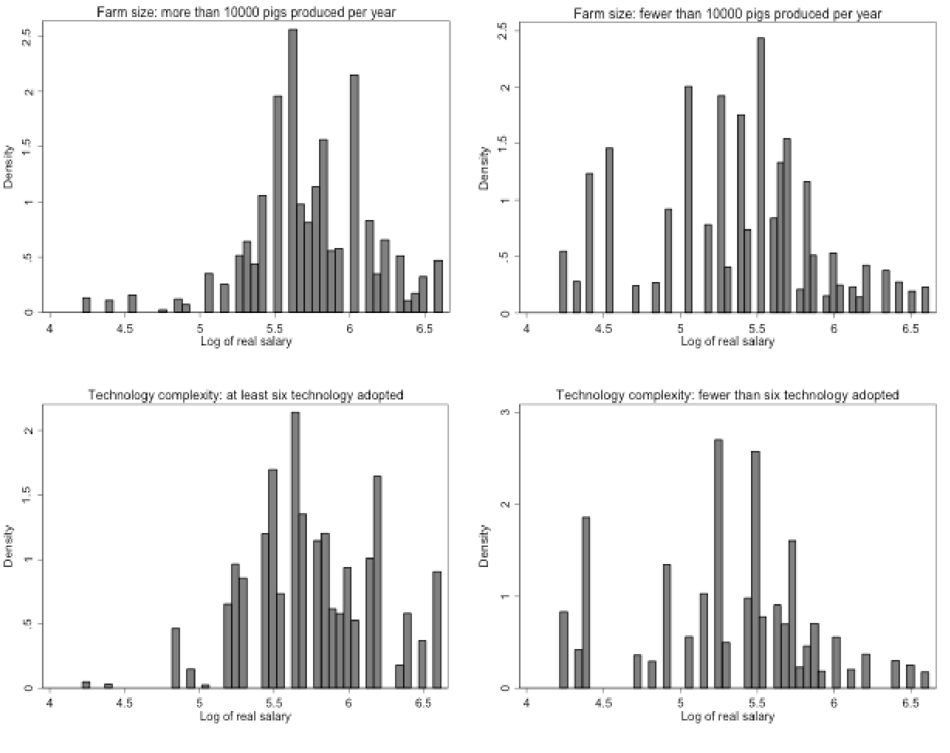

Figure 2: Log of Salary Distribution by Size and Technology Adoption

school and nearly 42% have at least a four-year university degree. It is likely that we under-sample the lower tail of the skill distribution, particularly workers who do not read, write, or speak English and would therefore be unlikely to subscribe to *National Hog Farmer Magazine (NHFM)*.

Table 2: Characteristics of Employees and Farms in the U.S. Hog Industry

		Full Sample		Large Farms		Small Farms		Farms with More Technologies		Farms with Fewer Technologies	
Variable	**Description**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
$\ln W$	Log of salary	5.40	0.54	5.74	0.40	5.36	0.54	.	.	.	.
$\ln W$a	Log of salary	5.42	0.55	5.75	0.40	5.37	0.55	5.76	0.41	5.33	0.54
Female	Gender of workers	0.08	0.28	0.11	0.31	0.08	0.27	0.06	0.25	0.10	0.30
Edu12	High school graduate	0.31	0.46	0.26	0.44	0.32	0.47	0.20	0.40	0.32	0.47
Edu14	2 year college diploma or equivalent	0.20	0.40	0.21	0.41	0.20	0.40	0.21	0.41	0.20	0.40
Edu16	4 year university degree or equivalent	0.33	0.47	0.40	0.49	0.33	0.47	0.40	0.49	0.32	0.47
Edu18+	Higher degree education level	0.09	0.28	0.06	0.24	0.09	0.28	0.18	0.38	0.08	0.27
Age	Age of workers	36.31	10.66	36.26	9.86	36.32	10.75	37.73	10.39	37.23	10.85
Tenure	Experience in the current farm	9.33	8.01	6.89	6.15	9.63	8.16	8.10	7.14	9.46	8.00
PrevExp	Binary, =1 if worked on a hog farm before	0.38	0.49	0.50	0.50	0.36	0.48	0.56	0.50	0.36	0.48
Raise	Binary , =1 if raised on a hog farm	0.54	0.50	0.43	0.50	0.55	0.50	0.50	0.50	0.51	0.50
Northeast	Binary, =1 if located in the northeast	0.08	0.28	0.06	0.23	0.09	0.28	0.02	0.14	0.11	0.31
Southeast	Binary, =1 if located in the southeast	0.14	0.34	0.19	0.39	0.13	0.34	0.16	0.36	0.13	0.34
West	Binary, =1 if located in the west	0.17	0.38	0.25	0.43	0.16	0.37	0.26	0.44	0.15	0.36
Farm Size	Number of pigs produced per year (unit: 10,000 heads)	0.62	1.20	3.19	2.29	0.31	0.25	.	.	.	.
Farm Size[a]		.	.	.	.	.	.	1.64	2.20	0.53	0.97
Number of technologies	Number of technologies used per year	3.81	1.98	5.65	1.67	3.53	1.87	6.64	0.75	3.02	1.41

Notes: Numbers in the parentheses are standard deviations. Salaries are discrete categories in the survey. We define salary as a continuous variable by taking the mid-point of the range for each category, adjusted by the consumer price index (CPI) from the Labor Statistics Bureau. CPI in 1990, 1995, 2000 and 2005 were 79.9975, 91.2177, 98.8768 and 110.4758, respectively. $\ln W$ is the natural log of the adjusted real annual salaries. Education variables are dummies based on high school dropout. Higher degree includes a master degree, a Ph.D. degree or a Doctor of Veterinary Medicine. Farms producing 10,000 or more pigs each year are large, otherwise small. a Statistics of the variable are based on surveys in 1995, 2000 and 2005.

Workers on hog farms have considerable experience. Average tenure at the current hog farm is 9.3 years, with 38% having had experience working on other hog farms and 54% growing up on a hog farm. Workers on larger and more technologically advanced farms are better educated and have more prior experience but have spent less time at their current farms and are less likely to have been raised on a hog farm.

Worker Returns Measured Using Propensity Score Matching

The inference from figure 2 and table 2 is that workers on larger farms are paid higher wages. We quantify the return to scale or technology adoption intensity 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 large farms and small farms based on their propensity scores. After matching, workers across farms can be viewed as being drawn from observationally equivalent distributions. The difference in wages between groups is the wage premium paid on large farms.

This strategy corresponds exactly to the variant of the Roback model sketched in figure 1. If workers' tastes are not conditioned on farm size, s, the comparison of wages between points A and B reflects the wage differential of added productivity associated with larger farm size. Workers of like observable skills are indifferent between the high wage-high rent jobs and the lower wage-lower rent jobs.

Note that because we calculate the wage differences for observably equivalent workers, we could also use a least squares approach to obtain returns to farm size or technology adoption. However, PSM has a critical advantage over least squares for our purposes.[7] PSM enables computation of returns at many points in the distribution of skills or the distribution of other relevant personal attributes rather than at a single point in the distribution of these worker characteristics. In this context, we have a particular interest in comparing the wages of observationally equivalent workers on large and small farms at various education levels, regions, time periods, and technologies as opposed to relying on a single estimated wage effect based on least squares.

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: $U = U(\boldsymbol{X}, \boldsymbol{V}_U)$, where $\boldsymbol{X}$ is a vector of observed workers' characteristics and $\boldsymbol{V}_U$ is a vector of unobservable factors. [8] Workers self select into the large farms $D = 1$ and receive the log wage $\ln W_1$ if $U > 0$; and are otherwise employed on small farms, $D = 0$ and paid $\ln W_0$. Subscripts 1 and 0 denote large and small farms respectively.

$$\ln W_1 = f(\boldsymbol{X}, V_1); \tag{3a}$$

$$\ln W_0 = f(\boldsymbol{X}, V_0); \tag{3b}$$

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

We seek to measure the treatment effect on the treated: $E(\ln W_1 - \ln W_0 | D = 1, \boldsymbol{X})$. $E(\ln W_1 | D = 1, \boldsymbol{X})$ on the large farms is known. However, the counterfactual, $E(\ln W_0 | D = 1, \boldsymbol{X})$, defined as the expected wage an individual on a large farm ($D = 1$) would receive if employed on a small farm ($D = 0$), is not readily available and must be constructed by matching. We observe the selection process into large and small farms and so the probability of being hired by a large farm, $\Pr(D = 1 | \boldsymbol{X})$, is known. Matching is based on the propensity score:

$$P(X_i) = \Pr(\mathrm{D_i} = 1 | \boldsymbol{X}_i); \quad 0 < \mathrm{P}(\boldsymbol{X}_i) < 1 \quad \text{for individual } i. \tag{4}$$

[7] Angrist and Pischke (2009) give an excellent review of Propensity Score Matching methods and necessary assumptions. Blundell, Dearden, and Sianesi (2005) and Jalan and Ravallion (2003) present two alternative applications of PSM methods.

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

According to Rosenbaum and Rubin's (1983) ignorability of treatment assumption, if: (i) $0 < P(\boldsymbol{X}_i) < 1$; and (ii) outcomes (in this case wages) are independent of D_i given $\boldsymbol{X}_i$. Using $\perp$ to denote independence, if $(\ln W_{1i}, \ln W_{0i}) \perp (D_i|\boldsymbol{X}_i)$, then the $\ln W$ is also independent of D_i conditional on the propensity score $P(\boldsymbol{X}_i)$, $(\ln W_{1i}, \ln W_{0i}) \perp (D_i|P(\boldsymbol{X}_i))$.[9] This allows us to construct the counterfactual mean: $E(\ln W_0|D=1, P(\boldsymbol{X})) = E(\ln W_0|D = P(\boldsymbol{X}))$.

Under the maintained hypothesis of independence, individuals in the two groups sharing the same probability of working on a large farm can be viewed as being drawn from the same universe. Under the maintained ignorability hypothesis, exact matching on $P(\boldsymbol{X}_i)$ will eliminate the bias caused by unobserved individual heterogeneity across the samples of workers in large and small farms. Therefore, we can control systematic differences, if any, in the average quality of workers in small as opposed to large farms. The difference in wages between groups is the wage premium paid on large farms or on farms with intense technology complexity, which is associated with productivity gain enjoyed in such farms.

Matching

Farm scale is measured categorically in the survey, as shown in table 1. To facilitate the analysis, we define the binary outcome D_i as follows: $D_i = 0$ when farm *i* produces no more than 10,000 pigs and these farms are designated as "small farms;" $D_i = 1$ when farm *i* produces more than 10,000 pigs and those are designated "large farms."[10] The 10,000 hog cutoff between large and small over the sample period reflects the dramatic change in farm size over the period. Farms with fewer than ten thousand hogs had a 78% market share in 1991, but only a 15% market share in 2006 (Lawrence and Grimes, 2007). We estimate the propensity scores as the fitted values of a probit model that predicts the probability that each individual works on a large hog farm. The probability of technology adoption is widely studied in the context of a human capital investment model.[11]

The Roback employment model implies that individuals choose to work on large or small farms based on a vector of observable characteristics $\boldsymbol{X}$. There are some notable differences in worker attributes between large and small farms, in addition to the wage and technology differences discussed. Our survey, as shown in table 2, includes detailed measures of worker skills such as education levels and work experience specific to the pork sector: tenure on the current farm, prior experience on hog farms and whether the individual grew up on a farm. To the extent that these skills complement new technologies, we would expect that workers with more skills tend to work on farms with intensive technologies. Propensity to work on large farms is less commonly examined, but we would expect that if scale can be viewed as another form of technology, incentives to work on large farms would mimic the incentives to adopt other technologies. The data presented in table 2 indicate that 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. Further, workers on large farms are more likely to have prior experience on other hog farms and employees on small farms are more likely to have been raised on a farm.

The estimated probit models of farm employment sorting are shown in table 3. The left model presents the less common equation explaining sorting into large scale farms. The most important factor explaining employment on large farms is time, as the probability of working on large farms rises as the market share of those farms increased. There was no clear pattern of employment on large farms by worker's education except that postgraduate degree holders were less commonly

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

[10] Our use of a binary definition of farm size may raise a concern that alternative cutoff points would yield different results. As an alternative, we divided farms into three farm size categories: small farms producing less than 10,000 pigs per year; medium farms producing between 10,000 and 25,000 pigs and large farms producing more than 25,000 pigs per year. We dropped the medium-sized farms and compared wages between the largest and smallest farms applying the Propensity score matching model. The implied size-wage premium is even larger than that reported in table 4.

[11] See Huffman (2001) for a comprehensive review of the incentives for an individual to adopt agricultural technologies.

Table 3: Probit Model of Employment on Large and Small Hog Farms / on Farm by Adoption of Many or Few Technologies

	Probit on Farm Size		Probit on Technology Complexity	
Variable	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
Female	0.13	0.99	−0.36*	−1.94
Edu12	−0.04	−0.23	0.87***	3.56
Edu14	0.16	0.97	1.23***	4.75
Edu16	0.15	0.91	1.24***	5.14
Edu18+	−0.37*	−1.76	1.54***	5.23
PrevExp	0.27***	3.78	0.40***	3.27
Raise	−0.21***	−2.85	0.05	0.40
Northeast	−0.24*	−1.69	−0.79***	−3.95
Southeast	0.29***	2.60	0.08	0.40
West	0.27***	2.67	0.32*	1.87
Year 1995	−0.05	−0.75	0.60***	4.14
Year 2000	0.52***	5.40	0.59***	3.76
Year 2005	0.76***	7.44	−2.43***	−8.99
Constant	−1.65***	−9.43	−0.36*	−1.94
Observations	2198		1171	
LR $\chi^2(13)$	125.9			
LR $\chi^2(12)$			88.0	

Notes: The dependent variable in the left model is a dummy variable indicating employment on a farm producing 10,000 or more hogs. The dependent variable in the right model is a dummy variable indicating employment on a farm using six or more technologies. The data cover the 1995 - 2005 surveys. Single, double, and triple asterisks (*, **, ***) denote variables significant at 10%, 5%, and 1% level.

found on the largest farms. Workers with more prior experience select larger farms. These findings are consistent with results reported by Key and McBride (2007). The second model presents a more traditional equation reflecting employment on technologically advanced farms. Consistent with standard results in the human capital literature (Huffman, 2001), propensity to adopt newer technologies rises monotonically with schooling and with previous hog farm experience.

Matching on fitted probabilities $\hat{P}(\boldsymbol{X}_i)$ appears to work quite well. As seen in figure 3, there is substantial overlap in the distributions of the estimated propensity scores $\hat{P}(\boldsymbol{X}_i)$ for workers on large and small farms, and so for every employee on a large farm there is a comparison group in which an observably equivalent employee works on a small farm but has a similar propensity score. The average probability of working on a large farm for those who actually do work on a large farm is 0.17. The average probability of working on a large farm for those who actually work on a small farm is 0.10.

Applying Smith and Todd's (2005) approach, the size impact estimator takes the form:

$$\hat{\tau} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} [\ln W_{1i} - \ln \hat{W}_{0i}];$$

$$\ln \hat{W}_{0i} = \sum_{j \in I_0} \hat{w}(i,j) \ln W_{oj}; \tag{5}$$

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 control sample 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. Many matching methods could be employed, all of which generated similar results.[12] We focus on the nearest neighbor matching method, both

[12] Results using caliper matching and kernel matching methods are available from the authors on request.

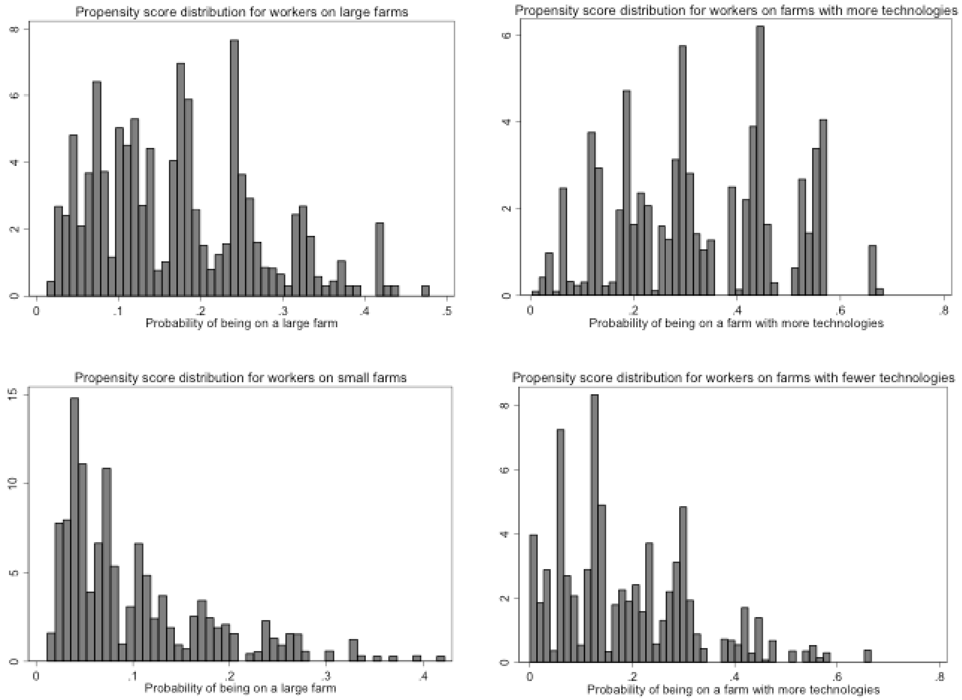

Figure 3: Propensity Score Distribution by Farm Size (left panel) and Technology Adoption (right panel)

because of its transparent simplicity and because it easily accommodates weighted samples which are important for our application. Distance weights are computed as:

$$\hat{w}(i,j) = \begin{cases} 1 & j = argmin_{k \in I_D} \mid\mid \hat{P}(\boldsymbol{X}_i) - \hat{P}(\boldsymbol{X}_k) \mid\mid \\ 0 & otherwise \end{cases} .$$

Matching is with replacement in the control group in order to reduce the bias and avoid the deterioration in match quality (Dehejia and Wahba, 2002).

Estimated Size- and Technology-Wage Effects Using Matching Estimators

Using the sample of farrow-to-finish farms, the average size-wage effect in terms of log of real wage is 0.245, implying that the salary paid on the largest farms is about 27.8% higher than that on small farms for observationally equivalent workers. The size-wage gaps are not identical across various demographic and skill groups, but they are consistently positive and large. As shown in table 4, the size-wage premium is large for all but the most educated workers, although not always statistically significant. Holders of post-graduate degrees appear to be paid equally across all farm sizes, a finding consistent with the lack of incentive for that group to locate on the largest farms implied by the information presented in table 3. The size-wage premium estimate is large in all regions of the country, but not precisely estimated for workers in the Northeast. There is no evidence that the premium is decreasing over time. The size wage premium varies across technologies, suggesting that some production methods are more complementary with farm size. Workers on large farms that have adopted Phase Feeding receive wage premiums of around 30% over comparable workers on small farms that employ the same technologies. The smallest size-wage premium of 15% is associated

Table 4: Estimated Wage Premium on Hog Farms Producing 10,000 or More Hogs, by Worker and Farm Attributes

	Nearest Neighbor Match			Mean $\ln W$	
	Premium ($\ln W$)	Std. Err.	Premium (%)	D = 1	D = 0
		4a. Estimation by education			
Edu9	0.22	0.16	24.3%	5.55	4.83
Edu12	0.31	0.05	36.8%	5.61	5.25
Edu14	0.24	0.07	26.7%	5.68	5.37
Edu16	0.24	0.05	26.8%	5.82	5.44
Edu18+	−0.04	0.13	−3.7%	6.17	5.84
		4b. Estimation by region			
Midwest	0.18	0.04	20.1%	5.69	5.35
Northeast	0.18	0.12	19.8%	5.64	5.43
Southeast	0.32	0.07	37.7%	5.84	5.47
West	0.29	0.11	33.4%	5.79	5.27
		4c. Estimation by year			
1990	0.26	0.04	29.9%	5.66	5.33
1995	0.26	0.07	29.1%	5.76	5.44
2000	0.20	0.14	22.0%	5.80	5.41
2005	0.32	0.04	37.8%	5.69	5.33
		4d. Estimation by technology adoption			
AI	0.15	0.05	15.6%	5.76	5.56
PF	0.27	0.04	31.3%	5.82	5.42
AIAO	0.24	0.05	27.6%	5.81	5.43
FM	0.22	0.04	24.4%	5.76	5.50
CU	0.23	0.03	25.5%	5.76	5.43

Notes: The estimated mean is the difference of log of salary between large farms and small farms. Tables 4a, 4b and 4c use the data set in all four survey years. All results about technologies in table 4d uses the data in 1995, 2000 and 2005 except Formal Management, which uses all four survey data sets.

with artificial insemination, which is also the most commonly employed technology across farm sizes.

The move from predominantly small to predominantly large hog farms between 1990 and 2005 is associated with persistent wage incentives for workers to shift to the larger farms. These larger farms have considerable cost advantages per hundredweight over more traditionally sized farms (Lawrence and Grimes, 2007). Apparently workers are able to extract some of the returns from the productivity advantages in the form of higher wages.

If workers are rewarded for their improved productivity on large farms, they must be rewarded for the sources of productive advantage, such as the use of more advanced technologies. Hence, if technologies raise farm productivity, some of the inframarginal rents earned by adopting technologies in the early stages of diffusion may be shared with the workers. Again, we need to control for individual attributes that sort workers into high and low technology farms that could confound any estimates of the returns to technology use.

Table 5: Estimated Wage Premium on Hog Farms Using Six or More Technologies, by Worker and Farm Attributes

Variable	Nearest Neighbor Match			Mean $\ln W$	
	Premium ($\ln W$)	**Std. Err.**	**Premium (%)**	**D = 1**	**D = 0**
		5a. Estimation by education			
Edu9	0.14	0.23	15.2%	5.73	4.79
Edu12	0.32	0.05	38.1%	5.64	5.26
Edu14	0.23	0.05	26.0%	5.73	5.33
Edu16	0.18	0.05	20.2%	5.71	5.46
Edu18+	0.09	0.17	9.4%	6.05	5.70
		5b. Estimation by region			
Mid-west	0.20	0.03	22.4%	5.72	5.33
Northeast	0.15	0.14	15.9%	5.86	5.45
Southeast	0.32	0.08	37.8%	5.88	5.44
West	0.24	0.09	26.8%	5.77	5.11
		5c. Estimation by year			
1995	0.28	0.03	31.8%	5.70	5.29
2000	0.17	0.06	18.9%	5.68	5.40
2005	0.19	0.08	20.6%	5.92	5.34
		5d. Estimation by farm size			
Large	0.15	0.04	16.6%	5.84	5.63
Small	0.19	0.06	21.3%	5.72	5.30

Notes: The first column under each matching method is the difference of log of salary between farms adopting many and few technologies. Estimation is based on 1995, 2000 and 2005 surveys.

In this application, the binary outcome D_i indicates that a worker is on a technology-intensive farm, defined as using at least six advanced technologies.[13] As shown in table 2, average number of technologies used on the more technology-intense farms is more than twice the average on the less intense farms when this cutoff is used.[14] Since 1995, farms have increasingly employed workers who operate on technology intensive farms. The probit model used to predict the propensity score for each observation is shown in the right-hand columns of table 3. Farms employing more educated and experienced workers are the most likely to be heavy adopters of technologies, and the likelihood of heavy technology adoption increases over time. The histograms on the right side of figure 3 show substantial overlap in the propensity score distributions, and so we have good comparisons for workers employed on the technologically intensive farms.

The same matching methods yield a technology wage effect of 0.220. Hence, the implied salary differential paid on the technology intensive farms averages 25%. As shown in table 5, the magnitude of the technology-wage premium varies across skill and demographic groups but is always positive. The largest technology-wage premiums correspond to the largest size-wage premiums. The largest

[13] The use of technology counts is most appropriate when technologies are complements to one another. If the technologies are substitutes, there is no natural counting of technologies, and technological intensity would instead have to be measured by comparisons across production methods in relative capital intensity, investment costs, or embodied intellectual property. As shown in Yu et al. (2012), technologies used in pork production tend to be complements when bundled together.

[14] As with the farm size cutoffs, we applied alternative technology cutoffs to check the robustness of our results with similar outcomes. For example, we define three levels of technology complexity across farms: using no more than three technologies, using four or five technologies, and using at least six technologies. Dropping the middle group and comparing the most with the least technologically intense firms results in a larger technology-wage premium than that reported in table 5.

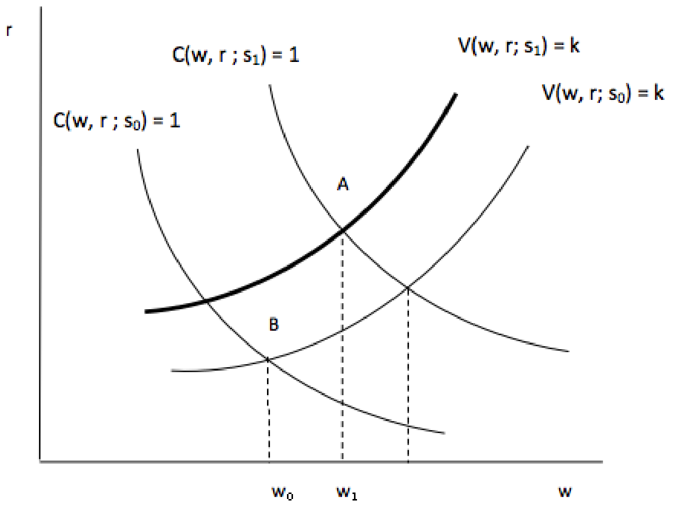

Figure 4: Equilibrium Wage and Rent on Farms of Large and Small Scale

Notes: Scale s takes two values with $s_0 < s_1$. Indirect utility function is also associated with scale s. The figure illustrates the case that there is positive utility from working on larger farms.

technology premium is earned by high school graduates; thereafter the premium declines with years of schooling. The effect points to a pervasive wage effect tied to technology adoption: average pay for a high school drop out on technologically advanced farms exceeds average pay for college graduates on farms using traditional methods.

Wage returns to more intensive technology use exceed 20% in all regions except the Northeast. The ranking of returns by region is the same for technology adoption as for farm size, with the largest premiums paid in the Southwest. The technology-wage premium trended downward modestly over time and was roughly two-thirds as large in 2005 (21%) as in 1995. Nevertheless, it was statistically significant at the end of the sample period. While large farms are more likely to adopt multiple technologies than are small farms, returns to technology use are not masking a farm size effect. Small farms that adopt technologies more intensively pay an even larger premium to attract workers than do larger, technology intensive farms. Regardless of how the sample is cut, workers earn substantial rents from the use of more technologies on hog farms. 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.

Do Workers Have Tastes for Farm Size and Technology Intensity?

Thus far, worker preferences are assumed not to vary with farm size, allowing us to claim that sorting into larger establishments is based only on observable worker attributes. However, if workers sort non-randomly across firm sizes based on unobserved worker tastes that are themselves correlated with wages, then such estimates will be biased. Extending the Roback model, an endogeneity problem occurs if the worker's indirect utility in equation (2) is of the form $V(w,t;\boldsymbol{X},s) = k$. In that case, a worker's indifference curve will shift as scale of operation increases as shown in figure 4. This could occur, for example, if workers are less satisfied in large firms than in small firms because large firms organize production in a less-flexible fashion (Idson, 1990). Alternatively, a larger s may involve working with greater hazards or environmental disamenities.

The resulting equilibrium relationship between s and w will reflect both worker tastes and productivity, and so we can no longer interpret the wage differential between points A and B in figure 1 as evidence of the presence or absence of relative efficiency on larger or more technologically advanced farms. A and B are now both on different indifference curves and different isocost lines.

One solution to the potential for non-random selection due to unobservable preference is to find instruments that shift the probability of working on a large farm but that have no direct impact on wages. Assuming that s varies due to local weather and geographic attributes, we investigated the use of local county variation in topography, January temperature, July temperature and humidity, and measured corn yields as plausible indicators of s. Wu-Hausman tests of endogeneity failed to reject the null hypotheses that farm size and technology were exogenous to wages, consistent with the maintained hypothesis underlying our matching estimates. Furthermore, the estimated effects of farm size and technology adoption become implausibly large, and much larger than the PSM estimates when the selection correction is applied. There is no evidence of nonrandom sorting of the type presumed in figure 4 that would have caused upward bias in our PSM estimates, indicating that the initial variant of the Roback model illustrated in figure 1 may be appropriate.[15]

Conclusion

This study examined evidence of the size-wage premium within a single narrowly defined industry with a competitive priced output and a commonly available mix of technologies. Zero economic profit in the competitive product market requires that the productivity advantage enjoyed by large farms or farms with technology advantages most likely must be counteracted by higher labor and/or land costs. Even in this narrowly defined hog market, there are large and persistent wage differentials favoring workers on large farms and farms with many advanced technologies. The higher wage is clearly due to increased productive efficiency and not market power. The premium is paid to all workers regardless of individual productive attributes, with the largest rewards going to the least skilled.

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

Our preferred explanation is that workers' skills complement farm size and technological complexity. For farmers to attract workers with those skills, they must bid up the cost of the needed complementary skills. These skills may be observable (education, specialized experience) or they may be unobservable to outside observers (motivation, ambition, reliability). It may be more plausible to believe that it is these unobservable skills that drive the wage premiums, particularly because we find similar wage premiums across education and experience groups.

Nevertheless, even if complementarity exists between observed skills and the technologies, we would observe a wage premium from taking a worker with the same observed skills off a smaller and less advanced farm to a larger and more advanced operation. Therefore, our results are consistent with wage premiums driven by more skilled workers employed on large scale, technologically intensive operations, whether the skills are observed or not.

However, wage premiums associated with farm size or technological complexity could result from local rigidities in the labor market.[16] If workers on smaller and remotely sited farms face large costs of job search, then those workers will not be making globally optimal job choices. In particular, their employers may be able to pay them substandard wages and the workers will not know their true opportunity wages at larger and more advanced farms. In this scenario, as illustrated in figure 4, workers are not indifferent between the two jobs but are stuck in the 'bad' job B rather than moving to the 'good' job A. Unlike the endogeneity case, however, workers preferences are not affected by the scale of operation s, but they are unable to move to their more favored outcome.

[15] Another solution to possible non-random selection into larger and more technologically advanced farms is to apply Heckman's selection correction, again using measures of topography, temperature, humidity, and corn yields as instruments. Tests failed to find significant selection bias on the wage effects of farm size or technology complexity.

[16] The authors would like to thank two anonymous reviewers for calling attention to this point.

We cannot distinguish empirically between this alternative explanation based on high search costs versus our explanation that assumes labor is freely mobile.

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Table A1: Description and Summary Statistics of Technologies in the Hog Production

Technology	Description	1995 Mean	2000 Mean	2005 Mean
AI	Artificial Insemination focuses on enhancing hog reproductive efficiency and improving the gene pools.	0.44 [0.50]	0.66 [0.48]	0.75 [0.43]
SSF	Split Sex Feeding feeds different rations to males and females. They have different diets for pigs of various weights and separate diets for gilts and barrows for maximum efficiency and carcass quality.	0.34 [0.48]	0.57 [0.50]	0.42 [0.49]
PF	Phase Feeding involves feeding several diets for a relatively short period of time to more accurately and economically meet the pig's nutrient requirements.	0.51 [0.50]	0.65 [0.48]	0.56 [0.50]
MSP	Multiple Site Production produces hogs in separate places in order to curb disease spread.	0.22 [0.41]	0.34 [0.47]	0.3 [0.46]
EW	Early Weaning helps to produce more piglets each year. It may include Segregated early Weaning technology (which gives the piglets a better chance of remaining disease-free when separated from their mother at about three weeks when levels of natural antibodies from the sow's milk are reduced), Medicated Early Weaning (which uses medication of the sow and piglets to produce excellent results in removing most bacterial infections) and Modified Medicated Early Weaning (which is same as MEW but less all-embracing. The range of infectious pathogens to be eliminated is not quite as comprehensive. MMEW can also be used to move pigs from a diseased herd to a healthy herd).	0.15 [0.35]	0.24 [0.43]	0.19 [0.40]
AIAO	All In/All Out allows hog producers to tailor feed mixes to the age of their pigs instead of offering either one mix to all ages or having to offer several different feed mixes at one time. It helps limit the spread of infections to new arrivals by allowing for cleanup of the facility between groups of hogs being raised.	0.54 [0.50]	0.63 [0.48]	0.61 [0.49]
CU	Computer usage	0.61 [0.49]	0.75 [0.43]	0.77 [0.42]
FM	Formal management	0.47 [0.50]	0.54 [0.50]	0.73 [0.44]
	Total number of technologies	3.27 [1.85]	4.38 [2.07]	4.32 [1.85]

Notes: Numbers in the parenthesis are standard deviations. Information is based on the USDA animal and plant health inspection service and ERS, http://www.thepigsite.com/, and National Hog Farmer (http://nationalhogfarmer.com/).