Sub-therapeutic Antibiotics and the Efficiency of U.S. Hog Farms

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Abstract: Antimicrobial drugs are frequently fed to hogs at sub-therapeutic levels to promote feed efficiency and growth. However, in response to concerns that sub-therapeutic antibiotics (STAs) are promoting the development of antimicrobial drug-resistant bacteria, the U.S. Food and Drug Administration recently adopted a strategy to phase out antibiotics for such "production uses." This study uses a stochastic frontier model to estimate the costs to U.S. hog producers of a ban on STAs for growth promotion. To address potential sample selection issues, we employ a recently developed empirical approach that corrects for biases from both observed and unobserved variables.

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Introduction

For many years, governmental and professional organizations have expressed concerns that the overuse of antimicrobial drugs in livestock production is promoting the development of antimicrobial drug-resistant bacteria (USFDA, 2012). Since many of the antibiotics commonly added to livestock feed and water are the same or similar to drugs used in human health care, the development of drug-resistant organisms would present a serious threat to public health. Such concerns have prompted several European countries to ban the use of antimicrobial drugs for growth promotion on hog operations. In the United State, the use of sub-therapeutic antimicrobial drugs in hog production has recently come under increasing scrutiny from public interest groups and the U.S. Food and Drug Administration (FDA). In April, 2012, the FDA implemented a voluntary strategy to promote the "judicious use" of antibiotics in food producing animals (USFDA, 2012). Among other things, the FDA asked the pharmaceutical industry to remove antibiotics for "production uses" such as feed efficiency and growth promotion from their FDA-approved product labels.[1] The objective of this study is to estimate the relationship between the sub-therapeutic use of antibiotics and U.S. hog farm productivity in order to provide information about the potential costs of a ban on antibiotics used for growth promotion.

There are a number of reasons why banning the sub-therapeutic use of antibiotics could impose economic costs on producers. Researchers have known since the 1940's that feeding antibiotics to animals at low levels results in faster growth and improved feed efficiency (Hayes, 1991). Feeding antibiotics at sub-therapeutic levels can increase nutrient absorption, and hence feed efficiency, by suppressing the growth of gastrointestinal organisms that compete for nutrients (Cromwell, 2002). Sub-therapeutic Antibiotics (STAs) may also suppress disease-causing organisms in the animals' environment that hinder performance. Thus STAs use may allow farmers to reduce inputs allocated to certain hygiene-related practices or technologies, such as herd segregation, sanitary protocols, improved housing ventilation, biosecurity measures, and vaccines (MacDonald and Wang, 2011).

Several studies have attempted to estimate the economic consequences for hog production of a STA ban. Hayes et al. (2001) extrapolated from the European experience to the

[1] Unlike other uses of these drugs (e.g., for the treatment, control, and prevention of disease), these "production" or "sub-therapeutic" uses are not intended to manage a specific disease that may be ongoing or at risk of occurring.

U.S. by using technical data obtained from Sweden and Denmark. Their findings suggest a ban would increase weaning age, hog and pig mortality, and would decrease feed efficiency and pigs born per sow. Miller et al. (2003) used data from U.S. farms in the National Animal Health Monitoring System (NAHMS) to estimate the relationships between antibiotic use and productivity measures. Their results indicated that antibiotic use improved average daily gain, feed conversion, and hog mortality relative to non-use.

McBride, Key and Mathews (2008) were the first authors to account for possible sample selection bias in estimating the impact of feeding sub-therapeutic to hogs on productivity. They note that operations with sub-optimal environmental and management conditions, such as those with older or less clean buildings, or those with hogs of inferior genetic potential could enjoy the greatest productivity gains from STA use. Consequently, there could be an inverse relationship between operation productivity and the decision to use STAs. This correlation introduces a potential source of selection bias in estimating the effect of sub-therapeutic antibiotics on productivity.

McBride, Key and Mathews address the sample selection issue using a Heckman treatment-effect model. This approach accounts for the fact that unobservable variables, such as environmental or management conditions, may be correlated with both the decision to use STA and input productivity, allowing for an unbiased estimate of the impact of STA on productivity. A potential problem with their approach stems from the fact that their treatment variable – a productivity index (inverse unit cost) – is a function of factor prices. If STA use is correlated with factor prices, then we might observe a spurious correlation between STA use and the productivity index.

MacDonald and Wang (2011) also used a Heckman model to control for selection bias in their analysis of the impact of STAs on broiler production. They avoid the possibility that prices confound the relationship between antibiotic use and productivity by estimating a Cobb-Douglas production function in the second stage of the model. In their approach, an STA indicator enters the production function equation directly.

The production function approach used by MacDonald and Wang is based on the assumption that errors are symmetrically distributed around an underlying production function. In this framework deviations from the underlying production function occur because of measurement errors or because of unexplained random variation in farmer's abilities. An approach is to estimate a production frontier – the maximum amount of output that can be obtained given a set of inputs. Stochastic frontier production functions have a two-part error term composed of a symmetric error, representing measurement error and other random factors, and a one-sided random variable representing technical inefficiency (Aigner et al., 1977; Meeusen and van den Broeck, 1977). Technical efficiency is measured as the ratio of observed output to the maximum potential output – a measure of farmers' ability to effectively use the available production technology. A stochastic frontier estimation permits us to test whether STAs shift the production frontier or allow operators to produce closer to the efficient frontier.

There have been several recent efforts by researchers to control for sample selection bias in stochastic frontier model estimation. Mayen et al. (2010) use propensity score matching to address growers' self-selection into organic versus conventional dairy production. Their approach accounts for biases from observed variables. However, as with all matching approaches, it does not account for selection bias resulting from unobserved factors that are uncorrelated with observed factors (Heckman and Navarro-Lozano, 2004).

Kumbhaker et al. (2009) also compared the productivity of conventional and organic dairies, but did so by jointly estimate the production technology and technology choice decisions using a single-step maximum likelihood function. Their approach takes into account the endogeneity of the treatment (technology choice) and output, both of which could depend on unobservable factors.

Greene (2010) uses a similar approach to Kumbhaker et al. to control for unobserved factors that might be correlated with treatment variable of interest and the efficiency. However, he develops a different selection mechanism and he combines this selection model with a propensity score matching to control for observed factors. In this study we use Greene's approach to address the potential for self selection into antibiotic users versus non-users.

Data used in this study are from 2009 Agricultural Resource Management Survey (ARMS) of U.S. hog producers. The ARMS data include farm financial and operator information, and detailed information about the production practices and costs of hog production. In the survey, hog producers were asked whether they fed antibiotics for the purpose of growth promotion. The impact of such antibiotic use on technical efficiency is estimated for feeder pig-to-finish operations – the type of operation responsible for most finished hog output.

Empirical Approach

As discussed above, there are several biological mechanisms by which STAs could enhance the rate at which feed is converted to animal weight gain. STAs might also increase the productivity of labor or capital by substituting for practices or expenditure used to maintain a high level of hygiene in animal housing and transport vehicles In hog production, antibiotics are are typically added to livestock feed and many producers – particularly those with production contracts – do not know the quantity or costs of the antibiotics added. In a typical production contract, feed is provided by the contractor – and antibiotics are added at rates determined by a veterinarian employed by the contractor. Hence, for this study we treat the use of antibiotics as a discrete technology choice - analogous to producers' choice of organic versus conventional production. STAs could therefore affect the productivity of the variable inputs that we observe (feed, labor, capital, and other inputs). STAs might also allow producers to modify their equipment or practices, and thereby effectively alter the underlying production technology.

In this study we estimate the effect of STAs on productivity and technical efficiency using the stochastic frontier production function (SPF) model first proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). The stochastic frontier approach has been widely used to estimate the technical efficiency of a variety of crop and livestock production systems, including in a few studies of hog production (Sharma, Leung, and Zaleski, 1997; Key, McBride, and Mosheim, 2008). In the framework of the SPF model, STAs can increase productivity by shifting out the production frontier (altering the production technology) or by increasing technical efficiency (allowing producers to combine inputs so as to produce closer to the feasible frontier). The model has the form:

(1) $$y_i = x_i'\beta + v_i - u_i,$$

where $y_i = \ln q_i$ and q_i is the observed output of farm i, $x_i'\beta$ is the maximum quantity that can be produced with x_i (a vector of inputs) and a technology described by the parameters β. Production can deviate from this deterministic frontier because of random shocks v_i (which could be positive or negative) or because of productive inefficiency u_i, which reduces output ($u_i \geq 0$).

The technical efficiency of farm i is defined as the ratio of observed its output to its feasible output (output on the stochastic frontier):

$$(2) \qquad TE_i = \frac{q_i}{exp(x_i{'}\beta + v_i)} = \exp(-u_i).$$

This measure ranges between zero and one, with one being technically efficient.

As discussed in the previous section, unobservable factors could cause productivity or production choices to be correlated with the decision to use STAs. This correlation introduces a potential source of selection bias when estimating the effect of sub-therapeutic antibiotics on productivity. Some recent studies have estimated a stochastic frontier model and attempted to address the issue of sample selection using a Heckman two-stage approach (e.g., Solis et al. 2007). However, the two stage approach that incorporates an inverse Mills ratio from the first stage into the second stage is unsuitable for non-linear models such as the stochastic production frontier (Greene, 2010).

In this study, we use an approach developed by Greene (2010) to control for sample selection bias in our estimation the effect of STAs on the technical efficiency of hog operations. Greene first uses propensity score matching to control for biases from observed factors. Then Using the matched sample, he applies a selection model that allows for unobserved factors that influence selection (antibiotics/no antibiotics) to be correlated with errors in the stochastic production frontier. The model has a similar form to the standard Heckman selection model, with the selection equation:

$$(3) \qquad d_i = 1[\alpha' z_i + w_i],\ w_i \sim N[0,1],$$

where d_i is an indicator of antibiotics use. The production variables (y_i, x_i) corresponding to the stochastic production function (1) are observed for antibiotics users only if $d_i = 1$. Following the standard specifications, the inefficiency and error terms have the distributions:

$$(4) \qquad \begin{aligned} u_i &= \sigma_u |U_i|,\ U_i \sim N(0,1) \\ v_i &= \sigma_v V_i,\ V_i \sim N(0,1) \end{aligned}$$

As in the standard Heckman, sample selection bias arises because of the correlation between the unobservables in the production equation, with those in the selection equation:

(5) $$(w_i, v_i) \sim N_2[(0,1), (1, \rho\sigma_v, \sigma_v^2)]$$

Terza (2009) developed the log likelihood function for a general extension of Heckman's linear model to nonlinear models. Greene (2010) developed the function for the application to the stochastic frontier case. In practice, consistent estimates of $\propto$ are generated using a probit estimate of the selection equation (3), and these estimates are then taken as given in the log likelihood function. The conditional likelihood function can then be estimated with a conventional gradient based approach. See Greene (2010) for a derivation and specification the log likelihood function.

Data

Data used in this study are from the Agricultural Resource Management Survey (ARMS) of hog producers conducted by the Economic Research Service and the National Agricultural Statistics Service in 19 states in 2009. The data include financial information about farm income, expenses, assets, debt, farm and operator characteristic, and detailed information about the production practices and costs of hog production. While the survey included several types of hog operations, we limit the empirical analysis to feeder pig-to-finish operations.[2] Feeder pig-to-finish operations have become increasingly common in recent years and accounted for 76 percent of finished hog production in 2009. In addition to feeder pig-to-finish operations, antibiotics are also used on farrow-to-finish operations, nursery, and wean-to-feeder operations (McBride, Key, and Mathews, 2008). However, these types of operations are relatively less

[2] Hog production involves four phases: (1) breeding and gestation; (2) farrowing (birth of pigs and care until weaning); (3) nursery (care immediately after weaning until about 30-80 pounds); and (4) finishing (feeding hogs from 30-80 pounds to a slaughter weight of 225-300 pounds). Hog producers are commonly classified according to the number of production phases conducted on the operation: (1) farrow-to-finish (all four phases); (2) farrow-to-feeder pig (phases 1; 2; and 3); (3) feeder pig-to-finish (phase 4); (4) wean-to-feeder pig (phase 3); (5) farrow-to-wean (phases 1 and 2); or (6) wean-to-finish (phases 3 and 4).

common, and there is in an insufficient number of observations in the sample to conduct a similar empirical analysis.

The survey asked operators whether they fed their animals antibiotics and for what purpose. Of the 507 feeder pig-to-finish operations that were surveyed, 408 did not refuse to answer the questions on antibiotic use. Of these respondents, 44.7% fed antibiotics for growth promotion, 60.4% for disease prevention, and 66.7% for disease treatment. For this study, we define sub-therapeutic antibiotics (STA) use as antibiotics fed for the purpose of growth promotion. We limit our consideration to this category of antibiotic use because the 2012 FDA strategy explicitly seeks to phase out the use of antibiotics for production uses such as feed efficiency and growth promotion (USFDA, 2012).

The top half of table 1 presents summary statistics for the sample used in this study (14 observations from the full sample were dropped because of missing or invalid data, resulting in a total of 394 observations). Output is measured in hundredweight (cwt) of animal live weight gained, which is defined as the hundredweight of hogs sold or removed under contract, less purchased or placed under contract, plus the inventory change during the year. Inputs include feed (expenditures on all types of feed), labor (total hours of paid and unpaid labor), capital (estimated capital recovery cost for all buildings and machinery), and other inputs (expenditures on veterinary services, medicine, bedding, marketing, custom work, fuel, electricity, and repairs). Grower characteristics expected to influence productivity include the operator’s age, experience (years raising hogs), and education. Table 1 also presents three broad measures of economic performance: gross unit value, unit total costs and unit operating costs.

The last column in table 1 displays the test statistics for the null hypothesis that the means of the treatment (STA) and control (No STA) groups are equal. The results show that STA users produced significantly more output and used more feed and capital, than did non-users. In addition, STA users were younger and were significantly more likely to have attended college (43% versus 29%). Both users and non-users obtained similar prices for their finished hogs (averaging $55.47/cwt. gain), but antibiotic users had significantly lower total costs per unit and operating costs per unit. The apparently greater efficiency achieved by STA users might be explained by antibiotic use, or it could be explained by differences in scale, production technologies, or other factors. This is explored in the next section.

As discussed in the previous methodology section, we use propensity score matching to correct for biases from observed factors. To implement the matching technique we first estimate the probability that an operator used STAs. Then we generate control and treatment groups using one-to one nearest neighbor matching without replacement (Dehejia and Wahba, 2002). Since there are more controls than treated observations, this technique matches each treated observation with a single control.

Matching resulted in 330 observations (165 controls matched with the 165 STA users) which are summarized in the bottom half of table 2. For the matched sample there are fewer statistically significant differences between the between the means of the treatment and control groups, compared to the unmatched sample. Most strikingly, the differences in the aggregate measures of productivity (unit total cost and unit operating cost) between the users and non-users of STAs are no longer statistically significantly different from zero. When the t tests were conducted without accounting for the sampling weights, there were no statistically significant differences between the matched samples for any of the variables. This suggests that the balancing property of the covariates is satisfied for the matched samples (Leuven and Sianesi, 2003).

Results

For the unmatched sample, we estimate four SPF models. In the first model (column 1, table 2) STA users and non-users have the same available technology (i.e., same frontier model parameters). Consequently, differences in productivity derive only from differences in technical efficiency. In the second model (column 2), an STA indicator is included as a dependent variable. In this specification, the marginal productivity of the inputs does not vary for STA users and non-users, but STA use can "shift" the production frontier. The shift (percent change in production) does not vary across operations.

The first two models are estimated using the pooled (full) sample. Estimates of the differences in technical efficiency and productivity between STA users and non-users that are obtained from these models do not account for potential sample selection bias. The first column displays the results under the assumption of identical technologies for STA users and non-users. Because we use the translog functional form for the production function and normalized all inputs, the first four input coefficients can be interpreted as partial production elasticities at the sample mean. As shown in the first column, feed has the largest elasticity (0.66) of the four inputs, followed by capital (0.24) other inputs (0.10) and labor (0.04). The partial production elasticity for labor has the correct sign, but is not statistically significantly different from zero, perhaps because labor hours are measured with less precision than the other inputs. The sum of the partial production elasticities indicates the production technology exhibits increasing returns to scale (scale elasticity = 1.04).

Results indicate that an increase in operator age is associated with a decrease in efficiency. Controlling for operator age, the operator's experience is positively correlated with efficiency, though this association is not statistically significant. Operator age may be a better predictor of the vintage of the production technology (and hence capital productivity) than years of experience, if younger farmers are more likely to invest in modern buildings and machinery. Having a college degree does not appear to be significantly associated with efficiency. Use of a production contract has a large and significant positive association with productivity. This finding is consistent with other empirical studies (Key and McBride, 2003, 2008). Production contracts may enhance farm productivity by providing access to managerial expertise or high quality proprietary inputs – such as feed and genetic stock – that are not available to independent producers.

For the model in which the production technology does not vary, we estimate that technical efficiency of STA users is one percentage point higher for STA users compared to non-users (0.769 versus 0.759). The difference is not statistically significantly different from zero. Introducing an indicator for STA use (column 2) produces very similar model coefficients. However, the estimate of technical efficiency effect is negative: STA users have an average efficiency of 0.755 compared to 0.768 for non-users. The STA indictor parameter suggests that STA use is associated with a 6% increase in output, holding inputs constant. Hence, for the unmatched pooled sample, that does not control for sample selection bias, STA use appears to increase production by a statistically significant amount. We do not find a statistically significant difference between technical efficiency of STA users and non-users using the pooled sample.

Next we estimate separate production frontiers for STA users and non-users by allowing all the frontier model parameters to vary. Columns 3 and 4 of table 2 show the estimated SPF for STA non-users and users, respectively. A likelihood ratio (LR) test provides evidence that the technologies for the users and non-users should be estimated separately. The LR test statistic is computed as:

$$(6) \qquad \boldsymbol{LR = 2 * \left(lnL_P - (lnL_N + lnL_S)\right)},$$

where $\boldsymbol{lnL_P}$, $\boldsymbol{lnL_N}$, and $\boldsymbol{lnL_S}$ are the log-likelihood function values for the models estimated using pooled, No STA, and STA user samples, respectively. The estimated LR test statistic has a p-value less than 0.001, so we reject the null hypothesis that the parameters for the SPF models are equal. Hence, it is reasonable to place greater weight on results of the separate SPF model estimates compared to the results from the pooled sample.

Despite somewhat different operation and operator characteristics (table 1) and somewhat different SPF parameter estimates for the STA users and non-users (columns 3 and 4, table 2), the estimates of technical efficiency for both groups are almost identical (0.804 versus 0.803, respectively).

To examine whether STA use is associated shifts out the production frontier, we compute the difference in the predicted output at the mean of the full sample. The predicted increase in production is based on the separate parameter estimates from the heterogenous technology models:

$$(7) \qquad \text{Technology effect} = \bar{x}'\boldsymbol{\widehat{\beta}_i^{STA}} - \bar{x}'\boldsymbol{\widehat{\beta}_i^{No\ STA}},$$

where $\boldsymbol{\widehat{\beta}_i^{STA}}$ and $\boldsymbol{\widehat{\beta}_i^{No\ STA}}$ are the parameter estimates from models 3 and 4, respectively. Since output is expressed in log units, the log difference is approximately the percent change. Results indicate the STA use would results in about 6 percent more output, which is consistent with the estimate of the STA indicator model (the technical efficiency and technology effects are summarized in the final table).[3] However the effect is not statistically significantly different from zero.

[3] An alternative measure of the production effect is to compute the change in output for the average producer: $\bar{x}'\hat{\beta}^{STA} - \bar{x}'\hat{\beta}^{No\ STA}$. However, it is unclear how to compute the confidence intervals are for these estimates. This alternative measure produces somewhat smaller estimates than (7): 0.040 for the unmatched sample, and 0.034 for the sample selection model.

Correcting for biases from observed and unobserved variables

To account for biases from observed variables, we create a matched sample of observations, as was described in the data section. Re-estimating the four SPF models using the matched sample (table 3) produces parameter estimates that are consistent with those obtained using the unmatched sample. However, there are some key differences. For example, the STA indicator model, the estimated production effect is smaller (about 4% for the matched sample compared to 6% for the unmatched sample) and is no longer statistically significantly different from zero.

As with the unmatched sample, LR tests reject the hypothesis that STA users and non-users have identical production frontiers (p values < 0.001). Hence, for the matched sample, the results from the separate SPF estimates (columns 3 and 4) are preferred to the estimates from the pooled models. For the separate technology models, we obtain average efficiency estimates of 0.781 and 0.804 STA for non-users and users, respectively. However, the small increase in technical efficiency attributable to STA use is not statistically significantly different from zero. Unlike with the unmatched sample, results of the heterogenous technology models indicate no statistically significant effect on production technology.

Next, we account for biases from unobserved factors that might be correlated with the decision to use antibiotics and with efficiency. Table 4 shows the results of the probit model of antibiotic use for the matched sample. The null hypothesis that all the coefficients are zero is rejected (p-value < 0.001). Despite the fact that the nearest neighbor matching reduced the difference between the samples of antibiotic users and non-users (which tends to reduce the significance of the probit parameters) several of the parameters are statistically significantly different from zero. In particular, results indicate that operators who controlled for rodents, dewormed their hogs, and had a Pork Quality Assurance (PQA) certification were more likely to use STAs. In contrast, operators who had a biosecurity plan and who disinfected their livestock transportation vehicles were less likely to use STAs. These results are generally consistent with MacDonald and Wang (2011) who found that certain practices (e.g., pathogen testing and expanded sanitary protocols) were inversely correlated with the use of STAs in the case of broiler production. It is possible that our findings of a positive association with STA use for some practices might indicate that the practices are a response to a sanitary problem (rather than an indication of a good management practice).

The sample selection stochastic frontier parameters for the matched sample are displayed in table 5. The estimated coefficients are generally consistent with the heterogenous technology models estimated with the matched sample (columns 3 and 4, table 3). None-the-less, we obtain somewhat different results from the standard SPF in terms of the technical efficiency effects. The sample selection model indicates essentially no difference in technical efficiency between STA users and non-users, compared to a small positive effect (about 2 percentage points) for the conventional SPF.

In the selection model, the coefficient $\boldsymbol{\rho}$ was positive, though not significantly different from zero for either selection equation. This suggests that selection bias was not present in this analysis and that estimation with the conventional SPF model (using the matched sample) would not yield biased frontier estimates. However, the positive association between errors in the STA choice equation and the frontier indicated by the positive $\boldsymbol{\rho}$ means that STA users are more productive than we non-users, conditional on observables. Hence, the conventional SPF model over-estimates the technical efficiency effect, though in this case, the bias is not statistically significantly different from zero.

The estimates of the technical efficiency and productivity effects of STA use for all the models are summarized in table 6. With the unmatched sample, we found that STA use was associated with about a 6% increase in potential output for the pooled sample with an STA indictor and for the heterogeneous technology models. After we controlled for observable differences between STA users and non-users using propensity score matching, the technology effect was smaller and not significantly different from zero. For the heterogeneous technology and sample selection models the point estimates of the technology effect was less than one percent, though the standard errors associated with the estimates were relatively large.

Results indicate that the technical efficiency of STA users and non-users for both the unmatched and matched samples are not statistically significantly different. The finding of a small and not statistically significant STA effect on technical efficiency is maintained, even after we controlled for potential sample selection bias. It should be noted, however, that the confidence intervals associated with these estimates are fairly large. Using the estimates from the matched selection model, we are only able to rule out a technical efficiency effect larger than about 20 percent as statistically unlikely. The estimates lack precision to rule out smaller but potentially economically important effects on technical efficiency.

Conclusion

The FDA recently announced a strategy for assuring that medically important antimicrobial drugs are used "judiciously" on livestock operations in order to minimize the development of antimicrobial drug resistance. A key component of this strategy is the phasing out of antibiotics for the purposes of increasing animal weight gain or improving feed efficiency. This study used producer information from a 2009 national survey of feeder pig-to-finish hog producers to estimate the costs to producers of such a policy if fully implemented. The effects of a ban on STAs were estimated by comparing the technical efficiency and production of a matched sample of STA users and non-users.

Without controlling for selection bias, a conventional SPF model indicated that STA use would increase the productivity of feeder pig-to-finish operations by about 6%. This productivity effect was attributable almost entirely to a shift in the production frontier, rather than to a change in technical efficiency. However, these the productivity effects were diminished after we controlled for potential sample selection bias that might result if unobservable factors influence both the decision to use STAs and output. Results of the sample selection suggest that ban on the use of antibiotics for the purpose of promoting growth would have little effect on total productivity. More specifically, the point estimates indicate that STA use would increase productivity by less than one percent. However, these estimates have large standard errors and it is not possible to rule out a larger effect on the production frontier or on technical efficiency. In addition, it is worth noting that earlier studies found larger productivity effects for weanling and nursery pigs compared to feeder pig-to-finish operations. Consequently, the costs for farrow-to-finish operations and for the industry as a whole may be larger than was found here.

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Table 1. Summary Statistics: Matched and Unmatched Samples

	Pooled		No STA		STA		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t test
Unmatched Sample							
Output (cwt. gain)	16,530	84,194	14,292	69,705	19,302	99,655	2.66***
x1 (feed)	437,217	1,991,618	393,806	1,888,778	490,970	2,105,328	2.17**
x2 (labor)	2,090	9,062	1,992	7,110	2,211	11,221	1.07
x3 (capital)	129,028	617,951	108,304	437,563	154,689	789,379	3.37**
x4 (other inputs)	46,640	257,038	42,722	237,598	51,491	280,925	1.51
Operator age (years)	50.79	45.26	51.44	45.77	49.98	44.40	-1.43*
Experience (years)	28.25	52.20	28.73	51.09	27.66	53.72	-0.91
College (1/0)	0.35	2.15	0.29	1.99	0.43	2.30	2.81***
Production Contract (1/0)	0.67	2.11	0.66	2.09	0.69	2.14	0.81
Unit gross revenue ($/cwt. gain)	55.47	44.36	55.65	47.55	55.26	39.63	-0.39
Unit total cost ($/cwt. gain)[1]	52.72	149.36	58.17	181.68	45.97	76.05	-3.68***
Unit operating cost ($/cwt. gain)[1]	34.08	64.61	35.86	72.59	31.87	49.86	-2.76***
N	394		229		165		
Matched sample							
Output (cwt. gain)	17,129	79,796	14,835	51,306	19,302	99,655	2.34**
x1 (feed)	451,910	1,834,983	410,680	1,501,508	490,970	2,105,328	1.83*
x2 (labor)	2,163	9,243	2,113	6,735	2,211	11,221	0.44
x3 (capital)	140,104	648,646	124,710	459,849	154,689	789,379	1.93*
x4 (other inputs)	48,633	237,879	45,617	185,027	51,491	280,925	1.03
Operator age (years)	50.06	42.98	50.14	41.63	49.98	44.40	-0.15
Experience (years)	27.92	51.46	28.19	49.22	27.66	53.72	-0.43
College (1/0)	0.38	2.23	0.33	2.13	0.43	2.30	1.73*
Production Contract (1/0)	0.70	2.10	0.71	2.05	0.69	2.14	-0.33
Unit gross revenue ($/cwt. gain)	55.11	42.04	54.95	44.44	55.26	39.63	0.30
Unit total cost ($/cwt. gain)[1]	47.85	109.56	49.83	134.69	45.97	76.05	-1.47
Unit operating cost ($/cwt. gain)[1]	32.66	57.98	33.48	65.05	31.87	49.86	-1.16
N	330		165		165		

Note: The t test is of the null hypothesis of equal means for the No STA and STA samples. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels. ARMS sampling weights were used to calculate summary and test statistics.

[1]Operating costs include costs for feed; veterinary and medicine; bedding and litter; marketing; custom services; fuel; repairs; and operating interest. Total costs include operating costs plus the annualized cost of maintaining the capital (economic depreciation and interest) used in hog production; costs for non-real estate property taxes and insurance; opportunity costs for land and unpaid labor; and allocated costs for general farm overhead items.

Table 2. Stochastic Production Frontier Estimates: Unmatched Sample

	Pooled		Separate Samples/Technologies	
	Same Technology	STA Indicator	No STA	STA
Constant	0.728**	0.707**	0.669	0.808*
	(0.353)	(0.344)	(0.413)	(0.465)
x1 (Feed)	0.662***	0.665***	0.654***	0.664***
	(0.038)	(0.038)	(0.047)	(0.063)
x2 (Labor)	0.036	0.043	0.123***	-0.062
	(0.027)	(0.027)	(0.040)	(0.040)
x3 (Capital)	0.240***	0.231***	0.142***	0.256***
	(0.037)	(0.037)	(0.046)	(0.066)
x4 (Other inputs)	0.098***	0.096***	0.132***	0.144***
	(0.025)	(0.025)	(0.038)	(0.042)
Translog terms[1]	yes	yes	yes	yes
Log operator age	-0.220**	-0.223**	-0.266**	-0.222
	(0.107)	(0.103)	(0.126)	(0.145)
Log years experience	0.048	0.052	0.085*	0.018
	(0.036)	(0.035)	(0.045)	(0.056)
College education	0.011	0.003	0.027	-0.009
	(0.035)	(0.034)	(0.046)	(0.046)
Production Contract	0.307***	0.306***	0.381***	0.256***
	(0.043)	(0.042)	(0.066)	(0.073)
STA	-	0.062*	-	-
		(0.035)		
$\ln\sigma_v^2$ (Noise)	-3.384***	-3.424***	-3.229***	-3.367***
	(0.284)	(0.280)	(0.434)	(0.516)
$\ln\sigma_u^2$ (Inefficiency)	-2.048***	-2.037***	-2.488***	-2.504***
	(0.308)	(0.283)	(0.567)	(0.586)
RTS	1.04	1.03	1.00	1.05
Efficiency	0.764	0.763	0.803	0.804
(Std. Dev.)	(0.112)	(0.114)	(0.088)	(0.095)
Log Likelihood	-1144.2	-1097.1	-356.1	-136.9
N	394	394	229	165

Note: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.
[1] The translog production function second order terms are: x1x1, x2x2, x3x3, x4x4, x1x2, x1x3, x1x4, x2x3, x2x4, x3x4.

Table 3. Stochastic Production Frontier Estimates: Matched Sample

	Pooled		Separate Samples/Technologies	
	Same Technology	STA Indicator	No STA	STA
Constant	0.724*	0.733**	0.647	0.808*
	(0.382)	(0.373)	(0.493)	(0.465)
x1 (Feed)	0.646***	0.644***	0.611***	0.664***
	(0.047)	(0.047)	(0.055)	(0.063)
x2 (Labor)	0.038	0.043	0.129***	-0.062
	(0.029)	(0.030)	(0.037)	(0.040)
x3 (Capital)	0.234***	0.231***	0.147***	0.256***
	(0.041)	(0.041)	(0.044)	(0.066)
x4 (Other inputs)	0.093***	0.092***	0.098**	0.144***
	(0.028)	(0.028)	(0.040)	(0.042)
Translog terms[1]	yes	yes	yes	yes
Log operator age	-0.206*	-0.217*	-0.252*	-0.222
	(0.116)	(0.112)	(0.152)	(0.145)
Log years experience	0.044	0.050	0.121**	0.018
	(0.038)	(0.037)	(0.051)	(0.056)
College education	-0.000	-0.004	-0.006	-0.009
	(0.037)	(0.035)	(0.048)	(0.046)
Production Contract	0.275***	0.275***	0.300***	0.256***
	(0.046)	(0.045)	(0.061)	(0.073)
STA	-	0.041	-	-
		(0.035)		
$\ln\sigma_v^2$ (Noise)	-3.581***	-3.599***	-3.739***	-3.367***
	(0.304)	(0.297)	(0.289)	(0.516)
$\ln\sigma_u^2$ (Inefficiency)	-2.009***	-2.007***	-2.246***	-2.504***
	(0.291)	(0.275)	(0.260)	(0.586)
RTS	1.01	1.01	0.99	1.05
Efficiency	0.759	0.759	0.781	0.804
(Std. Dev.)	(0.121)	(0.122)	(0.118)	(0.095)
Log Likelihood	-774.2	-754.1	-32.5	-136.9
N	330	330	165	165

Notes: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.
[1] The translog production function second order terms are: x1x1, x2x2, x3x3, x4x4, x1x2, x1x3, x1x4, x2x3, x2x4, x3x4.

Table 4. Probit Model Estimates: Matched Sample

	Pooled
Constant	-0.852**
	(0.356)
Medium size farm	0.006
	(0.186)
Large size farm	0.155
	(0.187)
PQA certified	0.671***
	(0.197)
Rodent control	0.665**
	(0.300)
Bio-security plan	-0.409**
	(0.159)
Vehicle disinfect	-0.317*
	(0.185)
Bird-proofing	0.019
	(0.230)
De-wormed hogs	0.427**
	(0.170)
χ^2	30.68***
Log Likelihood	-213.4
N	330

Note: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

Table 5. Sample Selection Stochastic Production Frontier: Matched Sample

	Sample	
	No STA	STA
Constant	1.224*	0.495
	(0.675)	(0.697)
x1 (Feed)	0.619***	0.604***
	(0.064)	(0.054)
x2 (Labor)	0.113**	-0.026
	(0.049)	(0.041)
x3 (Capital)	0.184**	0.309***
	(0.073)	(0.061)
x4 (Other inputs)	0.075**	0.135***
	(0.037)	(0.044)
Translog terms[1]	yes	yes
Operator age	-0.421*	-0.143
	(0.224)	(0.228)
Experience	0.131	0.019
	(0.083)	(0.077)
Education	-0.048	-0.010
	(0.049)	(0.052)
Production Contract	0.248***	0.259***
	(0.051)	(0.061)
σ_v (Noise)	0.180***	0.190***
	(0.045)	(0.039)
σ_u (Inefficiency)	0.326***	0.327***
	(0.045)	(0.067)
$\rho_{w,v}$	0.591	0.307
	(0.527)	(0.618)
RTS	1.00	1.02
Efficiency	0.773	0.781
	(0.118)	(0.103)
Log Likelihood	-113.1	-121.0
N	165	165

Notes: All continuous variables are in natural logs. Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels.

[1] The translog production function second order terms are: x1x1, x2x2, x3x3, x4x4, x1x2, x1x3, x1x4, x2x3, x2x4, x3x4.

Table 6. Summary of Technical Efficiency and Technology Effects for All Models

	Technical Efficiency			Productivity Effect
	No STA	STA	Difference	
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Err)
Unmatched Sample				
Same technology	0.759	0.769	0.010	-
	(0.111)	(0.114)	(0.115)	
STA indicator	0.768	.755	-0.013	0.062*
	(0.111)	(0.118)	(0.117)	(0.035)
Different technology	0.803	0.804	0.001	0.059
	(.088)	(.095)	(0.091)	(0.101)
N	229	165		
Matched sample				
Same technology	0.755	0.763	0.008	-
	(0.120)	(0.123)	(0.121)	
STA indicator	0.763	0.754	-0.009	0.041
	(0.119)	(0.125)	(0.122)	(0.035)
Different technology	0.781	0.804	0.023	0.005
	(0.118)	(0.095)	(0.107)	(0.080)
Sample Selection SPF	0.780	0.781	0.001	0.007
	(0.103)	(0.103)	(0.103)	(0.074)
N	165	165		

Notes: Asterisks denote significance at the 10% (*), 5% (**), and 1% (***) levels. The “Productivity Effect” is the coefficient on the STA indicator in the STA indicator model and is the difference in the predicted outputs at the mean for all operations in the other models. See text for details.