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Econometric Estimation of Investment Utilization, Adjustment Costs, and Technical Efficiency in Danish Pig Farms using Hyperbolic Distance Functions¹

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Abstract:

Based on a theoretical microeconomic model, we econometrically estimate investment utilization, adjustment costs, and technical efficiency in Danish pig farms based on a large unbalanced panel dataset. As our theoretical model indicates that adjustment costs are caused both by increased inputs and by reduced outputs, we estimate hyperbolic distance functions that account for reduced technical efficiency both in terms of increased inputs and reduced outputs. We estimate these hyperbolic distance functions as “efficiency effect frontiers” with the Translog functional form and a dynamic specification of investment activities by the maximum likelihood method so that we can estimate the adjustment costs that occur in the year of the investment and the three following years. Our results show that investments are associated with significant adjustment costs, especially in the year in which the investment was made. The highest investment utilization is two years after the investment.

¹ This is a revised version of Olsen and Henningsen (2011)

Introduction

Farmers' investments are usually aimed at maintaining capital capacity by reinvesting, or expanding farm capacity. As new technologies are often associated with investments in new production units or machinery, it is expected that investments increase productivity.

In the theory of investment and production, the optimal level of investment and production given the current level of accumulated capital and given a set of prices depends on adjustment costs. The theory assumes further that the marginal adjustment costs increase with increasing investments (Jorgenson, 1972). The specification of adjustment cost functions has been intensively investigated in the literature (e.g. Gould, 1968; Chang & Stefanou, 1988; Hsu & Chang, 1990; Lundgren & Sjöström, 2001; Cooper & Haltiwanger, 2006) because this is a central element in determining the optimal investment level. This literature shows that the optimal specification of the adjustment cost function depends on the type of adjustment costs and empirical considerations, and varies over industries (Gould, 1968) and between individual decision makers (Gardebroek and Oude Lansink, 2004). However, Pindyck (1993) questions the role of adjustment costs when determining the optimal investment level and argues that adjustment costs are unimportant under perfect competition and constant returns to scale and that uncertainties rather than adjustments costs are the primary cause of lower than optimal investment levels.

We employ a method for estimating farmers' adjustment costs by analyzing the effect of investments and lagged investments on technical efficiency. Our model econometrically estimates the adjustment costs after the investment has been completed, whereas the above-mentioned models all estimate the adjustment costs based on the investment decision and on the assumption that the decision maker invests according to theory. We are interested in the adjustment costs per se and hence, our model investigates the adjustment costs after the investment.

The objective of this paper is to empirically investigate the size and timing of adjustment costs as well as the investment utilization in Danish pig production. As pig farmers are faced with a multitude of regulations and legal restrictions in Denmark, classical models for adjustment costs would be inappropriate for our analysis. Given that the average investment of Danish pig producers is rather large, we expect adjustment costs to be of a considerable size. We specify and estimate stochastic frontier hyperbolic distance functions that measure the size and timing of adjustment costs as the effect on technical efficiency. Finally, we derive the marginal effects of current and past investments on technical efficiency.

Our theoretical model about adjustment costs and investment utilization indicates that adjustment costs after investments decrease output and increase inputs, particularly labor, capital and feed (Olsen and Henningsen 2011).

Empirical specification

In our empirical analysis, we model the production technology by the distance function approach, because this approach does not require prices, aggregation or behavioral assumptions. However, neither a conventional output distance function (which measures technical inefficiency in terms of radially decreased outputs, while all inputs remain constant) nor a conventional input distance function (which measures technical inefficiency in terms of radially increased inputs, while all outputs remain constant) would be a suitable specification for our empirical analysis, because our theoretical model indicates that adjustment costs are caused both by increased inputs and by reduced outputs (see Olsen and Henningsen 2011). In order to apply an empirical specification that complies with our theoretical model, we estimate a hyperbolic distance function that measures technical inefficiency both in terms of increased inputs and reduced outputs. The hyperbolic distance function got its name from the hyperbolic path, in which technical inefficiency is measured as the distance toward the production frontier. We estimate Translog hyperbolic distance functions as stochastic production frontiers, which can be seen as flexible approximations of the unknown “true” production technology T .

Distance functions must satisfy different properties that are derived from microeconomic theory. The hyperbolic distance function must be “almost homogeneous” of degree 1 in outputs and of degree -1 in inputs². The reason to utilize the homogeneity property of (input, output, or hyperbolic) distance functions in the econometric estimation is that the dependent variable, i.e. the “distance,” is a latent variable.

Basically we begin by assuming a production technology T that transforms a vector of K inputs $x = (x_1, \dots, x_K) \in R_+^K$ into a vector of M outputs $y = (y_1, \dots, y_M) \in R_+^M$. So the technology is represented by the set:

$$T = \{(x, y): x \text{ can produce } y\}$$

The corresponding specification of a stochastic Translog distance function for $i = 1, 2, \dots, N$ firms (farms) in $t = 1, 2, \dots, T$ time periods (years) is given by:

² See Lau (1972) for the general definition of almost homogeneity property.

$$\begin{aligned}
\ln D_{it} = & \alpha_0 + \sum_{m=1}^M \alpha_m \ln y_{mit} + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln y_{mit} \ln y_{nit} \\
& + \sum_{k=1}^K \beta_k \ln x_{kit} + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{kit} \ln x_{lit} \\
& + \sum_{k=1}^K \sum_{m=1}^M \delta_{km} \ln x_{kit} \ln y_{mit} + v_{it},
\end{aligned} \tag{1}$$

where $\alpha_{mn} = \alpha_{nm}$, $\beta_{kl} = \beta_{lk}$, v_{it} is a random error term, and $D_{it} \in]0,1]$ is a distance measure with $D_{it} = 1$ and hence, $\ln D_{it} = 0$, indicating fully technically efficient production and $D_{it} < 1$ and hence, $\ln D_{it} < 0$, indicating technically inefficient production. The only differences between output, input, and hyperbolic Translog distance functions are the homogeneity conditions. For the Translog hyperbolic distance function, the conditions for almost homogeneity of degree 1 in outputs and of degree -1 in inputs are (Cuesta and Zofio 2005):

$$\sum_{m=1}^M \alpha_m - \sum_{k=1}^K \beta_k = 1, \tag{2}$$

$$\sum_{m=1}^M \delta_{km} - \sum_{l=1}^K \beta_{kl} = 0, (k = 1, 2, \dots, K), \tag{3}$$

$$\sum_{n=1}^M \alpha_{mn} - \sum_{k=1}^K \delta_{km} = 0, (m = 1, 2, \dots, M). \tag{4}$$

So that we get following empirical specification (Cuesta and Zofio 2005):

$$\begin{aligned}
-\ln y_{1it} = & \alpha_0 + \sum_{m=2}^M \alpha_m \ln \left(\frac{y_{mit}}{y_{1it}} \right) + \frac{1}{2} \sum_{m=2}^M \sum_{n=2}^M \alpha_{mn} \ln \left(\frac{y_{mit}}{y_{1it}} \right) \ln \left(\frac{y_{nit}}{y_{1it}} \right) \\
& + \sum_{k=1}^K \beta_k \ln(x_{kit} y_{1it}) + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln(x_{kit} y_{1it}) \ln(x_{lit} y_{1it}) \\
& + \sum_{k=1}^K \sum_{m=2}^M \delta_{km} \ln(x_{kit} y_{1it}) \ln \left(\frac{y_{mit}}{y_{1it}} \right) + v_{it} + u_{it},
\end{aligned} \tag{5}$$

where it is assumed that the random error term v_{it} follows a normal distribution with $v_{it} \sim N(0, \sigma_v^2)$, $u_{it} = -\ln D_{it} > 0$ accounts for technical inefficiency and follows a truncated normal distribution with $u_{it} \sim N^+(\mu_{it}, \sigma_u^2)$, and μ_{it} is modeled as follows:

$$\begin{aligned} \mu_{it} = & \delta_1 I_{it}^r + \delta_2 I_{it-1}^r + \delta_3 I_{it-2}^r + \delta_4 I_{it-3}^r + \delta_5 Age_{it} + \delta_6 Age_{it}^2 + \delta_7 Size_{it} \quad (6) \\ & + Age_{it}(\delta_8 I_{it}^r + \delta_9 I_{it-1}^r + \delta_{10} I_{it-2}^r + \delta_{11} I_{it-3}^r) \\ & + Age_{it}^2(\delta_{12} I_{it}^r + \delta_{13} I_{it-1}^r + \delta_{14} I_{it-2}^r + \delta_{15} I_{it-3}^r) \\ & + Size_{it}(\delta_{16} I_{it}^r + \delta_{17} I_{it-1}^r + \delta_{18} I_{it-2}^r + \delta_{19} I_{it-3}^r), \end{aligned}$$

where I_{it}^r indicates (real) investments of farm i in period t , Age_{it} indicates the farmer's age, $Size_{it}$ indicates the size of the farm, and δ are parameters to be estimated.

The elasticity of scale can be obtained by the equation (Cuesta and Zofio 2005):

$$\varepsilon_{it} = - \frac{\sum_{k=1}^K \partial \ln D_{it} / \partial \ln x_{kit}}{\sum_{m=1}^M \partial \ln D_{it} / \partial \ln y_{mit}} \quad (7)$$

A Translog hyperbolic distance function with a constant elasticity of scale, i.e. $\varepsilon_{it} = \varepsilon$, at all observations requires (similar to the conditions for constant returns to scale in Cuesta and Zofio 2005):

$$\sum_{k=1}^K \beta_k = - \frac{\varepsilon}{1 + \varepsilon} \quad (k = 1, 2, \dots, K), \quad (8)$$

$$\sum_{l=1}^K \beta_{kl} = 0 \quad (l = 1, 2, \dots, K), \quad (9)$$

$$\sum_{k=1}^K \delta_{km} = 0 \quad (m = 1, 2, \dots, M). \quad (10)$$

Imposing a constant elasticity of scale ε results in the following empirical specification (similar to imposing constant returns to scale in Cuesta and Zofio 2005):

$$\begin{aligned} & - \left(\frac{\varepsilon}{1 + \varepsilon} \right) \ln y_{1it} + \left(\frac{\varepsilon}{1 + \varepsilon} \right) \ln x_{1it} \quad (11) \\ & = \alpha_0 + \sum_{m=2}^M \alpha_m \ln \left(\frac{y_{mit}}{y_{1it}} \right) + \frac{1}{2} \sum_{m=2}^M \sum_{n=2}^M \alpha_{mn} \ln \left(\frac{y_{mit}}{y_{1it}} \right) \ln \left(\frac{y_{nit}}{y_{1it}} \right) \\ & + \sum_{k=2}^K \beta_k \ln \left(\frac{x_{kit}}{x_{1it}} \right) + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln \left(\frac{x_{kit}}{x_{1it}} \right) \ln \left(\frac{x_{lit}}{x_{1it}} \right) \\ & + \sum_{k=1}^K \sum_{m=2}^M \delta_{km} \ln \left(\frac{x_{kit}}{x_{1it}} \right) \ln \left(\frac{y_{mit}}{y_{1it}} \right) + v_{it} + u_{it} \end{aligned}$$

Data

We use accounting data which was collected from Danish pig producers for 13 years (1996 to 2008) by the Danish Knowledge Centre for Agriculture. These farm accounts are audited and the total number of observations in the dataset is 30,218. However, the dataset is unbalanced and the inclusion of three years of lagged investments requires the removal of several observations so that the final dataset used for the estimation contains 9,167 observations. The largest cross-section is during the year 1999 with 1,408 farms in the dataset which declines to 603 in 2008.

Our model has multiple inputs and outputs. The inputs are: feed, intermediate livestock inputs (e.g. veterinary products and services), intermediate crop inputs (e.g. seed, fertilizer, pesticides), land, labor, capital, and general inputs. All inputs are measured in thousand Euros and deflated to 1996 prices, except for land, which is measured in hectares, and labor, which is measured in hours. The outputs are animal outputs (net production of pigs) and crop outputs (mainly cereals), which are also measured in thousand Euros deflated to 1996 prices.

Table 1: Summary statistics of Danish pig farms from 1996 to 2008

Variable name	Variable	Unit	Mean	Std Dev.
Animal output	Y_1	Thousand Euro (1996)	457	351
Crop output	Y_2	Thousand Euro (1996)	128	94
Feed	X_1	Thousand Euro (1996)	221	151
Intermediate pig input	X_2	Thousand Euro (1996)	28.3	24.0
Intermediate crop input	X_3	Thousand Euro (1996)	19.2	14.5
Land	X_4	Hectare	103.9	71.7
Labor	X_5	Hours	4355.1	2202.3
Capital	X_6	Thousand Euro (1996)	93.2	66.7
General input	X_7	Thousand Euro (1996)	40.2	28.6
Only piglet production	H_1	Product dummy	0.39	0.49
Only slaughter pig production	H_2	Product dummy	0.19	0.40
Soil quality	H_3	Share of land, clay	0.48	0.45
Net investments	I_t^r	Thousand Euro (1996)	29.9	144.6
Net investments	I_{t-1}^r	Thousand Euro (1996)	30.2	133.7
Net investments	I_{t-2}^r	Thousand Euro (1996)	31.7	119.7
Net investments	I_{t-3}^r	Thousand Euro (1996)	37.1	117.9
Age	Age	10 years	4.61	0.88
Size	Size	Standard gross margin, Thousand Euro (1996)	25.5	18.1

Size is measured as Standard Gross Margin (SGM) (Eurostat, 2012), which indicates the expected gross margin of the farm under ‘normal’ conditions and is used by the EU’s Farm

Accountancy Data Network (FADN) to measure the economic size of farms. Our sample consists of all farms that are categorized as pig farms, i.e. more than one third of their SGM comes from pig production and more than two thirds of their SGM comes from the sum of pig production and crop production³. 39 percent of the farms only produce piglets and 20 percent only produce slaughter pigs, while the remaining 41 percent are integrated producers with both piglet and slaughter pig production. Summary statistics of the data are shown in Table 1. More detailed definitions and description of the variables are available in Olsen and Henningsen (2011).

Results and discussion

All calculations and estimations were conducted within the “R” statistical software (R Core Team 2013) using the add-on package “frontier” (Coelli & Henningsen 2013) for estimating the stochastic frontier models. The distance elasticities of the inputs and outputs that we derived from the estimated Translog hyperbolic distance function in equation (5) are presented in Table 2. The elasticity of scale is on average unrealistically large. This implies that the frontier is very “low” for small farms, which makes small farms appear to be extremely technically efficient (close to the frontier), while the frontier is very “high” for large farms, which makes large farms appear to be extremely technically inefficient (far below the frontier). This problem is at least partly caused by the high multicollinearity among the explanatory variables in the hyperbolic distance function and the high correlation between the explanatory variables of the distance function and the “size” variable that explains technical inefficiency. While the explanatory variables of the output distance function are $\ln(y_m/y_1)$ and $\ln x_k$, the explanatory variables of the hyperbolic distance function are $\ln(y_m/y_1)$ and are $\ln(x_k y_1)$ (as well as their quadratic terms and interaction terms in both cases), which results in all transformed input variables, $\ln(x_k y_1)$, being highly correlated with each other and with the farm size. In order to alleviate these problems, we imposed a constant elasticity of scale by estimating the specification in equation (11) and setting the elasticity of scale equal to $\varepsilon = 1.06$, which is a realistic value and approximately equal to the average elasticity of scale that we obtained by estimating an output distance function (see Olsen and Henningsen 2011). The distance elasticities of the inputs and outputs that we derived from the estimated Translog hyperbolic distance function with a constant elasticity of scale of $\varepsilon = 1.06$ imposed are presented in Table 3. The monotonicity properties are more often violated when a constant elasticity

³ In the investigated period, Danish legislation required that livestock farmers had to own a specific amount of land depending on the number and type of livestock they kept. Hence, virtually all Danish pig farmers also had some crop production, which was either sold or used to feed their own livestock.

scale of $\varepsilon = 1.06$ is imposed (compare tables 2 and 3) and a likelihood ratio test rejects the model with a constant elasticity scale of $\varepsilon = 1.06$. However, as the results of the unrestricted model are very unrealistic, we conduct our analysis of the adjustment costs and investment utilization with the model with a constant elasticity scale of $\varepsilon = 1.06$ imposed.

Table 2: The distance elasticities of the Translog hyperbolic distance function without CRS imposed

Variable	Mean of distance elasticities	Distance elasticities at mean values	Median of Distance elasticities	monotonicity violations:	
				number of observations	percent of observations
Crop output	0.200	0.192	0.197	0	0.0
Animal output	0.170	0.171	0.174	7	0.1
Feed input	-0.244	-0.243	-0.246	0	0.0
Intermediate pig input	-0.013	-0.014	-0.011	2749	30.0
Intermediate crop input	-0.044	-0.043	-0.043	234	2.6
Land	-0.128	-0.136	-0.129	19	0.2
Labor	-0.121	-0.114	-0.121	139	1.5
Capital	-0.048	-0.049	-0.047	142	1.5
General costs	-0.033	-0.039	-0.033	891	9.7
Time	0.011	0.011	0.011	*8753	*95.5
Elasticity of scale	1.720	1.756	1.689		

Note: * observations with technological regress

Table 3: Distance elasticities of the Translog hyperbolic distance function with constant elasticity of scale of 1.06

Variable	Mean of distance elasticities	Distance elasticities at mean values	Median of distance elasticities	monotonicity violations:	
				number of observations	percent of observations
Crop output	0.271	0.270	0.268	0	0.0
Animal output	0.214	0.215	0.218	8	0.1
Feed input	-0.265	-0.262	-0.267	0	0.0
Intermediate pig input	-0.025	-0.024	-0.021	2567	28.0
Intermediate crop input	-0.045	-0.044	-0.043	465	5.1
Land	-0.112	-0.114	-0.114	65	0.7
Labor	-0.002	-0.004	-0.001	4505	49.1
Capital	-0.060	-0.060	-0.059	15	0.2
General costs	-0.005	-0.006	-0.004	3731	40.7
Time	0.014	0.014	0.012	*8274	*90.3
Elasticity of scale	1.060	1.060	1.060		

Note: * observations with technological regress

Table 4 shows that farms that invest 1,000,000 Euros are on average about one percentage point less technically efficient in the year of the investment and about three percentage points more technically efficient two years after the investment compared to farms that have not invested in the previous three years.

Table 4: The effects of investments derived from the Translog hyperbolic distance function with constant elasticity of scale of 1.06

Variable	Mean Marginal effect	Median marginal effect	Marginal effect at mean values
Net investments (I_t^r)	-0.01137	-0.00907	-0.00930
Net investments (I_{t-1}^r)	-0.00228	-0.00188	-0.00297
Net investments (I_{t-2}^r)	0.03053	0.02330	0.03165
Net investments (I_{t-3}^r)	-0.00113	0.00419	0.01021

Note: in order to improve readability, the marginal effects of the investment variables (I_t^r) are multiplied by 1,000 so that the figures indicate the effect of investing €1,000,000.

Conclusion

We econometrically estimate the unknown production technology of Danish pig producers by hyperbolic distance functions, where we explain technical inefficiency by current and past investments (among other variables). We obtain implausible estimation results most likely due to problems of multicollinearity between the explanatory variables in the hyperbolic distance function and the high correlation between the explanatory variables of the distance function and the “size” variable that explains technical inefficiency. We estimate the hyperbolic distance function with a constant elasticity of scale (slightly increasing returns to scale) imposed and get mostly plausible results. These results show that the farms that invest have a significantly lower technical efficiency in the year of the investment and a slightly lower technical efficiency in the year after the investment (compared to farms that have not invested in the previous 3 years). This supports our expectations of the existence of adjustment costs. In year two after the investment, farms are significantly more technically efficient than farms that have not invested in the previous three years. This positive effect vanishes in the third year after the investment. This indicates that the highest investment utilization is two years after the investment.

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