Agglomeration Externalities and Technical Efficiency in Pig Production

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Abstract— **The objective of the paper is to assess the effects of agglomeration on technical efficiency of French pig farms. We use a two-stage method to evaluate the effects of agglomeration on technical efficiency. The first stage consists in calculating pig activity's efficiency scores with the non-parametric method Data Envelopment Analysis (DEA). The second stage is a truncated regression of these scores on agglomeration variables. Data are for 899 French pig producers in 2004. Results suggest that these farms were as much affected by positive agglomeration externalities (that are knowledge spillovers due to farms' density, and also arise from farms' closeness to downstream market) as any other businesses. There was however no evidence of negative externalities in the form of constraints in farmers' land demand due to legal disposition relating to manure spreading.**

Keywords— **Agglomeration, Externalities, Data Envelopment Analysis.**

I. INTRODUCTION

Agglomeration externalities are an increasing function of the number of firms and the distance between them. They arise because of the presence of specialized local markets for labor and intermediate products. The most frequently cited sources of positive agglomeration externalities are knowledge spillovers, specialized labor supply, demand matching, and input sharing (Duranton and Puga [1]). Although previous literature gives evidence of how agglomeration economies can have positive effects on the technical efficiency of industrial, the specific issue of agglomeration effects on technical efficiency in agriculture has rarely been investigated: the single reference in agricultural sector to our knowledge is the study by Tveteras and Battese [2], which deals with aquaculture. Pig production is an interesting agricultural sector to study, as it might be subject to both positive and negative externalities implied by spatial concentration.

The organization of pig production has considerably evolved since the 60s in different countries such as Canada, Denmark, France, Germany and the United States. The dynamism of the sector was driven by producers' groupings. In France, those gathered as much as 90 percent of the production in 2000 against 31 percent only in 1972. Following this, the pig production in France increased from 1.1 million tons in 1962 to 1.5 in 1985 and 2.3 in 2000, and from the 80s onwards the farms steadily expanded their size. Hence, small farms disappeared gradually: they were 250,000 in 1969 against 65,000 in 2000. Pig farms of more than 100 sows, which were not numerous in the 60s, represented one third of the livestock in 1988 and more than 70 percent in 2000. At the same time, there was a geographical concentration of the production, mostly in the West. Today the Western regions (Brittany, Pays de la Loire and Basse-Normandie) collect three quarters of the workforce in pig production. Brittany, in particular, accounted for 55 percent of this workforce in 2000, against 30 percent in 1969. Thus, the French livestock production has expanded during the last decades, while at the same time both structural and geographical changes have occurred: today, pig farms have become more specialized and larger, and have more and more concentrated in specific areas in order to benefit from a more favorable technical and economic environment with the aim of 'productivity constantly stepped-up'. However, more recently concentration seems to have had harmful consequences. Intensive pig production causes pollution due to manure, and environmental regulations in France require that pig producers spread their manure on a minimum area of land. Thus, there is now increasing competition for land in pig production, and thus there exist negative agglomeration externalities, which need to be taken into account in the analysis of the impact of agglomeration on pig farm technical efficiency.

The objective of our paper is therefore to assess the effects of agglomeration externalities on the technical efficiency of French pig farms. For this, we take a different approach from Tveteras and Battese's [2] econometric one: we employ the non-parametric Data Envelopment Analysis (DEA), and in a second-stage truncated regression we investigate the impact of agglomeration externalities based on theoretical expectations. Using data about pig activity for 899 French farms in 2004, our results showed that farm technical efficiency is as much increased by concentration as it is the case for other businesses. Reasons may be knowledge spillovers, labor force matching and proximity to upstream and downstream market. By contrast, the analysis did not reveal any constrain due to increased land demand following the environmental regulation.

The paper is structured as follows. The next section explains our theoretical expectations, while sections 3 and 4 describe the methodology and data used, respectively. Section 5 presents and discusses the results and Section 6 summarizes them.

II. THEORETICAL BACKGROUND

Productivity gains induced by the geographic concentration of firms are a standard result in the urban economics literature. What is less clear, however, is the nature and sources of these positive externalities. A number of possible explanations had been advanced: *(i)* productivity changes which are external to firms, and *(ii)* efficiency gains associated with internal economies of scale. Our paper focuses on the first type of explanation derived from Marshall's externalities concept in the 20es. The latter suggests that producers within the same industry agglomerate to gain advantages arising from localized knowledge spillovers, labor market pooling, and availability of specialized input and services (Fujita and Thisse [3]). The underlying microeconomic mechanisms of agglomeration are sharing, matching, and learning processes (Duranton and Puga [1]), which generate increasing external economies of scale that cause agglomeration. Positive spatial externalities in pig production may arise from access to input services (e.g. feed processing plants and veterinary services), from diffusion of information and knowledge through producer organizations and farming extension services, and from the pooling of skilled workers for the pig production activity. During the last decades, although a profusion of theoretical analyses (from Henderson [4] to Fujita and Thisse [3]) have considered agglomeration externalities as an explanation of productivity gains, empirical studies have appeared only lately to confirm these expectations (see Rosenthal and Strange [5] for a review).

Within this empirical literature, the specific issue of agglomeration effects on technical efficiency in pig sector has never been investigated. The only reference in agriculture to this day is the study by Tveteras and Battese [2], which deals with aquaculture. The authors examined the influence of agglomeration externalities at the regional level on the productivity of Norwegian salmon farming[1]. They distinguished between the effects on the production possibility frontier (the hypothesis being that information spillovers lead to technological progress) and on the technical inefficiency (the hypothesis being that knowledge spillovers enable farms to reduce their optimization errors). In their econometric model, the authors integrated two explanatory variables, namely regional size of industry and regional density of farms, in order to investigate how agglomeration externalities influenced technological change as well as technical efficiency. The authors found that an increase of industry regional size led to technological progress, and that farms located in regions with larger industry were more technically efficient. On the other hand, farm regional density had a negative effect on the shift of the frontier, but a positive effect on technical efficiency. The authors concluded that there were positive externalities due to the transfers of knowledge and to an increased supply of specialized production factors, but negative externalities of congestion through fish diseases. Their article is a cornerstone in the literature about the contemporary stakes of empirical spatial economics. As underlined by Rosenthal and Strange [5], the main stake is to go

[1] For that purpose, the authors estimated a stochastic frontier production function on an unbalanced sample of 577 salmon farms during the period 1985-1995.

beyond the analysis of economic agglomeration leaning on data that are geographically aggregated, and to estimate the benefits in terms of economic performance that the individual firms gain from the agglomeration.

Based on existing literature (including Tveteras and Battese [2] and Roe *et al*. [6]) and background of the pig sector in France, we formulate three theoretical expectations.

1. The concentration of farms has a positive influence on their technical efficiency, in the way that farmers' spatial proximity facilitates their relationships, and thus creates knowledge spillovers (information, social capital, etc.) and matching labor force.
2. Farms' closeness to upstream and downstream sectors has a positive influence on technical efficiency. Concentration of the pig sector is largely due to integrations which are as much horizontal as vertical, and thus we expect that better market access increases technical efficiency because of input sharing (upstream sector: industrial or non-industrial pig feed) and demand matching (downstream sector: capacity of slaughtering houses).
3. While the first two expectations deal with positive externalities, farm concentration might have a negative influence on technical efficiency, due to the negative externalities that have lately appeared in the pig sector. As mentioned above, these are due to increasing competition for land following the introduction of a law governing polluting activities.

III. METHODOLOGY

The concept of efficiency is based on the distance of a firm to the production frontier. Technical efficiency refers to a physical notion, independent of input and output prices as well as the availability of inputs[2]. It indicates whether a firm is able to attain the maximum outputs from a given set of inputs. Clearly, the closer a firm operates to the frontier, the more technically efficient it is. Measuring efficiency implies therefore measuring the potential input reduction or potential output increase, relative to a reference. A crucial issue is therefore to define this reference, that is to say, to construct the efficient frontier. In this paper, we use a non-parametric approach to define the frontier. This choice is based on the fact that, in practice, only inputs and their output realizations are observed, and thus the production function is unknown. Rather than specifying a production function with parametric methods, we constructed the frontier in the output-input space by enveloping all observations of our sample. With such non-parametric method, misspecification errors are avoided. In order to fulfil our objective, namely to investigate the impact of agglomeration externalities on technical efficiency of pig farms, our analysis will be carried out in two stages.

A. First stage: Calculation of technical efficiency

In the first stage, the non-parametric method DEA is used to calculate farm technical efficiency. Based on the distance concept of Farrell [7], DEA constructs with linear programming a piece-wise frontier over the sample's best performing data points, so that all observations of the sample lie on or below this efficient frontier (Charnes *et al*. [8]). The distance from a firm to the frontier enables to calculate its efficiency score, which lies between 0 and 1. Higher scores indicate larger efficiency, while a firm located on the frontier is identified as totally efficient and is attributed an efficiency score of 1. We have privileged DEA for the main reason that it does not require the specification of a functional form for the frontier or of the distribution of disturbances, and therefore avoids misspecification errors. Additionally, DEA allows the partition of total technical efficiency into pure technical efficiency and scale efficiency. Total technical efficiency is calculated assuming that firms operate under constant returns to scale (CRS). By contrast, the term pure technical efficiency is used when computing efficiency under variable returns to scale (VRS) and represents management practices. As for the residual ratio between CRS efficiency and VRS efficiency, it is called scale efficiency and can be used to identify optimally sized firms. Figure 1 illustrates the concepts of technical and scale efficiencies. CRS and VRS frontiers are depicted in a one output-one input dimension. All farms located on the VRS frontier are purely technically efficient, that is to say, they have optimal management practices whatever

[2] In opposition, a firm is allocatively efficient if its outputs and inputs maximise its profit (or minimize its cost) at given prices.

their operational scale. This is the case of farms A and B, but not of farm C. In addition, farm A is located on the CRS frontier, indicating that, unlike B, it is totally technically efficiency that is to say it has an optimal scale. While distances to the frontier represent farms' inefficiency, the efficiency scores are calculated as ratios. Relating to Figure 1, total (i.e. under CRS) and pure (i.e. under VRS) technical efficiencies of farm C are given by equations (1) and (2). Scale efficiency is given by the ratio between total technical efficiency and pure technical efficiency; thus, on the figure the scale efficiency of farm C is given by equation (3).

technical efficiency of farm C under CRS:

$$OcC'/OcC \qquad (1)$$

technical efficiency of farm C under VRS:

$$OcC''/OcC \qquad (2)$$

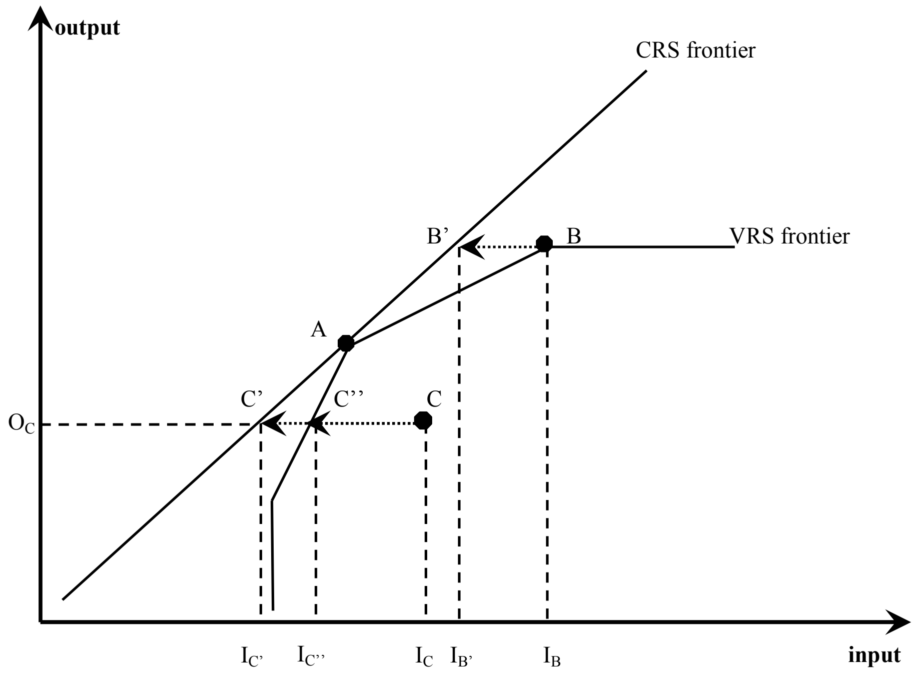
scale efficiency of farm C:

$$OcC'/OcC'' \qquad (3)$$

Moreover, with DEA it is possible to identify whether farms that are not scale efficient have decreasing (DRS) or increasing returns to scale (IRS). DEA has two alternative orientations: input and output. The input-oriented model calculates the proportional decrease in the use of inputs as output remains unchanged, while the output-oriented model computes the proportional increase in outputs that could be attained with constant inputs. We calculated efficiency scores using both orientations and found extremely similar results. We therefore present in this paper only results from the output orientation.

Our DEA model is multi-output and multi-input. Inputs include the number of sows, labor use, feed expenditures, depreciation and other expenditures (energy, water, maintenance and repair, health expenditures, etc). Pig producers in our sample must be separated between three main orientations, due to a discrepancy in their production technologies. The inputs are the same for all three orientations, but their outputs are different. Based on a typology given by experts, the three sub-samples of farms are: only-breeding farms, breeding-and-fattening farms, and after-weaning-and-fattening farms. Only-breeding farms' sole output is the number of piglets, and after-weaning-and-fattening farms' sole output is the number of swine, while both outputs are included for breeding-and-fattening farms.

Figure 1. DEA frontiers under CRS and under VRS



Source: after Coelli *et al*. [9] (Figure 6.3)

B. Second stage: Impact of agglomeration

In the second stage, the efficiency scores obtained in the first stage are regressed on several explanatory variables capturing agglomeration. Due to the bounded nature of DEA efficiency scores (bounded on the right at 1), a truncated regression is used instead of Ordinary Least Squares (OLS). Truncated regression models are employed in cases where some observations are fully missing, so that neither the dependent nor the independent variables are known. These models are often confused with censored regression models where only the value of the independent variable is unknown, while the value for dependent variables is available. In other words, truncated data occur when some observations are not included in the analysis. The econometric second stage is widely used in the literature (for example see Latruffe *et al.* [10]), although usually the bounded nature of DEA scores is frequently not considered, and thus standard OLS are used. The second stage allows estimate the impact, on efficiency, of variables on which the farmer has no control. For example, in the sectors of hospital and transportation, these variables concern generally the type of firm (public or private), the governmental regulations, the location, etc. In agriculture, the variables used will be rather the location and socioeconomic variables (such as the age of the farmer), as well as other variables which represent the quality of the production factors when it is available.

In our study, several agglomeration variables are considered. Agglomeration variables that are tested include various density ratios at several administrative levels: sub-county ("Canton"), county ("Département", level 3 of the European NUTS Classification), and region ("Région", level 2 of the European NUTS Classification). Some ratios relate some farming sector's characteristics (upstream and downstream sectors) to the number of farms in the administrative sections. Additionally, some ratios capture the pollution externalities incurred by local residents, the legal constraints faced by farms for nitrogen discharge (e.g. farmers are allowed to spread the manure on 70 percent only of their utilized agricultural area), and the possible positive spillovers effects or congestion problems implied by farm proximity. As for the other explanatory variables usually included in efficiency papers (such as human capital variables), we do not use them in our model, as they are available for very few observations only (see next section). More specifically, the following models are used for the estimations.

$$\begin{aligned} y_n = \beta_0 + \beta_1 Z_{1,n} + \beta_2 Z_{2,n} + \beta_3 Z_{3,n} + \beta_4 Z_{4,n} \\ + \beta_5 Z_{5,n} + \beta_6 Z_{6,n} + \beta_8 Z_{8,n} + \beta_9 Z_{9,n} \\ + \beta_{10} Z_{10,n} + \beta_{11} Z_{11,n} + \beta_{12} Z_{12,n} + u_n \end{aligned} \tag{4}$$

$$\begin{aligned} y_n = \beta_0 + \beta_1 Z_{1,n} + \beta_2 Z_{2,n} + \beta_3 Z_{3,n} + \beta_4 Z_{4,n} \\ + \beta_7 Z_{7,n} + \beta_8 Z_{8,n} + \beta_9 Z_{9,n} + \beta_{10} Z_{10,n} \\ + \beta_{11} Z_{11,n} + \beta_{12} Z_{12,n} + u_n \end{aligned} \tag{5}$$

where

- n is a subscript denoting the farms;
- y is the farms' efficiency score, in turn total technical efficiency (models 4a and 5a), pure technical efficiency (models 4b and 5b), scale efficiency (models 4c and 5c);
- Z_1 to Z_{12} are explanatory variables listed in Table 2; two models are used in turn for each efficiency: models (4a,b,c) exclude Z_5 and Z_6 (sub-county's density of pig farms and its spatial lag, respectively) while models (5a,b,c) exclude Z_7 (county's density of pig farms); it was not possible to include those three variables together because of multicollinearity;
- u is a random term.

The three sub-samples were merged for the second-stage estimation, as carrying out the regression on each separately did not return any significant findings. The merged sample therefore consists of 899 farms. However, to control for the difference in orientation, we included one dummy variable for the biggest sub-sample, the breeding-and-fattening sub-sample (explanatory variable Z_{11}). In total, six regressions have been carried out (models 4a, 4b, 4c, 5a, 5b, 5c, all on the whole sample).

IV. DATA

This study employs farm-level data from a technical survey and a bookkeeping survey of pig farms carried out by the French Institute of the Pig Sector (IFIP) in 2004. Both surveys enclose a large range of data about outputs, inputs, management, as well as technical and social variables for a sample of about 3,600 farms (IFIP [11]). Only farms that had non-missing and reliable information for the selected outputs and inputs are included in the DEA model. From this reduced sample of 899 farms, the three sub-samples (only-breeding farms, breeding-and-fattening farms, after-weaning-and-fattening farms) are created, and one DEA frontier is constructed for each sub-sample. 43.1 percent of the sample's pig producers are located in Brittany and about 72 percent in Western regions (Brittany, Pays de la Loire, Basse-Normandie, Poitou-Charentes). Moreover, Midi-Pyrénées (in South East France) and the central regions (regrouping the three regions Centre, Limousin and Auvergne) gather respectively 8.4 percent and 9.3 percent of the sample farms. This is consistent with the location of pig production in France. Regarding the three orientations, 74 percent of the sample is breeding-and-fattening farms (of which more than three quarters are located in Western regions), 9.5 percent are only-breeding farms (concentrated more in Centre and Poitou-Charentes) and 16.5 percent are after-weaning-and-fattening farms (located mainly in Western regions).

A. First stage data

Descriptive statistics of the three sub-samples' outputs and inputs used in DEA are presented in Table 1. These outputs and inputs are for the porcine activity only, even for farms not fully specialized in pig production. Only-breeding farms produced on average more piglets than breeding-and-fattening farms, which is intuitive as the latter have a dual production. By contrast, although breeding-and-fattening farms produce two outputs, they produce on average more of the second output (swine) than the fully specialized after-weaning-and-fattening farms. One explanation is that it is easier to produce swine and piglets at the same time. Regarding the inputs, except for the number of sows, breeding-and-fattening farms use much more of any input than only-breeding farms, which is consistent with the fact that input values are calculated with the average input use per livestock head times the number of heads.

Table 1. DEA outputs and inputs (three sub-samples).

	Mean	Std. Dev.	Min.	Max.
Only-breeding farms (167 farms)				
Outputs				
Number of piglets	2,178	1,411	536	8,537
Inputs				
Number of sows	106	61	32	401
Labor (hours)	1,450	754	395	4,698
Feed (euros)	26,106	15,786	827	85,746
Depreciation (euros)	6,353	6,552	11	39,835
Other expenditures (euros)	15,550	12,193	153	75,224
Breeding-and-fattening farms (583 farms)				
Outputs				
Number of piglets	244	286	1	1,358
Number of swine	2,060	1,046	380	5,987
Inputs				
Number of sows	117	51	33	323
Labor (hours)	2,328	1,023	367	5,990
Feed (euros)	146,939	65,811	33,871	383,655
Depreciation (euros)	19,633	14,117	103	70,418
Other expenditures (euros)	33,645	18,533	3,483	102,066
After-weaning-and-fattening farms (149 farms)				
Outputs				
Number of swine	1,476	743	315	4,363
Inputs				
Labor (hours)	850	398	197	2,198
Feed (euros)	105,113	50,534	24,814	288,824
Depreciation (euros)	10,928	8,474	299	41,763
Other expenditures (euros)	90,420	48,859	20,212	266,232

Among all three orientations, after-weaning-and-fattening farms used in general less input, except for other expenditures (energy, water, maintenance and repair, health expenditures, etc).

B. Second stage data

For the regression of efficiency scores, agglomeration variables at different administrative levels are calculated with data from the 1999 Agricultural Census and data from other surveys, which give detailed information about farm environment and upstream and downstream sectors. Several variables are calculated with a weighted distance matrix and measure farms' access to further sub-county than the one they operate in. Descriptive statistics are displayed in Table 2.

Table 2. Second-stage variables (whole sample).

	Mean	Std. Dev.	Min.	Max.
(Z_1) Regional production of industrial pig feed per farm (1,000 t)	547	1,177	7	4,482
(Z_2) Sub-county's available non-industrial pig feed per farm (ha) [a]	7,951	5,641	558	26,578
(Z_3) Sub-county's number of slaughtered heads (1,000 heads)	16	112	0	1,526
(Z_4) Spatial lag of capacity of nearest sub-county's slaughterhouses (1,000 heads) [b]	10.8	13.3	0.9	81.0
(Z_5) Sub-county's density of pig farms (number/ha)	0.10	0.11	0	0.73
(Z_6) Spatial lag of sub-county's density of pig farms in nearest sub-counties (number/ha) [c]	3.5	3.6	0.14	19.5
(Z_7) County's density of pig farms (number/ha)	0.06	0.06	0	0.36
(Z_8) Sub-county's remaining nitrogen discharged by livestock (kg/ha) [d]	65	52	- 58	169
(Z_9) Spatial lag of sub-county's remaining nitrogen discharged by livestock in nearest sub-counties [e]	72	20	-63	170
(Z_{10}) Sub-county's population (number of inhabitants)	9,273	8,449	947	151,279
(Z_{11}) Dummy for breeding-and-fattening farms	0.65	0.48	0	1
(Z_{12}) Dummy for Brittany region	0.08	0.27	0	1

[a]: Weighted hectares (included sub-county *i* and nearest sub-counties): the weights decrease with increasing distance from the farm in sub-county *i* (weight=0 for cereal fields in counties further than 100 km).
[b]: Weighted heads (nearest sub-counties without sub-county *i*): the weights decrease with increasing distance from the farm in sub-county *i* (weight=0 for slaughterhouses in counties further than 300 km).
[c]: Weighted number (nearest sub-counties without sub-county *i*): the weights decrease with increasing distance from the farm in sub-county *i* (weight=0 for population in counties further than 60 km).
[d]: Calculated as the legally authorized limit of nitrogen (quota) minus the sub-county's nitrogen quantity. Negative ratios thus indicate that sub-counties are in excess and that their farmers need to find land in neighboring sub-counties to spread their manure.
e: Weighted ratio (nearest sub-counties without sub-county i): the weights decrease with increasing distance from the farm in the sub-county i (weight=0 for sub-county further than 100 km).

V. RESULTS

A. Total technical efficiency and its components

Descriptive statistics of total technical, pure technical and scale efficiency for the output-orientation are presented in Table 3. Due to the way DEA constructs the efficient frontier, the maximum score found was unity for each DEA model. Therefore only minima are reported in this table. The share of farms with efficiency score of unity, that is to say on the frontier, is presented too. Total technical efficiency scores are on average between 0.80 and 0.86, depending on the sub-samples. For example, the after-weaning-and-fattening sample had an average total technical efficiency score of 0.86. This score indicates that these farms could have increased their outputs by 14 percent on average and still used the same level of inputs. Despite this, this sub-sample is the most efficient on average, in terms of total technical efficiency and pure technical efficiency. This suggests a larger homogeneity in management practices. Scale efficiency was high and similar for all specializations (averages of 0.95-0.96), suggesting that bad management practices caused more inefficiency than sub-optimal scale did. Regarding the share of farms with efficiency score of 1, breeding-and-fattening farms had the smallest share of all sub-samples, possibly be due to their dual output (more activities implying worse management practices).

Table 3. Descriptive statistics of DEA efficiency scores

	Mean	Std. Dev.	Min.	Share of efficiency score of 1 (%)
	Total technical efficiency			
Only-breeding farms (167 farms)	0.82	0.13	0.43	13.2
Breeding-and-fattening farms (583 farms)	0.80	0.11	0.39	5.1
After-weaning-and-fattening farms (149 farms)	0.86	0.09	0.57	10.1
	Pure technical efficiency			
Only-breeding farms (167 farms)	0.87	0.11	0.53	22.2
Breeding-and-fattening farms (583 farms)	0.84	0.10	0.49	8.7
After-weaning-and-fattening farms (149 farms)	0.90	0.09	0.63	24.2
	Scale efficiency			
Only-breeding farms (167 farms)	0.95	0.07	0.55	15.0
Breeding-and-fattening farms (583 farms)	0.95	0.06	0.53	8.1
After-weaning-and-fattening farms (149 farms)	0.96	0.06	0.58	22.1

Table 4. Shares of farms operating under CRS (i.e. scale efficient), IRS and DRS (%)

	CRS	IRS	DRS
Only-breeding farms (167 farms)	15.0	77.8	7.2
Breeding-and-fattening farms (583 farms)	8.8	77.7	13.5
After-weaning-and-fattening farms (149 farms)	22.1	47.0	30.9

The shares of farms operating under CRS (i.e. scale efficient), IRS and DRS, presented in Table 4, indicate that the majority of farms operated at sub-optimal size, particularly in the breeding-and-fattening sub-sample: only 8.8 percent farms were scale efficient, against more than 15 percent in the two other sub-samples. More than three quarters of both breeding sub-samples (only-breeding and breeding-and-fattening) operated under IRS, that is to say farms were too small, suggesting that these orientations could gain efficiency by increasing their size.

B. Impact of agglomeration on farm efficiency

Table 5 shows the estimation results (namely the elasticities) for the models including the county's density of pig farms (explanatory variable Z_7), while Table 6 shows the results for the models including the sub-county's density and its lag (explanatory variables Z_5 and Z_6). Results presented in Table 5 are firstly commented. They show that the breeding-and-fattening orientation is the least efficient in terms of total and pure technical efficiency, as the coefficient for the dummy variable is negative and significant in models (4a) and (4b). This confirms that this sub-sample is the least homogenous orientation in terms of management practices. As mentioned above, this can be explained by the diversification of activities (breeding and fattening activities) for such farms. However, this sub-sample is as homogenous as the two other sub-samples in terms of optimal size (no significant influence of the dummy variable on scale efficiency in model (4c)), as was identified in Table 3.

Regarding agglomeration effects, results in Table 5 suggest that they are present at various administrative levels. However, not all our theoretical expectations are validated.

Table 5. Influence of agglomeration on efficiencies: results of the truncated regression on models (4a,b,c). *Elasticities*.

	Total technical efficiency (4a)		Pure technical efficiency (4b)		Scale Efficiency (4c)
Intercept	0.63384	***	0.64861	***	0.01404
(Z_1) Regional production of industrial pig feed per farm (1,000 t)	-0.00007	***	-0.00004	**	-0.00002
(Z_2) Sub-county's available non-industrial pig feed per farm (ha)	2.96 e-06	***	2.39 e-06	***	1.17 e-06
(Z_3) Sub-county's number of slaughtered heads (1,000 heads)	-5.54 e-06		-0.00001		0.00001
(Z_4) Spatial lag of capacity of nearest sub-county's slaughterhouses (1,000 heads)	0.00102	*	0.00033		0.00105
(Z_7) County's density of pig farms (number/ha)	0.39798	***	0.40111	***	-0.01926
(Z_8) Sub-county's remaining nitrogen discharged by livestock (kg/ha)	0.00013		-0.00002		0.00014
(Z_9) Spatial lag of sub-county's remaining nitrogen discharged by livestock in nearest sub-counties	0.00015		9.45e-06		0.00008
(Z_{10}) Sub-county's population (number of inhabitants)	1.03 e-06	**	0.77 e-06	*	0.40 e-06
(Z_{11}) Dummy for breeding-and-fattening farms	-0.03541	***	-0.02263	***	-0.00082
(Z_{12}) Dummy for Brittany region	0.18461	**	0.09045		0.05938
Wald χ^2	54.35	***	34.57	***	2,81

***, **, *: significance at 1, 5, 10 percent
e-06: multiplied by 10 exponent -6.

1. Our first theoretical expectation is confirmed, as county's pig farm density has a positive and significant influence on total and pure technical efficiency. This suggests that proximity of farms increases knowledge spillovers, and is consistent with the study by Tveteras and Battese [2] on salmon farms.

2. As for the second theoretical expectation regarding market access, it is confirmed for the downstream market: the head capacity of the farms' nearest sub-counties' slaughterhouses has a positive and significant impact on technical efficiency; additionally, the larger the population in the nearest sub-counties, the larger the efficiency suggesting demand matching. However, regarding the upstream market, there is no clear-cut conclusion: on the one hand, proximate available non-industrial pig feed seems to have a positive impact, while on the other hand, regional production of industrial pig feed has an unexpected negative impact.

3. Regarding the last theoretical expectation, it is not validated. Firstly, the remaining quantity of nitrogen discharged per ha in the farms' sub-county has no significant effect on technical/scale efficiency, indicating that in sub-counties where pollution is much less than the authorized level, farms are not more efficient. Secondly, the positive and significant coefficient of the population in the sub-county where the farm is suggests that its efficiency is not affected by the competition for land. Thus, in opposite to what we expected, the need of land does not decrease efficiency.

While Larue *et al*. [12] have shown that environmental regulations have a negative influence on pig production in Denmark, we find that such regulations in France does not affect pig producers' technical efficiency. Although the countries investigated, and thus the contexts, are different, this may reveal that farmers are able to adjust their input use in order to maintain their technical efficiency despite a reduction in production caused by pollution legislation. Nevertheless, our finding may question Porter's hypothesis that 'environmental regulations might lead to improved competitiveness' (Porter and Van der Linde [13]). Indeed, if farms face no constraint, they may not feel the pressure to change their management practices or input-output combination and may thus remain inefficient. However, our study investigates the issue at one point in time. By contrast, Piot-Lepetit and Le Moing's [14] analyzed the relationship between technical efficiency and environmental regulation in the French pig sector over a 5-year period (1996-2001). The authors found that the relationship was positive, highlighting the absorption of inefficiency due to changes in the production process. Besides an effect on changes in the technology over time, the environmental legal provisions may affect pig farms' input and output mix because of their prices. Le Goffe and Salanie [15] have for example shown, theoretically and numerically in Brittany, that land prices increase with pig density. They explain this results by the capitalization in land prices of the manure quota, that is to say the authorized limit of nitrogen. In this case, allocative efficiency of pig farms would have to be investigated. However, such an issue is beyond the scope of the paper.

Table 6 confirms all findings listed above, except for the farms' density. While Table 5 indicated that the density in the county where the farm was located played a positive role on its technical efficiency, Table 6 suggests that the density in the sub-county of the farm and its nearest sub-counties has no influence. Thus, farms benefit mainly from sharing knowledge and labor force with more distant farms. Although the elasticities of the explanatory variables are very low (e.g. -0.00007 for the regional production of industrial pig feed, Table 5), the elasticity of the county's density of pig farms is much higher, approximately 0.40, indicating that farms' total technical efficiency could increase by 0.40 if one more farm was located in the county. This result is important on a policy recommendation point of view: although dispersing pig farms may reduce the pollution externalities incurred by the local population, such a measure may have a negative impact on farm performance.

Table 5. Influence of agglomeration on efficiencies: results of the truncated regression on models (5a,b,c). *Elasticities*.

	Total technical efficiency (5a)		Pure technical efficiency (5b)		Scale Efficiency (5c)
Intercept	0.65095	***	0.66507	***	0.01356
(Z_1) Regional production of industrial pig feed per farm (1,000 t)	-0.00004	**	-0.00002		-0.00002
(Z_2) Sub-county's available non-industrial pig feed per farm (ha)	2.94 e-06	***	2.32 e-06	***	1.18 e-06
(Z_3) Sub-county's number of slaughtered heads (1,000 heads)	-6.23 e-06		-0.00002		0.00001
(Z_4) Spatial lag of capacity of nearest sub-county's slaughterhouses (1,000 heads)	0.00099	*	0.00020		0.00109
(Z_5) Sub-county's density of pig farms (number/ha)	0.01948		0.02938		- 0.00323
(Z_6) Spatial lag of sub-county's density of pig farms in nearest sub-counties (number/ha)	0.00162		0.00252		- 0.00061
(Z_8) Sub-county's remaining nitrogen discharged by livestock (kg/ha)	0.00009		- 0.00008		0.00015
(Z_9) Spatial lag of sub-county's remaining nitrogen discharged by livestock in nearest sub-counties	0.00005		- 0.00008		0.00008
(Z_{10}) Sub-county's population (number of inhabitants)	1.04 e-06	**	0.78 e-06	*	0.40 e-06
(Z_{11}) Dummy for breeding-and-fattening farms	-0.03509	***	-0.02277	***	-0.00062
(Z_{12}) Dummy for Brittany region	0.14086	*	0.03740		0.06387
Wald χ^2	49.07	***	30.31	***	1.20

***, **, *: significance at 1, 5, 10 percent
e-06: multiplied by 10 exponent -6.

Tables 5 and 6 indicate that there is no agglomeration effect on scale efficiency. This might be explained from a methodological point of view: scale efficiency scores are very high for most of the farms, and therefore the variation in the dependent variable might not be sufficiently large. Another explanation might be that farm individual characteristics, in particular its initial size, influence this efficiency more than aggregate characteristics. This is supported by Table 7, presenting the correlation coefficients between farms' utilized agricultural area and their three efficiency scores (total technical, pure technical, scale). This investigation was carried out on a reduced sample of 225 farms only (out of 899) as the land area was available for a limited number of farms.

Table 7. Correlation between farms' efficiency and utilized agricultural area (225 observations)

	Total technical efficiency	Pure technical efficiency	Scale efficiency
Spearman coefficient	0.0734	0.0158	0.1777
Probability	0.2729	0.8141	0.0075 ***

***, **, *: significance at 1, 5, 10 percent

For this reduced sample, the average area is 84 ha, with a minimum of 0 ha and a maximum of 500 ha. Table 6 shows that only the relationship between farm's area and scale efficiency is statistically significant. The coefficient is positive, suggesting that larger farms are more scale efficient.

VI. SUMMARY

This paper investigated the impact of agglomeration on technical and scale efficiency of French pig producers in 2004. The results indicate that efficiency is affected by agglomeration externalities, mainly in a positive way. Positive externalities are in the form of knowledge spillovers facilitated by the spatial proximity of farms, and in the form of closeness to downstream market (in terms of slaughterhouses). Negative externalities were expected in terms of land competition due to legal disposition relating to manure spreading that could potentially constrain farmers in their land demand, but empirical results did not support our expectation.

Although our paper can be extended in different ways, our analysis is the first one that deals with the role of geographical concentration on farms' technical efficiency. It has shown that the theory applies as much as farms as other businesses, with farms' performance increasing with concentration because of knowledge spillovers, matching labor force and easier access to upstream and downstream sectors.

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