Frontier analysis with heterogeneous technologies: the case of low input and high input dairy farming in Flanders

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Abstract

Benchmarking farms, in order to advise farmers to cure inefficiency, may be biased in case heterogeneity is not accounted for. Heterogeneity influences investment motives and production strategies, but is not always clear-cut, for example gradation in external inputs use. The paper explores gradual heterogeneity in efficiency analysis, aiming at identifying peers/reference farms while reflecting on their significance for benchmarking. The gradual differentiation between low and high input dairy farms in Flanders is used as a case, based on a five-year balanced panel data for 58 farms. DEA meta-frontier approach is used to account for heterogeneity. The study concludes that low and high input dairy farming in Flanders are different strategies. However, neither of the strategies is superior to the other even though LI farms on average have higher technical efficiency levels than the HI farms.

Key words: Dairy farming, Input intensity, Peers, Data envelopment analysis

1. Introduction

Although, productive efficiency analysis, based on constructing a frontier to observed production data, is a valuable technique for farm advisors to obtain information on benchmarks, efficiency and improvement potential, the method usually assumes homogeneity of the production function (Coelli et al., 2005; Van Meensel et al., 2012). This assumes that all farms are engaged in the same production process, have comparable measures of efficiency as defined by input and output combinations and are operating under similar conditions (Haas and Murphy, 2003). Heterogeneity in dairy farming, however, exists and has been recognized as a key issue in efficiency analysis. As a result, various approaches to take it into account have been used such as meta-frontier analysis (Battese et al., 2004; Espinoza et al., 2018; Jiang and Sharp, 2015; O'Donnell et al., 2008), threshold estimation techniques (Almanidis, 2013; Almanidis et al., 2019), stochastic frontier latent class models (Bahta et al., 2018; Chang and Tovar, 2017; Pino and Tovar, 2019), Markov Chain Monte Carlo technique (Areal et al., 2012; Olalotiti-Lawal and Datta-Gupta, 2018; Turner et al., 2015) and cost dominance models (Boussemart et al., 2016).

The paper's objectives are i) to examine whether the tool box for the efficiency analysts, adapted for technological heterogeneity provides sufficient anchor points for a strategy-dependent differentiated benchmarking in case of gradual differentiation in technology and ii) to determine whether low input (LI) and high input (HI) strategies are equally efficient. The hypothesis is that HI and LI strategies are different production technologies and LI strategy is superior to HI. As such, the paper contributes to estimating a meta-frontier with a non-parametric technique to account for strategy dependent heterogeneity in dairy farming. To the best of our knowledge, this is the first study to combine peer information with efficiency scores to determine the strategy superiority.

The paper starts by explaining the relevance of accounting for heterogeneity followed by materials and methods in section 3, results in section 4, discussion of results focused on the added value of heterogeneity exploration for differentiation in diagnosis and improvement potential in section 5 and finally the conclusions in section 6.

2. Relevance of heterogeneity in production frontier analysis

Production frontier analysis usually assumes that all firms under investigation use similar technology and operate under similar conditions (Kumbhakar et al., 2015). This is due to the difficulty in accounting for differences between firms, though some of these differences must be accounted for, if reliable results are to be generated (Battese et al., 2004; Huang, 2004). The need for a differentiated analysis stems from both corporate and public concerns. At the firm level, differentiated insights will contribute to both fixing the direction and estimating the potential for improvement. At public level, differentiation facilitates policies which address specific issues among the targeted category of the affected population (Baráth and Fertő, 2015).

Additionally, homogeneity assumption, overestimates inefficiency since researchers are likely to label firms using outdated/inferior technology as inefficient even when they are fully utilizing their technology (Almanidis, 2013; Hockmann et al., 2007). This may lead to erroneous efficiency ranking of firms and making wrong conclusions about the measure of returns to scale. To address these concerns, accounting for technological heterogeneity in productivity analysis is vital.

3. Materials and methods

A five year (2011-2015) balanced panel dataset of 58 specialized dairy farms consolidated from Flemish Farm Accountancy Data Network (FADN) was used to perform detailed analysis. LI, Medium input (MI) and HI farms were distinguished based on the ratio of external input costs (EIC) divided by the number of dairy cows (Dcow). EIC were a sum of the fertilizers, pesticides, energy, contract services and other variable costs used for on-farm roughage production plus the value of the concentrates and energy used by the dairy cows. The computation of EIC differed from that of other studies which used the grazing livestock units as the denominator instead of Dcow (Bijttebier et al., 2017).

Quartiles for the EIC/Dcow were calculated and all farms that had a value less than the first quartile (546.84 Euros per cow per year) plus two other farms which had the lowest values in the second quartile were classified as LI, farms that had a value greater than the third quartile (826.85 Euros) as HI and the rest as MI. The classification resulted in 17, 15 and 26 LI, HI and MI farms respectively. Descriptive statistics were generated and differences among the farms identified, factors influencing milk productivity per cow between LI and HI farms determined after which their efficiency levels were determined. DEA meta-frontier analysis was conducted using DEAP software where group specific frontiers and a meta-frontier were estimated.

3.1. Meta Frontier analysis

Meta-frontier analysis calculates comparable technical efficiencies and technology gaps for firms operating under different technologies relative to the best practice frontier (Battese et al., 2004). Meta-frontier concept is illustrated in an isoquant representation (input oriented DEA-model) in Figure 1. The method estimates the technical efficiency based on the estimation of the group-specific frontiers T_1, T_2 and T_3 and the meta-frontier M. Technology gaps are calculated from the ratio of the observed output of a group-specific frontier relative to the potential output defined by the meta-frontier function, given all the observed data. These technology gaps reflect the improvement potential for the different groups (Li and Lin, 2015). The technology gap can be calculated to show how far the group-specific frontier is from the meta-frontier. Whereas OB/OB'' is the efficiency score with respect to the own strategy-dependent frontier T_1 also known as the intra-technology efficiency (IA), OB/OB' is the efficiency score with respect to the meta-frontier M or the inter-technology efficiency (IE). The technology gap is then given by the ratio of OB/OB'' to OB/OB'. Therefore, technology gap = OB'/OB''.

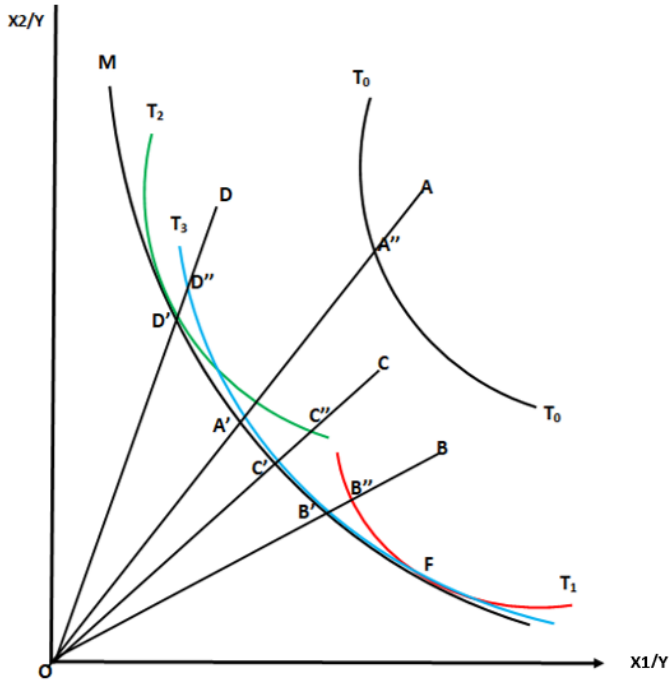

Figure 1: Graphical representation of the Meta-frontier and the group-specific frontiers groups

The same applies for farms C and D. This makes it only meaningful to compare efficiency levels within own group frontiers and the meta-frontier, but not across the group-specific frontiers. For instance in Figure 1, we cannot compare the efficiency scores generated from T_2 with those generated from T_1 but all the efficiency levels can be compared with those estimated by meta-frontier M. There is also a challenge of farms that are in between, not clearly defined whether they belong to T_1 or T_3, such as farm F. Moreover, in our case the two distinct strategies stem from a gradual normally distributed variable and majority of points would have the more "*middle-of-the-road*" situation similar to that of farm F. Additionally, from the illustration, it is impossible to say that T_1 is superior to T_2 because both contribute to the estimation of the meta-frontier. However, if some firms were using strategy T_0, one would easily conclude that T_0 is inferior to T_1, T_2 and T_3 since it does not contribute in the estimation of the meta-frontier.

3.2.Empirical method

DEA was used because it does not assume any functional form and is more appropriate for advisory support since it works with real farms as benchmarks. The technique also reveals the peers against which the performance comparison is done to generate the relative efficiency scores. This is critical information for farmers and farm advisors. Three group specific models and a meta-frontier were estimated using one output (Total farm revenues) and four inputs namely intermediate, land, capital rent and labour costs by employing an input-oriented model. These inputs were selected because they are assumed to account for all the production costs involved in dairy farming hence accurate estimation of the production frontier. The four inputs are also suitable for the DEA model given the number of observations in the LI, MI, HI and pooled samples i.e. 17,15,26 and 58 respectively. These are in line with Banker et al. (1989) who recommends that the number of decision making units (DMUs) should at least be three times the number of factors to fit a good DEA model.

3.2.1. Group-specific frontiers and Meta-frontier

Even though the DMUs considered in this study come under the broader category of specialized dairy farms, the production technology used varies due to differences in EIC. Therefore, measuring technical efficiency of individual farms using a common frontier for all DMUs as the benchmark may not provide a complete picture (Vipin and Bhandari, 2016). Rather, a group frontier for each of its constituting sub-categories may be formed using the DMUs within that particular group. A meta-frontier is then created using all the DMUs belonging to the broader category of specialized dairy farms to envelope the group-specific frontiers. A particular DMU can thus be evaluated against these two frontiers, i.e. the group-specific and meta frontiers.

To construct group-specific frontiers, categorization of the DMUs into different groups is done based on the ratio of EIC/Dcow. Suppose N DMUs are observed, $J = 1, 2, \ldots, N$ and these DMUs are classified into H number of distinct groups, where g^{th} group containing N_g number of DMUs, such that: $\boldsymbol{N = \sum_{g=1}^{H} N_g}$ Equation 1

We then partition DMUs into non-overlapping subsets given as: J_g = [j: DMU j belongs to group g;(g =1,2,…H)]. In this study, H= 3 and j= number of farms in each group. Therefore, the production possibility set for group g will be:

$$T^g = (x, y): x \geq \sum_{j\in J_g} \lambda_{gj} x_g^j \,; y \leq \sum_{j\in J_g} \lambda_{gjy_g^j}; \sum_{j=Jg} \lambda_{gj} = 1; \lambda_{gj} \geq 0 \qquad \text{Equation 2}$$

The set T^g in Equation 2 is the free disposal convex hull of the observed input-output bundles of DMUs from group g and (x^j, y^j) are the observed input-output bundle of an individual DMU j in a sample of N_g DMUs in the data. Therefore, a measure of within-group technical efficiency (TE_g) of DMU k belonging to group g can be given as: $TE_g^k = \theta_g^k$ Equation 3

Where θ_g^k solves the linear program in equation 4:

$$Minimize\ TE_g^k = \theta_g^k \qquad \text{Equation 4}$$

Subject to: $\sum_{j\epsilon Jg} \lambda_{gjx_g^j} \leq \theta_g^k x_g^k \sum_{j\epsilon Jg} \lambda_{gjy_g^j} \geq y_{g\lambda_{gj}}^k \geq 0$ Equation 5

The linear programming problem in *equation 5* is then solved for each DMU in every group and an extra convexity constraint added since we assume the Variable returns to scale $\sum_{j\epsilon J_g} \lambda_{gj} = 1$ Equation 6

3.2.2. Technology gap ratio (TGR)

TGR is given as the ratio of the technical efficiency of the DMU on the meta-frontier to the technical efficiency of the same DMU as estimated by the group specific frontier. For group *g*, this can be given by: $\boldsymbol{TE_g(g)} = \left(\prod_{K=1}^{N_g} \boldsymbol{TE_g^k}\right)^{\mathbf{1}}/_{\boldsymbol{N_g}}$ Equation 7

Similarly, the average TE of group *g*, measured from the meta-frontier, will be:

$$\boldsymbol{TE_G(g)} = \left(\prod_{k=1}^{N_g} \boldsymbol{TE_G^k}\right)^{\mathbf{1}}/_{\boldsymbol{N_g}} \qquad \text{Equation 8}$$

For group *g*, technology gap ratio (TGR), given by: $\boldsymbol{TGR\ (g)} = \frac{\boldsymbol{TE_G\ (g)}}{\boldsymbol{TE_g\ (g)}}$ Equation 9

4. Results

4.2. Characteristics of specialized dairy farms in Flanders

The average annual amount of milk produced per cow is lowest among the LI farms (5664.14L) as compared to the HI farms (Table 1). There is also a huge difference in the Fat Protein Corrected Milk (FPCM) produced per cow between the LI and HI farms. Similarly, FPCM/MILK ratio is significantly different between the LI and HI farms. This means that HI farms produce better quality milk with high fat and protein content. Despite the significant difference in the amount and quality of milk produced by the HI farms, there is no significant difference between the milk sales both quantity and value for the HI and LI farms. MI input farms have the highest milk sales and revenues and this significantly differs from that of the LI farms but not from the HI farms. The number of cows and utilizable agricultural area available are not significantly different which makes their stocking rates not to differ significantly. To meet the dietary requirements of the dairy cows, HI farms spend significantly more on concentrate per milking cow as compared to the LI farms. Averagely milk sales contribute 64% and 69% to the total farm revenues for LI and HI farms respectively, which is a significant contribution. However, this ratio and the profitability ratio do not significantly differ between the HI and LI farms.

Table 1:Statistical differences between LI, MI and HI farms

Name of the variable	LI	MI	HI
Fertilizer per cow (EUR)	87.66[a]	106.36[b]	112.39[b]
Pesticides per cow (EUR)	28.08[a]	31.08[a,b]	32.35[b]
Contract service per cow (EUR)	157.26[a]	161.66[a]	165.85[a]
Other variable costs per cow (EUR)	24.85[a]	47.32[b]	43.66[b]
Energy per cow(Eur)	22.24[a]	26.25[a,b]	30.36[b]
Concentrates per cow (EUR)	236.32[a]	481.34[b]	651.35[c]
Milk per cow (L)	5664.14[a]	7878.94[b]	8302.83[c]
Number of cows	65.19[a]	79.86[b]	73.63[a,b]
Stocking rate (Cows/ha)	1.48[a]	1.54[a]	1.63[a]
FPCM/cow (L)	5896.03[a]	8304.64[b]	8789.46[c]
FPCM/Tot MILK	1.04[a]	1.05[b]	1.06[b]
Total costs	214427.14[a]	339774.90[b]	338595.94[a,b]
Farm revenues	181392.86[a]	298928.10[b]	287808.70[a,b]
Milk sales: Farm revenue	0.64[a]	0.69[a]	0.67[a]
Farm revenues - Total costs	-95976.36[a]	-132920.92[a]	-132400.32[a]
Profitability ratio	0.61[a]	0.73[a]	0.55[a]
Milk sales (€)	118450.78[a]	206853.98[b]	206195.62[a,b]

Milk sales (Liters)	360901.79[a]	609175.17[b]	604862.60[a,b]
Total Labour (Hours)	3899.19[a]	5282.04[a]	4740.61[a]
Calving interval	412.51[a]	416.30[a]	415.79[a]
Utilizable Agriculture Area (ha)	44.90[a]	53.21[b]	46.55[a,b]

A,b,c are significant at $P<0.01$ and $P<0.05$

4.3. Significance of technological heterogeneity in determining factors that influence milk productivity per cow

Determinants of milk productivity per cow were predicted using four separate models. These included a model with all specialized dairy farms, followed by LI model, then MI model and lastly the model with only the HI farms. The determinants are different across the models (Table 2). The difference in these could be due to differences in the farm priorities, goals and resources use by the different farm strategies. In addition, the variables in the predicted model explain 56.3% variability in milk productivity per cow in the general model, 60.1% for LI, 51.7 % for the HI farms and only 22.4% for the MI farms. In all the four predicted models, the value of concentrates per cow is a significant determinant for milk productivity per cow.

Some variable coefficients show different signs depending on the farm strategy. For instance, the average number of dairy cows negatively and significantly influences milk productivity per cow for the LI farms. On the contrary, this positively and significantly increases milk productivity per cow on HI farms. This could be attributed to the low input levels on the LI farms hence an increase in the number of dairy cows would reduce the amount of input allocated per cow which results in reduced milk productivity. On the other hand, the input levels on the HI farms are high thus increasing the number of dairy cows might lead to appropriate distribution of inputs per cow hence increased output. Furthermore, while an increase in labour costs significantly reduces milk productivity per cow for LI, increased labour costs increase milk productivity per cow among the HI farms.

Table 2: Factors that influence milk productivity per cow

Name of the variable	Model1(all farms) Coef (SE)	Model 2 (LI) Coef (SE)	Model 3 (MI) Coef (SE)	Model 4 (HI) Coef (SE)
Concentrates per cow (Euros)	0.555(0.396)***	0.514 (1.424)***	0.353(0.753)***	0.154(0.693)***
Average number of dairy cows	-0.013 (2.23)	-0.617(9.960)***	0.061(2.959)	0.528(2.379)***
Fixed costs per cow (Euros)	0.210(0.179)***	0.500(0.392)***	0.015(0.217)	-0.184(0.239)
Cows per ha (Stocking rate)	-0.015(165.5)	0.325(384.580)***	-0.237(206.113)**	-0.512(202.947)***
Roughage per cow (Kg)	0.019 (0.020)	0.033(0.034)	0.026(0.027)	-0.172(0.028)*
Labour per cow (Euros)	-0.076(0.274)	-0.276(0.760)*	-0.001(0.380)	0.218(0.361)*
Veterinary per cow (Euros)	-0.008(1.441)	0.066(4.257)	-0.054(2.004)	-0.198(1.455)*
Insemination per cow (Euros)	0.237(2.689)***	0.030(6.995)	0.164(3.126)	0.610(3.201)***
R^2	**0.563**	**0.601**	**0.224**	**0.517**

****=significant at 10%, **= significant at 5%, ***= significant at 1% and () standard error, SE = standard error, coef = coefficient***

4.3. Technical efficiency and returns to scale for LI and HI farms

LI farms have the highest mean technical efficiency (MTE), both in the pooled sample (Meta-frontier) and the group specific models. The MTE for LI and HI farms are 0.925 and 0.920 respectively using pooled sample; 0.973 and 0.965 for group specific models. The group specific frontiers reveal that 27 farms are experiencing increasing returns to scale, 13 of which are LI farms and only 4 are HI farms. This means that these farms can increase their output through increasing their current input levels hence still have potential for improvement even without changing their current production technology. On the other hand, 12 farms are experiencing decreasing returns to scale, none of which is LI farm and 3 are HI farms. Such farms would need to reduce their input levels per cow to operate efficiently. Twenty farms are operating under constant returns to scale meaning that a unit increase in the input results in only a unit increase in output. Most of these farms are HI farms.

In Table 3, results from the group-specific models are always condensed in the same column to ensure that both the meta-frontier and the group-specific models are comparing results generated from the same farm. Comparison with the meta-frontier reveals the improvement potentials for farms using different strategies as shown by the TGR. Farms with TGR of 1 mean that they do not have any improvement potential since no technological gap exists for such farms. The smaller this ratio is for a particular farm, the more the farm needs to improve to produce efficiently. For instance, farms 46 and 52 have their TGR as 0.77 and 0.82 respectively which are the lowest thus require to improve greatly to be efficient.

4.4. Heterogeneity and efficient peers

Farms 24, 27 and 48 are peers to the largest number of farms while using the pooled sample. Farm 24 is a peer to 14 farms, farm 27 to 14 farms and farm 48 to 18 farms. Farm 27 and 48 are MI farms while farm 24 is a LI farm. However, farm 48 is a peer to 5 HI, 7 LI and only 6 MI farms in the pooled model. On the other hand, farm 24 which is a LI farm is a peer to 5 HI, 4 LI and 5 MI farms. Farm 27 is a peer to 10 MI, LI and 3 HI farms. This illustrates the possibility to have peers both within and across the strategies depending on what needs to be done to trigger efficient production. This possibility could be due to the nature of the classification of the strategies (based on gradual separation). Therefore, although the farms under different strategies tend to differ in some characteristics, they also share some similarities in the way they combine their inputs to produce a certain level of output.

While using the group-specific model, farm 24 is a peer to 5 farms, farm 27 to 9 farms, 41 which is a HI farm to 5 farms and farm 48 to 6 farms. Therefore, in the pooled model, farms 24, 27 and 48 are the most influential in determining the DEA results while in the group-specific models, farm 24 is most influential for the LI-DEA model, 27 and 48 for MI-DEA model and 41 for the HI-DEA model.

4.5. Significance of peers and references in bench marking

Farm 1 refers to farms 33, 41, 47 and 34 as peers. This means that for this farm to work towards being efficient, it has to mimic the input-output combinations of these reference farms. There are 22 efficient farms on the meta-frontier. On the group frontiers, there are 9 farms on the HI-farm frontier, 11 farms are on the LI-farm frontier and 13 farms on the MI-farm frontier. However, from such a result one cannot know which of the efficient farms are the best but looking at the number of references, we can easily identify farms 48 and 27 on the meta-frontier and group specific frontiers respectively as the best farms. This is because these farms are used as references for the biggest number of farms in the sample. This could be because they have attractive input-output combinations. Farms 9,10,18 and 43 are not performing as good as the other efficient farms because they are not referred to by any of the farms in the sample. This means that none of the existing farms find their input-output combination attractive as regards improving their efficiency.

Table 3:Comparison of efficiency scores and peers from the model assuming homogeneity and the separate models that assume heterogeneity in production technology

Farm No	TE _MTF	TE_GFs	TGR= TE_MTF/ TE_GFs	SE_ MTF	SE_GFs	Farm type	Peer for the MTF	No of references for the MTF	Peers GFs	No. of references for GFs
1	0.977	0.995	0.98	0.926 irs	0.940 irs	LI	33 41 47 34	0	24,35,47	0
2	0.773	0.773	1.00	0.992 irs	0.992 irs	LI	34 24	0	34,24	0
3	0.853	0.892	0.96	0.936 drs	0.923 drs	MI	14 27 29	0	31,27,5	0
4	0.865	1.000	0.87	0.955 drs	0.949 drs	HI	7 21 31 24	0	4	0
5	0.993	1.000	0.993	0.871 drs	0.950 drs	MI	27 29 14	0	5	2
6	0.946	1.000	0.95	1.000 crs	1.000 crs	LI	48 27 16	0	6	0
7	1.000	1.000	1.00	0.970 drs	1.000 crs	MI	7	6	7	4
8	0.873	0.926	0.94	0.979 irs	0.976 irs	HI	41 24 35 33 48	0	39,41	0
9	1.000	1.000	1.00	0.728 irs	0.733 irs	LI	9	0	9	1
10	1.000	1.000	1.00	0.986 irs	1.000 crs	HI	10	0	10	0
11	0.956	0.979	0.98	0.943 irs	0.930 irs	LI	33 35 48 47	0	35,38,9,24	0
12	0.864	0.918	0.94	0.997 irs	0.983 irs	MI	27 41 24 35	0	7, 43,33	0
13	0.874	0.880	0.99	0.953 drs	0.948 drs	MI	27 29 31	0	27,5,31	0
14	1.000	1.000	1.00	1.000 crs	1.000 crs	HI	14	2	14	2
15	0.819	0.894	0.92	0.961 irs	0.920 irs	MI	16 27 48	0	27,18	0
16	1.000	1.000	1.00	1.000 crs	1.000 crs	HI	16	4	16	1
17	0.805	0.814	0.99	0.943 irs	0.950 irs	MI	52 27 16 48	0	48,27,18	0
18	1.000	1.000	1.00	0.730 irs	0.804 irs	MI	18	0	18	2
19	0.985	1.000	0.99	0.926 drs	0.961 drs	MI	21 29 41	0	19	0
20	0.785	0.851	0.92	0.931 irs	0.894 irs	LI	24 48 34	0	35,38,6,24	0
21	1.000	1.000	1.00	1.000 crs	1.000 crs	MI	21	7	21	2
22	0.864	0.957	0.90	0.868 irs	0.800 irs	LI	47 48 24 34	0	35,56,24,47	0
23	0.998	1.000	1.00	0.906 drs	0.904 drs	MI	7 29 21	0	23	0
24	1.000	1.000	1.00	1.000 crs	1.000 crs	LI	24	14	24	5
25	0.723	0.819	0.88	0.987 drs	0.972 drs	HI	7 41 24 21	0	14,41,4,16	0
26	0.936	1.000	0.94	0.938 irs	0.936 irs	LI	39 35 48 47	0	26	0
27	1.000	1.000	1.00	1.000 crs	1.000 crs	MI	27	10	27	8
28	0.929	0.985	0.94	0.969 drs	0.995 irs	MI	7 24	0	7,33	0
29	1.000	1.000	1.00	0.919 drs	1.000 crs	HI	29	7	29	1
30	0.857	0.919	0.93	0.976 irs	0.999 drs	MI	35 33 24 48	0	48,27,7	0

31	1.000	1.000	1.00	0.933 drs	0.976 drs	MI	31	4	31	2
32	0.784	0.893	0.88	0.990 irs	0.996 irs	HI	24 34 48	0	39,41	0
33	1.000	1.000	1.00	0.938 irs	0.980 irs	MI	33	4	33	3
34	1.000	1.000	1.00	0.929 irs	0.929 irs	LI	34	5	34	1
35	1.000	1.000	1.00	1.000 crs	1.000 crs	LI	35	5	35	5
36	0.969	1.000	0.97	0.992 irs	1.000 crs	LI	24 41 57 21	0	36	0
37	0.910	0.994	0.92	0.873 irs	0.838 irs	MI	27 48 41 39	0	27,33,48	0
38	1.000	1.000	1.00	0.743 irs	0.745 irs	LI	38	1	38	2
39	1.000	1.000	1.00	1.000 crs	1.000 crs	HI	39	4	39	3
40	0.772	0.877	0.88	0.966 irs	0.990 irs	HI	27 24 48	0	16,39,41	0
41	1.000	1.000	1.00	1.000 crs	1.000 crs	HI	41	9	41	5
42	0.915	1.000	0.92	0.719 drs	0.666 drs	MI	7 29 31	0	42	0
43	1.000	1.000	1.00	0.967 irs	1.000 crs	MI	43	0	43	1
44	0.879	0.974	0.90	0.993 drs	0.969 drs	HI	14 29 27	0	4,29,14	0
45	0.782	0.794	0.98	0.922 irs	0.949 irs	MI	48 38 16	0	18,48	0
46	0.764	0.992	0.77	0.884 irs	0.733 irs	LI	57 48	0	51,56,35,47	0
47	1.000	1.000	1.00	0.756 irs	0.780 irs	LI	47	4	47	3
48	1.000	1.000	1.00	0.951 irs	1.000 crs	MI	48	18	48	6
49	0.658	0.660	1.00	0.969 irs	1.000 crs	MI	27 24 48	0	7,27,48	0
50	0.838	0.860	0.97	0.964 irs	0.987 irs	MI	57 21 41	0	27,21,57	0
51	0.818	1.000	0.82	0.905 irs	0.862 irs	LI	57 41	0	51	1
52	1.000	1.000	1.00	0.893 irs	1.000 crs	HI	52	1	52	1
53	0.945	0.991	0.95	0.870 irs	0.955 irs	HI	48 39 41 27	0	39,58,41,52	0
54	0.965	0.981	0.98	0.953 drs	0.998 drs	MI	7 21 27 31 24	0	48,27,7	0
55	0.966	0.973	0.99	0.923 irs	0.917 irs	MI	41 21 57	0	21,57	0
56	0.933	1.000	0.93	0.864 irs	0.923 irs	LI	57 48	0	56	2
57	1.000	1.000	1.00	0.983 irs	1.000 crs	MI	57	5	57	2
58	0.945	1.000	0.95	0.893 irs	1.000 crs	HI	48 41 27 39	0	58	1

Irs= Increasing returns to scale, drs= Decreasing returns to scale, crs = Constant returns to scale, TE=technical efficiency, MTF= Meta-frontier, GF= Group specific frontier, TGR=Technological Gap Ratio, SE= Scale efficiency, diff_eff = difference between the technical efficiency from the meta-frontier and technical efficiency from the group specific frontiers

5. Discussion

There is a significant difference in concentrate use between LI and HI strategy of technology, the quality and quantity of milk production per cow and the way certain production factors influence milk productivity. Whereas in the MI group correlation with the inputs was less significant, the correlation is more expressed in the LI and HI farms with different signs of the estimated parameters. The difference in their determinants for milk productivity per cow among the farms using these strategies confirms that these technologies are dissimilar. This means that agricultural advice and policies targeted towards increasing productivity among dairy farmers should always take these differences into consideration, if they are to have milk productivity increased. The results show that HI farms may need to increase levels of certain inputs to increase their productivity while LI inputs will need to reduce the levels of those similar inputs to have their milk productivity increased. This is in agreement with Baráth and Fertő (2015) who recommended that extension programs should stop using "*one size fits all* " or " *blanket"* solutions but rather allow farmers to choose different measures based on the production technology used. These observations are consistent with some of the efficiency analysis outcomes in particular those of economies of scale. Indeed, all LI farms are experiencing increasing returns to scale, while HI farms are experiencing decreasing and constant returns to scale.

Observed differences in the characteristics of both LI and HI strategies do not allow to conclude on the profitability and efficiencies of the strategies. LI farms produce significantly lower amount of milk and FPCM per cow compared to the HI farms, but the milk sales both in volume and value of the two strategies do not significantly differ. Most farms from both technologies have negative net revenues and this makes it difficult to decide which technology is more superior than the other. Furthermore, regardless of the low milk productivity per cow by the LI farms, they have higher technical efficiency levels than the HI farms. This contradicts with the findings of Alvarez and del Corral (2010) who reported that more intensive dairy systems were more efficient than the less intensive ones. While comparing the efficiency levels of the group specific frontiers to the meta-frontier, farms from both strategies contribute in the estimation of the meta-frontier hence none of the technologies is superior to other but rather the farms using the individual technologies (within the technology) are not equally efficient.

Results indicate that some farms are referred to more than others which makes them peers to a larger number of inefficient farms. The higher the number of times a farm becomes a peer, the more influential it becomes to the DEA model results (Barrett, 1997). The number of times a farm becomes a peer similarly reflects the number of farms that have used its input-output relationship information as a bench mark. Therefore, for an inefficient farm to follow an improvement path towards efficient production, it has to mimic the input-output combination of the farms that it considers to be its peers (Goyal et al., 2018). In case farmer representatives per class are to be selected, the farms which are references to most of the inefficient farms should be of interest if their qualitative characteristics are known.

6. Conclusions

Based on predicted factors that influence milk productivity per cow and the way how they influence, low and high input dairy farming in Flanders are different strategies. This differentiation in two technologies is also supported by some efficiency analysis outcomes, in particular differences in returns to scale.

The study, additionally concludes that neither LI nor HI strategy is more superior than the other even though LI farms on average have higher technical efficiency levels than the HI farms. This is because both technologies had farms that were part of the meta-frontier. On the other hand it is also noticed that though some farms may be part of the frontier, they may not be adequate benchmarks. Therefore, to implement results in practice for agriculture advisory, efficiency analysis taking heterogeneity into account is helpful provided it is accompanied with a thorough peer analysis.

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