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Unraveling the impact of variable external input use on the cost efficiency of dairy farms in Europe

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ABSTRACT

There has been a global shift towards intensification in the dairy sector in recent years which may have considerable impact on the cost efficiency and economic returns of farms. Considering this, the goal of this study is to offer an empirical analysis of the effect of variable external input use on dairy farms. Employing a novel Activity Analysis Model (AAM), the study analysis was conducted in two distinct but complementary steps. In the first step, we discriminated two technologies (low and high inputs) which allow us to classify a sample of dairy farms according to their level of intensification, while in the second step, we evaluated two cost efficient frontiers instead of assessing individual farm inefficiency scores. With this approach, we explore different technologies within a sample of EU dairy farms. Our results, on average, shows that agricultural practices using low inputs dominates the high input ones for farms operating on a large scale while a slight dominance of high input over low inputs exist for small scale farmers. While we reckon that low input can be cost competitive with their high input counterparts, we also note that regional differences do exist. Thus, showing that the significant gap between the two discriminating frontiers depends not only on farm size but also on farm region. We found that increased cost efficiency can reduce the negative environmental impact of EU-dairy farms while simultaneously reducing farmers' production costs. The results of the study can therefore provide a direction to policymakers and dairy farmers alike as regards the efficient use of external inputs which may consequently reduce environmental burdens associated with dairy farms.

1. Introduction

The dairy farms in Europe in the last few decades have seen an increase in the use of external inputs like concentrates, fertilizer or crop protection products (Ma et al., 2018). This might be due to an increase in the number of dairy cows per hectare of land (Foote et al., 2015; Mounsey 2015; Ma et al., 2018) thereby resulting to changes in the techniques of production. Changes in production system has been attributed to a range of factors, which include enhancing productivity, overcoming pasture deficits and improving competitiveness (Ma et al., 2018). Most of these dairy farms are therefore increasingly not able to cover their on-farm feed resource need, thus increasing their susceptibility to rely heavily on the use of external (off-farm) inputs (Horn et al., 2014). While it is possible to achieve higher farm production by using more inputs, questions are also being asked as to whether such increase results from the efficient use of available resources in a cost-minimizing way. This is particularly important given the contribution of the dairy sector to social, economic and environmental issues like nutrient imbalances, water and air pollution and biodiversity losses (Caviglia-Harris, 2005; Leip et al., 2015; Adenuga et al., 2018a). Although, the use of high external inputs might contribute to achieving higher technical efficiency and consequently improvement in dairy productivity, it does not necessarily improve profitability (Kebreab et al., 2001; Bijttebier et al., 2017; Ma et al., 2018). The impact on profit or cost efficiency will depend more on the relative prices of inputs used and outputs produced (Kebreab et al., 2001; Bijttebier et al., 2017; Ma et al., 2018).

On the other hand, while research has shown that the use of low input technologies (hereafter LIT) in dairy farms might be desirable from the perspective of environmental sustainability, the extent of their economic competitiveness when compared to farms that employ high input technologies (hereafter HIT) require further investigation. Hence, concerns

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arising from the negative consequences of production intensification demands extra attention due to the importance attached to achieving environmental sustainability. This is because, while most farms might be efficient in terms of input-output productivity as a result of intensification, there are reasons why they might not be efficient from an environmental point of view (Adenuga et al., 2018b; Tyteca, 1996). Dairy farms generally contribute to greenhouse gas emissions (GHG-e), arising mainly from enteric methane and urinary nitrogen deposition on pasture (Adler et al., 2015). The high nutrient surpluses from dairy farms due to high intensification can also increase the vulnerability of soils to leaching which can lead to significant ecological impacts, constituting potential risk to ground and surface water quality (Adenuga et al., 2019). In this manner, dairy farming is under pressure to avoid the use of excessive external input to maintain soil fertility and biodiversity and to reduce GHG emissions (Peterson and Snapp, 2015). Currently, there are limited knowledge on the extent to which intensification affects the cost efficiency of dairy farms. This paper addresses this research gap by analyzing the cost efficiency dominance between LIT and HIT dairy farms across different regions in the European Union (EU) using a novel Activity Analysis Model (AAM). The methodology allows the exploration in terms of classification and comparison of different types of dairy farming techniques which distinguishes two cost optimal benchmarks for systems that are respectively defined with high or low external input technology.

Previous study by Van Meensel et al. (2017) on the competitiveness of low input dairy farms has shown that dairy farming in the EU is far too heterogeneous (Van Meensel et al., 2017). There exists a relatively good degree of variability in farm efficiency across regions because of differences in soil quality, farming practices, attitude and geographical climate (Dong et al., 2016; Jiang and Sharp 2015). In this study, we assess the prospects of technological heterogeneity from the perspective of EU-wide dairy farming systems. Specifically, we analyzed the cost efficiency differentials between LIT and HIT dairy farms for countries that are the main producers of cow milk in the EU. These countries include Germany, France, United Kingdom, Netherlands, Poland, which together (with Italy and Ireland) account for three quarters of total EU dairy production (EU Dairy farms report, 2018). The results of the study will be useful in assisting farmers with adjusting their farming practices sustainably and assist policy makers with the design of efficient farm policies.

To the best of our knowledge, this study provides the first attempt to empirically study the impact of high or low levels of external input use on cost efficiency dominance in dairy farms across different countries in Europe employing the AAM. Most traditional frontier models typically assume that the underlying production technology is the same for all decision-making units (DMUs) without accounting for heterogeneous technologies that exist among the different production units (Čechura, 2010; Barath and Ferto, 2015). This assumption is unrealistic in practice because of the differences in resource accessibility/use, institutional environment and development stage of the economy. This is particularly the case for dairy farming in the EU, where low input technologies may differ substantially from their high inputs counterparts with regional differences also existing between countries (Bijttebier et al., 2017). Thus, cost efficiency estimates might be overestimated, and conclusions that are based on these models might be biased. In this study, we employed a novel AAM model which takes into consideration the heterogeneity among DMUs by redefining the dairy farms production technology given a level of external input cost (EIC) per grazing livestock unit (GLU).

The number of dairy cows is a critical input affecting milk production. Using some livestock unit coefficient (dairy cows - 1.0, under 1 year old - 0.4, 1 or less than 2 years old - 0.7, beef and other cows 2 years and over- 0.8), we convert the number of dairy cows to their corresponding Grazing Livestock Units. Thus, GLU (used as a denominator) in combination with EIC (as the numerator) forms a categorizing indicator to identify LIT and HIT across EU dairy farming systems. In our application, we select GLU as another input (alongside the EIC) in order to explore the different technologies in terms of cost and also to include farm size covering all animals producing milk, milk products and their replacement cattle.

The originality of this paper is based on several elements. Firstly, since the selected criterion for distinguishing the two technologies was the level of EIC per GLU, it is worth noting that this indicator was exogenously treated. This means that the definition of the technology focused uniquely on the operational inputs that directly influence outputs. Therefore, the operational cost regroups components of cow cost such as cost of contract work, machinery hire, upkeep, car expenses and other specific livestock costs such as medicines, artificial insemination, castration, milk test, products for cleaning livestock, storage costs etc. and other intermediate inputs, but excludes expenses included in EIC (concentrated feeding stuff, fertilizer and soil improvers) explicitly. Secondly, instead of evaluating each observed dairy farms, exploration of technologies in terms of cost was established for different livestock mixes (specific to the countries explored in EU-dairy farming system) and several levels of size of the simulated production plans. With this, we are able to assess all of the cost functions in their respective size and country-specific orientation. Thirdly, it was very crucial to take into consideration the comparison of similar farming systems across the different parts of Europe due to the differences in external input use. As such, we explicitly introduce the concept of Hamming Distance (hereafter HD) to control the similarity of farming practices in the different countries when including farms in the AAM. In this way, we endogenously introduced the concept of HD in the linear programs to estimate the HIT and LIT minimal costs. This approach guaranteed that the optimal solution would have a similar comparison of the different dairy practices in the EU countries explored. Lastly, we adapted our cost model to a robust frontier approach to reduce the sensitivity of the cost frontier to the potential influence of outliers. Thus, instead of developing the usual econometric approach, cost frontier estimations were conducted empirically using AAM that imposes few assumptions on the production set and does not require any specific a priori functional form for the cost benchmark. This AAM allowed the assessment of the cost dominance between two different technologies characterized by different levels (sizes) of EIC per GLU.

The objective of this study is therefore to minimize the cost of producing milk using EIC per GLU as a discriminatory variable to distinguish our sample of EU-27 dairy farms into two unique technologies (LIT versus HIT). With this, we are able to explore high and low levels of variable external inputs use for different farm sizes and countries in the European Union (EU).

The rest of the paper is structured as follows: Section 2 outlines the existing literature and theoretical framework of dairy farms efficiency measurement. Section 3 describes the methodology used to assess the cost dominance between the two specified technologies (HIT and LIT). Empirical results are reported in section 4 and discussed in Section 5 while the final section concludes.

2. Literature review and theoretical framework

The relationship between intensification and production efficiency in dairy farms have been analyzed in few studies. Ledgard et al. (2004) for instance showed that increased intensity of production in dairy farms contributed to increase in economic and production efficiency but also resulted in decreased environmental efficiency. Similarly, Last, Hallam and Machado (1996) measuring production intensity as "the amount of feed intake per cow" found greater level of efficiency for high intensity dairy farms compared to the low intensity dairy farms. However a contrasting result was obtained when they measured intensity in terms of the "numbers of cows per hectare". Also Ma et al. (2018) using a fixed effects stochastic production frontier model and a balanced panel of 257 farms from 2010 to 2013 estimated the impact of feed use intensification on the technical efficiency of New Zealand dairy farms. Their technical efficiency results showed that New Zealand dairy farms is positively and significantly influenced by feed use intensification, herd size and milking frequency. With the use of farm business data, Ma et al. (2018) employed an econometric approach -the augmented inverse-probability weighted (AIPW)- to assess the impact of three types of dairy farming systems on milk production and financial performance of dairy farms. Their study showed that higher input system significantly perform better physically (but not financially) than lower input systems.

While most of the reviewed studies have focused on the relationship between feed use intensification and technical efficiency, only a few empirical studies have measured the impact of feed use intensification on cost efficiency. An example of such study is Alvarez et al. (2008) in which they estimated the relationship between farming intensity and cost efficiency using stochastic frontier approach. They utilized cluster analysis to classify farms in their sample by level of farming intensity and consequently estimated independent stochastic cost frontiers for each group of farms to calculate their levels of efficiency. They concluded from their study that intensive farms were more efficient than extensive farms thus, suggesting a positive relationship between intensification and efficiency.

To assess the efficiency of dairy farms, previous studies have employed either the parametric approach such as the stochastic frontier analysis (e.g Latruffe et al., 2004; Alvarez al. 2008; Jiang and Sharp 2015; Dong et al., 2016; Adenuga et al., 2019) or the nonparametric approach such as the data envelopment analysis (DEA) (e.g. Jaforullah and Whiteman 1999; Fraser and Graham 2005; Rouse and Chiu, 2009; Adenuga et al., 2018b). Both methods have their strengths and weaknesses. For example, while the parametric approach is able to take stochastic noise in the data generation process into consideration, it fundamentally requires a specific functional form for the frontier. As a consequence and due to potential misspecification error, this might result to biased results (Picazo-Tadeo et al., 2011). On the other hand, the nonparametric approach does not require the specification of a functional form and the technological frontier represents best practices, while the distance to it from each DMU in the sample is used to compute a measure of its relative performance (Picazo-Tadeo et al., 2011; March et al., 2016). However, it does not account for any stochastic variance from the frontier and attributes all deviations from the frontier to inefficiencies. As such, it can produce results that are susceptible to the influence of potential outliers, which can easily bias the cost function estimation (Aragon et al., 2005; Barath and Ferto 2015). However, this deficiency can be minimized through content-based plausibility checks and efficient data management (Cazals et al., 2002; Adenuga et al., 2018b).

This paper employs a nonparametric Activity Analysis Model (AAM) that involves the use of linear programming methods to construct a nonparametric frontier over the data. As originally developed by Koopmans (1951) and Baumol (1958), the approach modelling technique is ideal for modeling a production technology that has multiple inputs and outputs. The AAM literature has subsequently grew exponentially under the DEA label for measuring technical efficiency. Based on a more engineered approach rather than a pure statistical one, it is considered a useful alternative to econometric models. Thus, the main advantage of AAM is that it permits the estimation of cost functions without specifying any functional form between inputs and outputs. On the other hand, the non-parametric nature of the model avoids confounding the misspecification effect due to an arbitrary choice of functional forms of the technology and the inefficiency components. The meta-frontiers analytical technique is another methodology that can be considered in a study of this kind given that it cuts across different regions. For example, Leung and Sharma (2001) employed the stochastic-meta production frontier analytical technique to examine the inter-country differences in the levels of technical efficiency of semi-intensive/intensive and extensive carp pond culture systems among the major carp producing countries in South Asia. Similarly, Battese, et al. (2004) employed the meta-frontier analytical technique to analyze the technical efficiency measurement of garment firms in five different regions of Indonesia. They proposed a stochastic meta-frontier using pooled data from all study regions to draw the frontier. However, the use of the methodology assumes that the data used for analysis is comparable across regions. This is a very strong assumption that is difficult to justify and could result in bias estimates given the inherent differences and the lack of comparable data across countries (Lau and Yotopoulos 1989; Moreira and Bravo-Ureta, 2010; Chen and Song, 2008).

2.1. Defining low input technologies (LIT) and high input technologies (HIT)

The relevance of different technologies geared towards estimating technical efficiency and technological change in the dairy sector has been emphasized in a growing body of literature (Alvarez and del Corral, 2010; Alvarez et al., 2012; Sauer and Morrison Paul, 2013). In general, the few dairy studies that have adequately addressed the issue of farm heterogeneity (i.e., the presence of different technologies in a sample) have used expert knowledge to segregate the sample based on some specific characteristics. For example, Hoch (1962) divided his sample of Minnesota dairy farms into two groups based on where the farms are located while Bravo-Ureta (1986) classified his sample of farms based on herd breed. Tauer (1998), Katsumata and Tauer (2005) estimated different cost functions for farms using alternative milking systems. Newman and Matthews (2006) estimated independent stochastic distance functions for specialized and nonspecialized dairy farms. Adenuga et al. (2018b) computed the environmental efficiency in dairy farms separately for the two regions of Ireland and Northern Ireland using the directional output distance function approach. Alvarez et al. (2008) used a cluster analysis to classify the sample of dairy farms according to their level of intensification. Some other studies have differentiated the LIT and HIT farms on the basis of input ratios. For example, the Centre for European Agricultural Studies (CEAS) and European Forum for Nature Conservation and Pastoralism (EFNCP) classification (CEAS/EFNCP, 2000) is constructed based on different indicators like fertilizer use, concentrate feed, farm size, herd size, breed, milk yield, livestock density etc. Bijttebier et al. (2017) distinguishes LIT from HIT farms by using the ratio of external input cost to grazing livestock unit. Based on this concept, 25% dairy farms with the lowest value for the ratio are defined as LIT and the 25% farms with the highest value are specified as HIT. The farms in between represent the medium input (MI) group. The 25% cut off value is selected arbitrarily to create more distinct LIT and HIT groups which are less influenced by the MI farms and consequently allow for better comparisons between the groups, looking at competitiveness and strategies applied.

On the other hand, Boussemart et al. (2016) categorized LIT and HIT farms based on the ratio of external input (pesticide) per utilized agricultural area. The approach assumes that when the ratio of the external input per hectare of each observed farm is greater than the average of the ratio of all farms, then such farms are categorized as operating under HIT while it is LIT when each observed ratio is less than the average. Following Boussemart et al. (2016) and in view of our objective to explore the impact of variable External Input by farm size in EU-dairy farming systems, we used the ratio of external input costs per grazing livestock unit to discriminate the two technologies.

Why the assumption that efficiency is linked to the number of animals may not always be true due to differences in the use of production technologies and style of farm management practices (including other factors beyond the control of the farmers), it is employed in this study as a basis for distinguishing the farm types. This enables us to differentiate the two technologies considered based on their intensification levels in line with the study objective. The external input costs comprise costs for fertilizer, crop protection and purchased feed while the grazing livestock unit cover all animals producing milk and milk products and their replacement cattle and this is basically used in the exploration of the two technologies by farm size. Based on the ratio between these two components (EIC and GLU), both LIT and HIT farms are differentiated to give insight into how dairy farms characterized by low input use differ from farms that relatively use more inputs with a further exploration of how this differentiating profile might differ by farm sizes across dairy farms in Europe.

3. Methodology

It is essential to keep in mind that the main objective of this paper is to minimize the operational cost of producing litres of milk using EIC per GLU as a discriminatory variable to distinguish our sample into two unique technologies while keeping the level of milk production on the farm constant. Hence, we measure the gap between the two minimal costs for the same level of milk production in order to assess the cost dominance in operational input uses with respect to dairy farming systems having high and low external input levels.

This section therefore explains the AAM/DEA linear program. A production technology T is defined as the transformation of 'C and E inputs' into 'O' output for a number of 'N' dairy farms under two different technologies. We assume that 'N' dairy farmers, 1} = ϰ, …, N} face a production process with 'O' outputs 1} = ʊ, …, O}, operational inputs C = {1, …, C} and non-operational inputs (external inputs) E = {1, …, E}. We denote $\mathbf{y} = (y_1, \ldots, y_O) \in R_+^O$ as the vector of observed output quantities, $X = (X_1, \ldots, X_C) \in R_+^C$ is denoted as the vector of operational input quantities and $\mathbf{x} = (x_1, \ldots, x_E) \in R_+^E$ the external inputs. Finally, $\mathbf{w} = (w_1, \ldots, w_C) \in R_+^C$ and $\mathbf{w} = (w_1, \ldots, w_E) \in R_+^E$ are respectively operational and non-operational input prices. Following Kuosmanen et al. (2006) and Shephard (1953), the production possibility set of all feasible inputs and outputs vector is defined as follows:

$$T = \left\{ (X, x, \mathbf{y}) \in \mathbb{R}_+^{C+E+O} : (X, x) \ \text{can} \ \text{produce} \ \mathbf{y} \right\} \tag{1}$$

Given a level of external input cost per grazing livestock unit, equation (1) above is used to evaluate cost efficiency[1] of the dairy farmers under investigation. This is done using an Activity Analysis Framework while we avoid the use of the usual framework by redefining the production technology given a level of external input cost per grazing livestock unit.

$$T(L) = \left\{ (X, x, \mathbf{y}) \in \mathbb{R}_+^{C+E+O} : (X, x) \ \text{can} \ \text{produce} \ \mathbf{y} \ \text{given} \ \text{L} \right\} \tag{2}$$

The indicator signifying the ratio of external input cost per grazing livestock unit will therefore enable us to differentiate the two technologies based on their intensification levels $T(L)$. By substituting $T(L)$ with $T^{LIT}(L)$ and then with $T^{HIT}(L)$, it connotes the technology that defines intensification based on low and high levels of external inputs respectively. The technology $T^{LIT}(L)$ contains observed DMUs in the data set using low external input per grazing livestock unit relative to a given intensification level while on the other hand, the technology $T^{HIT}(L)$ is made up of observed DMUs that has an equal or higher ratio of external inputs per grazing livestock unit relative to a given intensification level. The given level of intensification is measured as the averages of all the observed farm both at aggregate and country levels. Equations (3) and (4) below are solved in order to explore the entire two cost functions over their whole domain by varying the dimensions of the farm sizes and their regional differences. Thus, for the same level of output, comparing the equations helps to assess the cost dominance in relation to external input use in dairy farming systems with high and low external input use. The solutions to the equations result in the estimated minimal costs, $\tilde{C}_{LIT}$ and $\tilde{C}_{HIT}$ for every production plan b. For each $\lambda^n \neq 0$, DMU n forms a part of the optimal linear combination which minimizes cost of plan b and is therefore deemed as a benchmark reference that defines the cost function.

$$\begin{aligned} &\min_{\lambda,} \ \tilde{C}_{LIT} = \sum_{n \in N} \lambda^n C^n \\ &\sum_{n \in N} \lambda^n y_o^n \geq y_o^b, \forall o \in O \\ &\sum_{n \in N} \lambda^n = 0, \exists I^n > I \\ &\sum_{n \in N} \lambda^n = 1 \\ &\lambda^n \geq 0, \forall n \in N \end{aligned} \tag{3}$$

$$\begin{aligned} &\min_{\lambda,} \ \tilde{C}_{HIT} = \sum_{n \in N} \lambda^n C^n \\ &\sum_{n \in N} \lambda^n y_o^n \geq y_o^b, \forall o \in O \\ &\sum_{n \in N} \lambda^n = 0, \exists I^n < I \\ &\sum_{n \in N} \lambda^n = 1 \\ &\lambda^n \geq 0, \forall n \in N \end{aligned} \tag{4}$$

The technologies defined from an observed sample of 'N' farms as detailed above are used in the estimation of the operational cost function which involves solving the linear programs in a bid to retrieve the estimated minimal cost functions of the two technologies $T^{LIT}(L)$ and $T^{HIT}(L)$.

3.1. Accounting for size and regional differences

In the event of comparing similar farming systems from both the size and regional perspectives, it is pertinent to consider the production heterogeneity among dairy farms. Programs 3 and 4 specifically departs from a traditional perspective of efficiency analysis and aims at comparing two minimal cost functions. This infer that instead of exploring individual farm inefficiency scores, we rather evaluate the gap between two efficient frontiers. Following the main goal of this research which is to evaluate the impact of variable External Input Cost per Grazing Livestock Units on EU dairy farming systems, we compare two efficient benchmarks. These two technologies are specific to each evaluated farm as it appears in programs (3) and (4). The notations $T^{LIT}(L)$ and $T^{HIT}(L)$ indicate that all DMUs do not face the same production system and this contradicts the usual assumption of traditional DEA. Comparing these two production systems for the same level of output helps in the assessment of cost dominance in relation to the use of external input in dairy farming systems and thereby, accounting for the size and regional differences across the EU-27 dairy farming systems.

In this study, we employed the HD concept to limit the degree of heterogeneity across EU dairy farms. Although, this concept has produced reliable result in the crop sector as used by Boussemart et al. (2016), we explored its first use in the dairy sector with the aim of contributing to the literature from a methodological point of view. This HD concept is derived from fuzzy set theory (Kaufmann 1975) to evaluate the proximity between two production plans a and b belonging to $T^{LIT}(L)$ or $T^{HIT}(L)$ according to their respective livestock structures.

Hamming distance[2] is measured by the sum of absolute deviations between two vectors defined on livestock units partition. For example, for DMUs b and c:$HD(b,c) = \sum_{o \in O} \left| s_b^o - s_c^o \right|$ Where s^o is the share of each livestock units in total livestock. Hamming distance has a maximum value of 2 when b and c are characterized by entirely different profiles of livestock units and a minimum value of 0 when the shares of all livestock

[1] Cost efficiency deals with the minimized cost of utilizing all the operational inputs (components of cow cost and other intermediate inputs) to produce a given level of output. This enables us to explore the cost dominance between HIT and LIT with the use of an exogenous EIC per GLU indicator.

[2] Using the Hamming distance, we group together farms that are very likely to have the same profile of External Input Use not only because they have the same production mix but because of the heterogeneity issue across different countries in EU-dairy farming systems. This would then lead to a uniform reduction in a similar bundle of External Input Use in these heterogenous dairy farms.

units are the same. So, if HD has a value of 0.2, it means 10% of its profile occur in different livestock units when comparing DMU b to DMU c.

By introducing the total livestock revenue as$R = \sum_{o\in O} p_o Y_o$ in place of 'O' output constraints and adapting cost models (3) and (4), we therefore have the following linear models (5) and (6):

$$\begin{aligned}
&\min_{\lambda,S^+,S^-} \tilde{C}_{LIT} = \sum_{n\in\Re} \lambda^n C^n \\
&\sum_{n\in\Re} \lambda^n R^n \geq R^b \\
&\sum_{o\in\mathfrak{O}} \sum_{n\in\Re} \lambda^n G_o^n = \sum_{o\in\mathfrak{O}} G_m^b \\
&\sum_{n\in\Re} \lambda^n G_o^n = G_o^b + S_o^+ - S_o^-, \forall o \in \mathfrak{O} \\
&\sum_{o\in\mathfrak{O}} (S_o^+ + S_o^-) \leq HD \sum_{o\in\mathfrak{O}} G_o^b \\
&\sum_{n\in\Re} \lambda^n = 0 \text{ if } \exists\, L^n > L^b \\
&\sum_{n\in\Re} \lambda^n = 1 \\
&\lambda^n \geq 0, \forall n \in \Re
\end{aligned} \tag{5}$$

$$\begin{aligned}
&\min_{\lambda,S^+,S^-} \tilde{C}_{HIT} = \sum_{n\in\Re} \lambda^n C^n \\
&\sum_{n\in\Re} \lambda^n R^n \geq R^b \\
&\sum_{o\in\mathfrak{O}} \sum_{n\in\Re} \lambda^n G_o^n = \sum_{o\in\mathfrak{O}} G_m^b \\
&\sum_{n\in\Re} \lambda^n G_o^n = G_o^b + S_o^+ - S_o^-, \forall o \in \mathfrak{O} \\
&\sum_{o\in\mathfrak{O}} (S_o^+ + S_o^-) \leq HD \sum_{o\in\mathfrak{O}} G_o^b \\
&\sum_{n\in\Re} \lambda^n = 0 \text{ if } \exists\, L^n < L^b \\
&\sum_{n\in\Re} \lambda^n = 1 \\
&\lambda^n \geq 0, \forall n \in \Re
\end{aligned} \tag{6}$$

To keep the linearity of the programs in (3) and (4), Hamming Distance constraints is introduced into programs (5) and (6), thus programs (5) and (6) can be solved with standard LP solvers. In order to limit the degree of heterogeneity between observations, we then add a constraint on the maximum tolerated Hamming Distance to the standard cost frontier models. The constraint $\sum_{n\in\Re} \lambda^n = 0$ if $\exists\, L^n > L^b$ and $\sum_{n\in\Re} \lambda^n = 0$ if $\exists\, L^n < L^b$ means that the technologies are not the same when the observed DMUs (b) in the data set are using low or high level of external input per grazing livestock unit than a given intensification level.

In terms of the different profiles of the livestock categories, the models in our application considered only one single aggregated output but include 13 specific livestock unit constraints and one total livestock units of all the observed farms (G) which are solved with the use of programs (5) and (6). The empirical applications compares cost functions estimated for similar livestock profile which was guaranteed through the introduction of the HD criterion. $S^+{}_o$ and $S^-{}_o$ are respectively positive and negative slack variables associated with the o constraints on the livestock categories. The possible closest degree of proximity in the sample is indicated by the exogenous Hamming distance. This connotes that if HD = 0, then the cost function is defined only as a DMU which has exactly the same livestock category than the evaluated production plan. If a tolerance of HD = α, is accepted, it means the cost function relies on referenced DMUs which have a maximum of $\frac{\alpha}{2}$% difference in livestock units shares. Hence, an increase in α will result to a reduced DMUs that will be able to define the technology that are comparable in terms of livestock mixes. Lastly, assuming HD = 2, this will infer that all observed DMUs will be included in the technologies $T^{LIT}(L)$ and $T^{HIT}(L)$ irrespective of their livestock mixes compared to the evaluated production plan. In that case (5) and (6) will return to (3) and (4) respectively.

Estimations from equations (3)–(6) can be biased when outliers are present. Therefore, to obtain the most robust estimates, different nonparametric model specifications have been used. In order to take into account heterogeneity and exogenous factors in dairy production and using Monte Carlo simulations, we computed the expected minimal cost in a robust way. This involves a selection of a large number of sub-samples from the reference sets of the two technologies which allows the resampling and computation of the minimal cost. This is estimated as the average of the successive minimal costs computed over all the previous sub-samples. The reference set then changes over the different samples and the evaluated DMU is not constantly benchmarked against potential outliers which can sometimes be present (or not) in the sub reference set. The final average cost can therefore be interpreted as the expected minimal level of cost needed to reach the observed output level (Simar et al., 2016).

Here, we describe the computational algorithm in the case of the technology $T^{HIT}(L)$, for a given evaluated production plan 'b' which is characterized by its total output value R^b and its livestock unit category $s^b = (s_1^b, s_2^b, \ldots, s_O^b)$, we define a sample b of size P with replacement drawn as follows:

$$\Lambda_{b,P}^{HIT}(L) = \{(C^n, R^n, s^n, L^n) : L^n \geq L, n \in \Re\} \tag{7}$$

Afterwards, the minimal cost is now defined on the sub-sample $\Lambda_{b,P}^{HIT}(L)$ and then computed following equation (6). Lastly, where B is the number of Monte-Carlo replications, we repeat this for b = 1 … B, therefore our final minimal cost is computed as:

$$\tilde{C}^{HIT} = \frac{1}{B} \sum_{b=1}^{B} \tilde{C}_{b,P}^{HIT} \tag{8}$$

In order to compute the two minimal expected costs $\tilde{C}^{LIT}$ and $\tilde{C}^{HIT}$, we duplicate the same procedure for the alternative technology $T^{LIT}(L)$. Under these robust cost frontier, two main parameters 'B' (number of replications) and 'P' (size of the sub-samples) are introduced to measure the minimal costs. The value of P tending to infinity would mean that the usual non-robust minimal costs would be recovered since all DMUs have the tendency to be included in each sub-sample. This invariably connotes that the cost functions are evaluated on all production plans of the initial reference sets. Following Dervaux et al. (2009), we opted for a relative value as a percentage of the sub-sample size and this guarantees the same proportion of observations in each sub-sample used in the 'B' replications.

3.2. Data exploration

For this study, data for 2011 of specialized dairy farms from Six EU countries which include Germany, France, UK, Netherlands, Poland and Belgium were obtained and used for analysis. While the first five countries are included because they represent the top producers of milk in the EU, Belgium is one of the four important partner countries involved in the SOLID (Sustainable Organic and LI Dairying) project (http://www.solidairy.eu/). The European FADN dataset includes farm accountancy data of 27 member states of the European Union for the period of 2004 until 2013. Within this period, the year 2011 was selected because the prior discriminatory variable 'external inputs per grazing livestock units' used to distinguish the LIT versus HIT farms was representative for the observed trend during 2004 and 2013 (Bijttebier et al., 2017). The database from the European FADN of technical and economic indicators enables us to analyze and compare the performances of 4570 specialized dairy farms throughout Europe. The farm technology was specified using one global output (milk) which aggregates 13 sub-output units (defined by their GLUs) and this include: other cattle (less than 1yr), male cattle (1 to less than 2years), female cattle (1 to less than 2years), male cattle (less than or equal to 2 years), breeding heifers, heifers for fattening, dairy cows, cull dairy cows, other cows, goats (breeding female), other goats, ewes and sheep.

To account for the gaps in the cost-efficient frontier between LIT and HIT dairy farms, components of cow cost, land and labour cost are chosen as the three main operational inputs while EIC is composed of concentrated feeding stuff, fertilizer and soil improvers. As regards land cost, rent paid per hectare is linked to utilizable agricultural area (UAA) including owned land as there is no other land cost available in FADN which is not already included in the operational costs. Paid labour price per hour on the other hand, is associated with total hours of labor since there are no convenient labor costs associated with family labour. A price per dairy cow is associated with the number of dairy cows. This price consists of all costs not included in the other input costs. In this study, the economic output from beef and veal is not considered as an output and so deducted from the costs that determines the dairy cow price. The denominator of the discriminating indicator that is GLU is selected as another input to include farm size and it cover all animals producing milk and milk products and their replacement cattle. Indeed, more cows have the possibility to produce more milk, *ceteris paribus*, so the number of dairy cows, is a critical input affecting milk production. This therefore drives our motivation for converting the number of dairy cows to livestock units as used in this paper. The components of cow cost include cost of contract work, machinery hire, upkeep, car expenses and other specific livestock costs such as medicines, artificial insemination, castration, milk test, products for cleaning livestock, storage costs etc.

4. Results

This section addresses the comparison and evaluation of the cost dominance of low input over high input technology in heterogeneous EU-dairy farms or vice versa.

Table 1 shows the extent to which farmers in the different EU countries rely on external inputs to carry out their farming practices. The share of external input in total costs is relatively high in Poland, UK, Germany, and France but relatively lower in Belgium and Netherlands with just 27 and 28 per cent, respectively.

The number of farms contained in LIT and HIT categories are presented in Table 2. Overall (EU-27), the total number of farmers operating under the LIT are more than those in the HIT category but this differ significantly by countries. Hence, the different country specifics and number of farming practices in each category reveal the heterogeneity in European dairy farming system as shown in the FADN data used for this analysis.

The six selected countries displayed in Table 2 shows and confirms that the top producers of milk have a large sample size which is more than half of the total number of farms in EU.

Given our sample, the aggregate external input cost per grazing livestock unit of all the observed farms as seen in Table 1 is €652. Overall, the LIT farms were estimated on 2471 dairy farms that used less external input than €652, while the HIT farms relied on 2099 dairy farms that utilized more external input than €652 (Table 1 and Fig. 2). However, these values differ significantly across the understudied EU countries thereby taking into account the regional orientation employed in this paper. Hence, a value of 0.2 was chosen as the Hamming Distance criterion to analyze the entire EU-27 dairy farms as well as the regional differences. By this tolerance, the best cost practices were selected. Finally, the two robust cost functions were estimated for A = 100 replications of each simulated production plan with a M parameter equal to 75% of the initial sample. The two-average cost curves were then compared to assess the dominance of the two technologies.

Table 3 shows that the components of cow cost appear to be complementary with the level of external input use. This indicates that a lower level of input use induces a less intensive technology in the main elements of direct cost. Otherwise, the LIT seems to use a little more labour than HIT especially in Germany, UK, Netherlands, and Poland. Although this gap does not seem important for Germany since the cost difference between their two technologies is due to 45 percent savings in intermediate consumptions. As expected from both the whole sample and country levels, farms operating on HIT pay a lower amount on rent compared to their LIT counterparts.

4.1. Size dimension: Exploring all EU-27 dairying by farm size

Overall, the result in Fig. 1 shows that LIT is more cost competitive than HIT for the simulated points between 135 and 275 grazing livestock units but considering the simulated points between 55 and 134 grazing livestock units, there is a slight dominance of HIT over LIT farms.

Thus, low input farming exceeds high input farming for all the EU-27 farms and this could pose an argument that a farmer who prioritize cost efficiency would also seek to reduce the use of external inputs as a means of improving gross margins. Thus, in conformity with the usual U-shaped average cost curve, the HIT farms present an optimal size of around 115 grazing livestock units, for which the average direct cost is the lowest (€1400), while the optimal size for the LIT farms varies between 100 and 155 GLUs at a minimum average cost of €1600. It is important to keep in mind at this stage that the level of output is the same for both HIT and LIT. So, in essence, cost differences infer higher margins in favour of LIT

Table 2
LIT and HIT farms of top producers of cow milk from EU 27 countries.

Countries	Number of farms in LIT	Number of farms in HIT	Total Number of farms
Germany	588	502	1090
France	310	257	567
UK	141	138	279
Netherlands	75	150	225
Poland	212	163	375
[a]**Belgium**	109	38	147
Total number of farms in the 6 Countries	**1435**	**1248**	**2683**
EU 27	**2471**	**2099**	**4570**

[a] Access to data and the research institute where this project was carried out was in Belgium. More so, Belgium and UK are important partners of the Sustainable Organic and LI Dairying (SOLID) project.

Table 1
Cost components and their corresponding output mean values
(OC= Operational Cost; EIC = External Input Cost; GLU = Grazing Livestock Unit).

Country	Output Value (milk) (€'000)	OC (€'000)	EIC (€'000)	Total Cost (€'000)	OC per GLU (€)	EIC per GLU (€)	Total Cost per GLU (€)	EIC Share in total Cost (%)
EU 27	193	144	80	224	1243	652	1931	0.34
Germany	207	149	88	237	1184	623	1880	0.33
France	132	110	51	161	1170	547	1712	0.32
UK	339	185	150	335	850	674	1537	0.44
Netherlands	319	252	98	350	1770	688	2448	0.28
Poland	76	31	31	62	535	498	1079	0.46
Belgium	156	142	54	196	1432	533	1973	0.27

Table 3
Cost per GLU by input components (€).

Countries	Farm technology	Cow Cost	Rent Cost	Labour Cost	Intermediate Consumptions	EIC (External Input Cost)
EU 27	LIT	932	204	795	5046	796
	HIT	1181	192	747	8335	1258
	Differences (%)	21	−6	−6	39	37
Germany	LIT	1026	251	769	6332	828
	HIT	1231	239	596	11 561	1289
	Differences (%)	17	−5	−29	45	36
France	LIT	1206	205	535	3673	724
	HIT	1426	193	577	4986	1143
	Differences (%)	15	−6	7	26	37
UK	LIT	577	189	581	8618	822
	HIT	697	153	513	11 226	1223
	Differences (%)	17	−24	−13	23	33
Netherlands	LIT	1393	228	841	7326	782
	HIT	1779	206	753	9021	1079
	Differences (%)	22	−11	−12	19	28
Poland	LIT	368	94	352	1540	540
	HIT	468	86	324	2171	993
	Differences (%)	21	−9	−9	29	46
Belgium	LIT	823	299	1157	4862	726
	HIT	1142	255	1207	6023	1142
	Differences (%)	28	−17	4	19	36

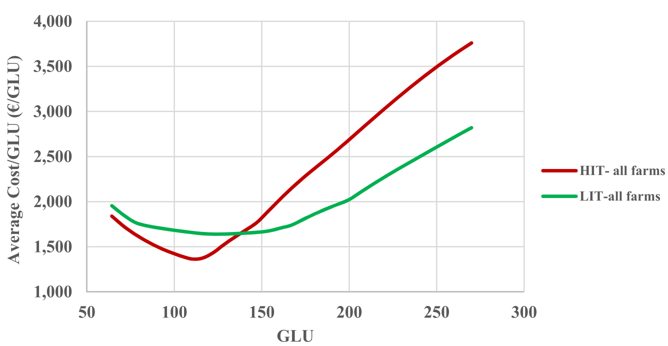

Fig. 1. Average Cost per Grazing Livestock Unit for Low and High Input Technologies.

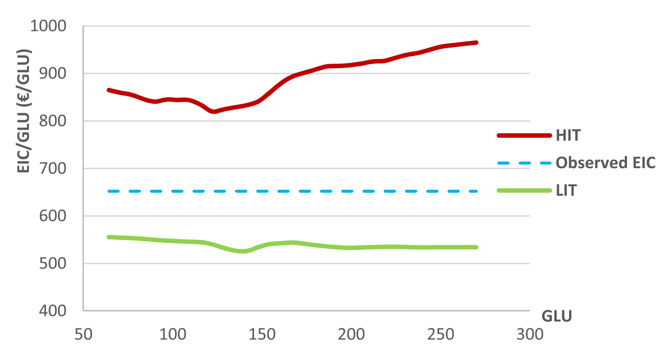

Fig. 2. : Average External Input Cost per Grazing Livestock Unit for Low and High Input Technologies.

for larger farms while it infers higher margins in favour HIT for smaller farms.

Since external input cost is a significant constituent of the total costs, similar comparisons of these specific input expenditures were made between the two technologies. The external input cost per grazing livestock unit is represented by a quasi-flat line as shown in Fig. 2 below, thus presenting a gap that exceeds 24% between the two technologies. This percentage is more significant than the difference in operational costs shown in Fig. 1.

The gap between the estimated EIC of the two technologies becomes wider with an increase in the size of grazing livestock unit (Fig. 2). Thus, changes in size has less effect on the average cost of low input than high input, this therefore explains why LIT dominates HIT at a large scale (Fig. 2).

4.2. Country-specific context: Exploring six EU countries by farm size

To extend the previous conclusion to the top producers of milk in the EU, we run new simulations with six different EU-countries and their related input practices thereby revealing the heterogeneity of EU-27 dairy farming system. Fig. 3 shows LIT-Germany dominating HIT-Germany at every point on the scale. From the robust approach, which considers the presence of outliers, the gap between the two cost curves surpasses 5% on average. The HIT-Germany presents an optimal size of around 130 grazing livestock units while the LIT-Germany presents an optimal size of around 170 grazing livestock units for which the average direct cost is the lowest (€5600).

Fig. 4 shows a conformity with the usual U-Shaped average cost curve with the frontier on HIT-France having an optimal size between 80 and 160 grazing livestock units for which the average direct cost is €8300 while LIT-France presents an optimal size of 90 GLU with an average direct cost of €7900. Thus, this Figure clearly shows that LIT is dominating their HIT counterparts in terms of direct cost of production

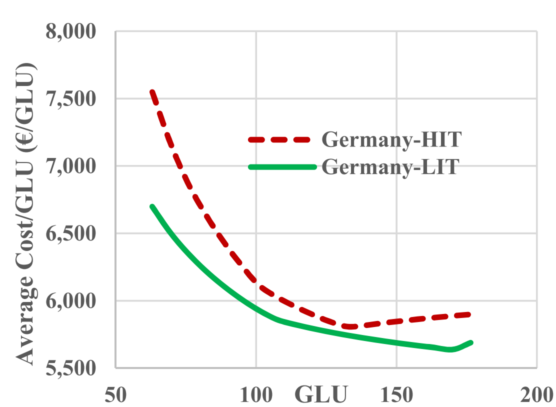

Fig. 3. Average Cost per Grazing Livestock- Germany (N_{LIT} =588 farms and N_{HIT} =502 farms).

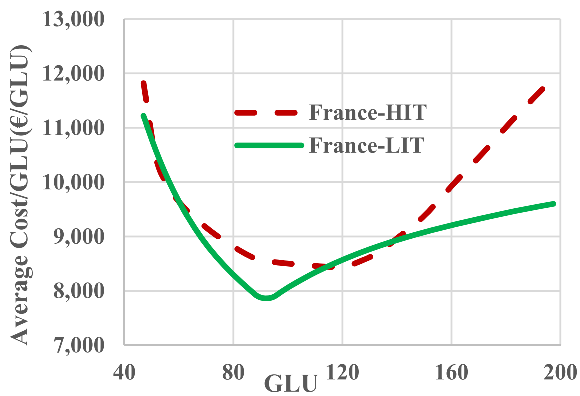

Fig. 4. Average Cost per Grazing Livestock- France (N_{LIT} =310 farms and N_{HIT} =257 farms).

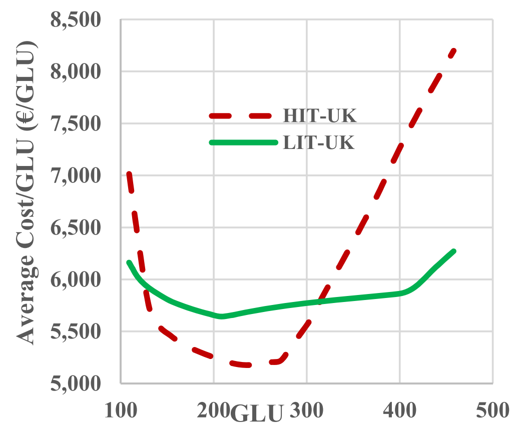

Fig. 5. Average Cost per Grazing Livestock- UK (N_{LIT} =141 farms and N_{HIT} =138 farms).

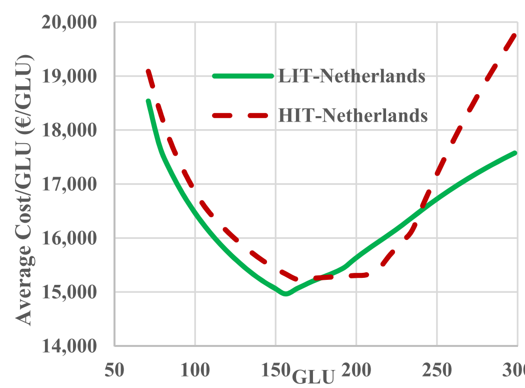

Fig. 6. Average Cost per Grazing Livestock- Netherlands (N_{LIT} =75 farms and N_{HIT} =150 farms).

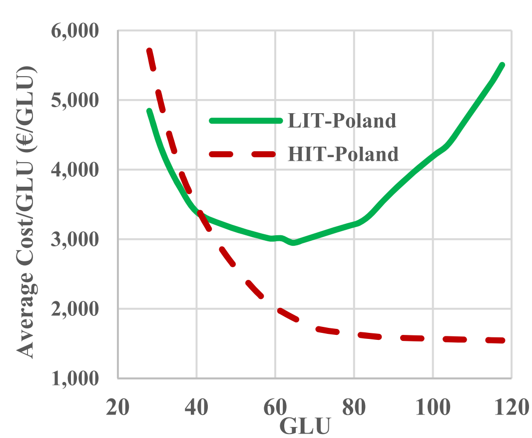

Fig. 7. Average Cost per Grazing Livestock- Poland (N_{LIT} =212 farms and N_{HIT} =163 farms).

especially for farmers with 70–200 grazing livestock units. In UK dairy farms, the farmers raised an average of 100–480 livestock units which seems to be a significant number of animals raised as compared to other countries. The exploration of Fig. 5 shows that grazing livestock units ranging between 100 and 110, LIT-UK dominates the high input ones while HIT- UK are dominating their low input counterparts for grazing livestock units between 110 and 310.

The LIT-Netherlands in Fig. 6 presents an optimal size of 155 grazing livestock units having a minimum average cost of €15 000. On the other hand, the optimal size for the HIT-Netherlands is between 150 and 210 grazing livestock units for which the average direct cost is 15 €200. Fig. 6 shows that, Low Input technology on Netherlands dairy farm is more cost competitive than their High Input counterparts. In Fig. 7, the HIT-Poland frontier presents an optimal size of around 60 grazing livestock units, for which the average direct cost is the lowest (€2000), while the optimal size for the LIT-Poland frontier varies between 40 and 70 GLUs at a minimum average cost of €3000.

Fig. 8 shows the HIT and LIT on Belgium dairy farms for the simulated points between 50 and 220 grazing livestock units, a slight dominance of LIT occurs between 50 and 110 grazing livestock units while the dominance of LIT kicks off between 110 and 220 grazing livestock units. This shows that LIT-Belgium is dominating HIT-Belgium on the small scale of production while LIT-Belgium dominates their high input counterparts on a large scale.

In estimating the cost efficiency dominance of EU-27 dairy farms, these figures clearly suggest that low input farms can be competitive with high input farms, but this largely depends on farm size and the regional location of the farm.

5. Discussion

Traditional frontier methods which do not account heterogeneous technologies often results to biased frontier estimates. This is corroborated by Van Meensel et al. (2010) who use a mechanistic approach to assess farm-specific production functions for a sample of homogeneous pig-finishing farms. Lin and Du (2014) also state that these differences in technology might be inappropriately labeled as inefficiency. To boost the vigor of technology heterogeneity in efficiency analysis, this issue is addressed in this research by distinguishing technologies and consequently controlling their heterogeneities. It is important therefore to state that despite a huge amount of published material and many available techniques, commitments invested in more cost-effective and environmentally-friendly farming methods is already widely prominent but unlikely to be enough in itself to ensure that current environmental targets are fully met (Loyon et al., 2016).

This study contributes to the existing literature by implementing an alternative approach to the one used in previous research. This paper however argues that the production technology among the HIT farms may be different from the technology used by the LIT farms. This issue is important because if the farms in the sample use different technologies, then supposing a single technology for all of them may cause serious econometric problems as it is done under a traditional comparison

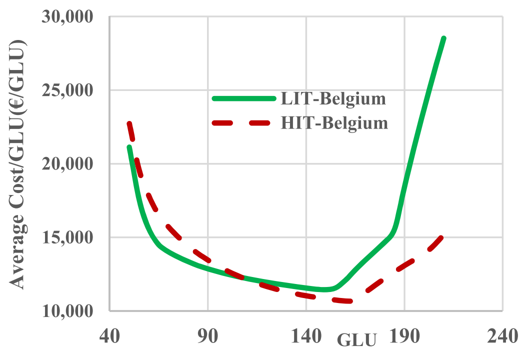

Fig. 8. Average Cost per Grazing Livestock- Belgium (N_{LIT} =109 farms and N_{HIT} =38 farms).

assumption. In this paper, we analyze the cost efficiency gap in the context of EU-27 dairy farms and utilized a HD approach to examine the effect of technological heterogeneity on cost efficient frontiers. Our analysis has some interesting methodological and policy implications. First and from a methodological point of view, we provide evidence that it is important to account for technological differences when examining EU dairy farming systems. Second, using the Hamming Distance approach, we limit the heterogeneity of EU dairy farmers that use different technologies and we find that farm size identified by the number of livestock units is one of the most important factors that differentiates our sample into unique technologies.

Thinking about the existence of these different dairy farming practices, it is obvious that it varies for several EU countries, thus suggesting a need for different technologies and adjusted policies. Martinho and Joao Pereira (2016) assert that one of the reasons for low reliance on external input by the Dutch dairy farmers is the increase in agricultural labour productivity which decreases the need for external input use and as a matter of fact he added that in Dutch dairy farms, greater labour productivity is accompanied by low external input use. In terms of farm size, there is more potential for Germany to reduce costs in the larger farms, than in the smaller farms. However, the smaller farms in Netherlands, France, UK, Belgium and Poland on the other hand have more potential to reduce their costs of production than the big farms. This shows that various countries have different potentials in relation to adopting a specific technology. Martinho and Joao Pereira (2016) again opined that the Dutch dairy farms, namely those with environmental concerns use lower external input, specifically because of the farming management techniques that made huge differences in terms of agricultural input-use efficiency. Samson et al. (2016) hinted that production levels in Dutch regions would increase after the abolition of the milk quota system, thereby making active dairy farmers to follow an expansion strategy.

Milk production in the Netherlands is intensive and relies heavily on purchased inputs. As a result, it achieves one of the highest milk yields in the EU with almost 8000 kg per cow. The Netherlands produces just under 9 per cent of EU milk output. The sector pride itself in its high productivity and assures relatively large gross margins for Dutch dairy farmers. However, the intensive nature of the Dutch dairy system has raised concerns especially regarding manure application; this is because EU dairy farming is bound by environmental regulations through the EU Nitrates directive that limits the amount of nitrogen and phosphate that can be put on the land. The Dutch government implemented the 'Dairy Law' in January 2015 in a bid to further prevent nitrogen and phosphate excesses on farms (Groeneveld et al., 2016). Thus, improving farm efficiency which is essential for the survival of dairy farms.

The significant gap between the frontiers (Figs. 3–8) in the identified countries could be due to different strategies of farm operation which is characterized by variabilities in external input use. The results involve a comparison between technologies in terms of direct input cost while excluding the input components of the external costs which was conducted for different sizes of the grazing livestock units, and external input use levels. This was made possible by exploring the direct cost function over its whole domain of definition with the use of a framework that assesses the cost dominance between technologies exogenously distinguished by high or low external input costs per grazing livestock units. Our exploration of the top milk producing countries in the EU shows that farming systems vary markedly with respect to average cost per Grazing Livestock Units. It is therefore evident that dairy farm size differs across countries which is reflected in the comparison of the two heterogeneous technologies.

Figs. 3–8 therefore shows the extent of heterogeneity in EU-27 dairy farms and it explores the cost dominance of the LIT over HIT and vice versa. The cost performance of the farmers using External Input Cost per Grazing Livestock Units as a discriminating variable is used to compare and assess the performance of LIT and HIT farms in EU-27 and to account for regional differences. Overall results in EU-27 dairy farms show that low input dairy farms can dominate their high input counterparts in terms of cost but differences in farm sizes and regional differences exist. LIT farms may benefit from cost dominance if they transform their external inputs, land, labour and operational/intermediate inputs into milk revenues more technically efficiently compared to HIT farms, because they use inputs in a less cost minimizing proportion.

These results corroborate the work of Bijtebier et al. (2017) where they opined that high input use lead to high productivity, hence a high level of revenue but with a higher cost. However, they found out that the cost performance of farmers is affected by large differences in input use intensity across EU regions/countries. Furthermore, our findings on cost dominance is also illustrated by Scollan et al. (2017) where they show different results across countries. For example, in Finland, organic dairy farming structurally (in terms of farm size and organization), resembles low-input systems, whereas farms in the UK are structurally more similar to high-input farms. LIT farms have lower costs for some inputs, but this is not always sufficient on all farms to act as compensation for higher costs. The comparison between Germany, France, the Netherlands, the UK, on the one hand, and Poland, Belgium, on the other hand, shows that in the former regions, LIT succeed in obtaining a better level of cost efficiency compared to HIT farms. Thus, except for Belgium and Poland, the results show that agricultural practices using low input are dominating the high input for farms operating on a large scale while a slight dominance of high input over low inputs exist for small scale farmers.

Overall, there is cost advantage for farmers who could significantly reduce their input use. This is an important finding in terms of environmental policy implications as it implies that dairy farms can reduce their environmental impact by using low external input while achieving their profitability objective. Previous study by Adenuga et al. (2019) has also shown that dairy farms have the potential to simultaneously increase dairy outputs and reduce environmental impacts through better input management and the adoption of best farming techniques. However, the outcomes from these two scenarios suggest that technological heterogeneity plays an important role in EU dairy farming systems, which are traditionally assumed to use homogeneous technologies.

6. Conclusion

This study contributes to the literature by analyzing the impact of supplementary feed use (referred to external input) intensification on cost efficiency of dairy farms using an Activity Analysis model to assess the influence of technological heterogeneity on the competitiveness of EU dairy farms. The value of external input costs per grazing livestock unit is used as an indicator to distinguish dairy farms into high and low input technologies. Specifically, by utilizing Hamming Distance to control the heterogeneities of EU-27 dairy farms, we evaluated two major frontiers that are cost efficient rather than focusing on individual farm inefficiency scores. The comparison of these two helps in the exploration of various farm sizes and country difference arising from optimal input use. Thus, in Europe, low input farms can dominate their high input counterparts, but much depends on the region where the farm is situated. In general, this paper shows that depending on the country and the size of farms, LIT can be less competitive compared to HIT but in order to be more competitive, LIT farms must use inputs in a more technically efficient way. While our results indicate that on average, there is cost advantage for farmers who could better manage their input use, we reckon that regional difference exist. The exploration of the theoretical review of literature points out that a farmer who prioritize reduced input usage can still make cost minimization and environmental efficiency a priority. Thus, increased cost efficiency can reduce the negative environmental impact of EU-dairy farming systems while consequently reducing farmers' cost of production. However, future research that aims at focusing on profit maximization as an objective may consider exploring the impact of variable external input use on milk production as this is beyond the scope of this present paper. This paper which investigated the cost dominance of HIT over LIT and vice versa can provide valuable information about the necessity and importance attached to differentiating technologies. The results of the study can therefore provide a direction to policymakers and dairy farmers alike as regards the efficient use of external inputs which may consequently reduce environmental burdens associated with dairy farms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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