Technical efficiency and technology heterogeneity of beef farms: a latent class stochastic frontier approach

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Abstract

A high degree of heterogeneity has been observed amongst Irish beef farms, with a diverse range of production systems employing different practices and technologies. Such variation can compromise the estimates obtained when stochastic frontier analysis is used to estimate the frontier under which farms in the sector operate, since it relies on the assumption that all farms operate under the same technology. A latent class stochastic frontier model is implemented using an unbalanced panel dataset constructed from farm level data for Irish beef farms between the years 2000 and 2013, in order to identify different technologies. Results obtained suggest that a single frontier model overestimates technical inefficiency compared to the model where technology heterogeneity is taken into account. Overall results highlight the importance of correctly addressing technology heterogeneity in order to obtain reliable technical efficiency measures; and the comparison of the main characteristics for different classes identified suggest the need of targeted policy measures.

Keywords - latent class model, beef production, technical efficiency, stochastic frontier

JEL codes - Q18 - Agricultural Policy • Food Policy < Q1 - Agriculture < Q - Agricultural and Natural Resource Economics, Q12 - Micro Analysis of Farm Firms, Farm Households, and Farm Input Markets < Q1 - Agriculture < Q - Agricultural and Natural Resource Economics.

I. Introduction

The Irish beef farming sector is very heterogeneous with a diverse range of production systems operated on farms. Variation among farms reflects diversity in cattle breeds and genetics; as well as production practices such as feeding systems and disparities in the rate of uptake of new technologies (Frawley and Commins, 1996). The most general distinction among beef enterprises is between those which mainly deal with breeding and rearing calves from the suckler herd and those that focus their activity on the fattening and finishing of animals (Finneran and Crosson, 2013). However, wide variety of finishing systems can also be found, depending on the age and type of animal produced. For example, some farms focus on finishing male beef animals as bulls, with the fattening period going from 16 months to up to 20 months, resulting in different weights when they are slaughtered. These systems are very different to the traditional steer finishing systems, where there is also wide variation in the amount of months the animal is kept on farm can be found, with a general tendency to longer fattening time (Teagasc, 2015). Moreover, all these systems have different feeding requirements and different intensity of production. In addition, cattle farms operate under varying agro-climatic conditions and soil qualities, which could influence their production possibilities (Hassine and Kandil, 2009), since Irish beef production is predominantly grass based and environmental conditions affect grass growth in different ways. To our knowledge, no comprehensive review of the implications of technology heterogeneity on the assessment of farm economic performance, and more specifically on the analysis of farm level technical efficiency, in the beef sector in Ireland has been carried out to date. This analysis intends to fill this gap.

In addition, the main policy tools implemented in the sector since the 00s, have been rather untargeted and have generally not taken into account technology heterogeneity (Murphy and Meredith, 2014). The bulk of the Common Agricultural Policy (CAP) subsidies are received by farmers in the form of income support. The 1992 MacSharry Reform introduced direct payments coupled to agricultural production in order to compensate the progressive elimination of price support and protectionist measures in place until then. Direct payments were then decoupled from production with the introduction of the Single Farm Payment (SFP) in the 2003 Midterm Review of the CAP, meaning that farmers are not currently required to stock livestock or grow crops in order to receive them. Instead, the amount of payments they receive is based on the possession of entitlements usually allocated based on historical production. Following the 2013 Reform of the CAP, the SFP will be replaced by the Basic Payment Scheme (BPS), which is also based on the possession of entitlements; therefore this element of the new payment is roughly designed in a very similar way to the SFP. This analysis offers interesting applications for policy makers, since it is especially important when analysing policy effects to take into account possible biases in the technology parameters and the technical efficiency scores estimated caused by the presence of heterogeneous technologies, since such biases can affect the policy implications of empirical research.

The paper is organised as follows. Section II will provide a review on previous efficiency analysis addressing technology heterogeneity and on previous examples of empirical research applying latent class models. Section III will describe how the latent class model works and the advantages it offers; while Section IV will provide a description of the data and variables used and of the empirical model implemented in this paper. Section V will be focused on the analysis of the key results obtained from the estimation of the latent class model. Finally Section VI will provide some concluding comments.

II. Technology heterogeneity and technical efficiency

The possible presence of heterogeneous technologies in the Irish beef sector has not been explicitly taken into account before in farm level technical efficiency and productivity analyses. To the best of our knowledge, Newman and Matthews (2007) was the only previous paper explicitly considering the implications of such heterogeneity. They performed a Lagrange multiplier test for the presence of technology differences and found some evidence of differences between ‘specialist cattle’ (i.e. farms producing beef as a single output) and ‘cattle other’ (i.e. farms producing more than one output) sub-samples and highlighted the need to measure productivity with respect to their respective frontiers. However they limited the analysis to the estimation of two separated frontiers for farms classified in the two sub-samples. Other analyses also divided Irish beef farms into groups taking into account a single exogenous characteristic. This was done in Carroll *et al.* (2008) and Finneran and Crosson (2013), who analysed the efficiency of Irish cattle farms splitting the sample in a first step and then estimated separated frontiers. However no explicit analysis of technology heterogeneity was performed in either of the aforementioned analyses.

In order to account for technology heterogeneity, several approaches can be found in the efficiency literature. First, it is common to consider a single specific exogenous characteristic in order to divide the sample and estimate separated frontiers (as in the already mentioned Newman and Matthews, 2007; Carroll *et al.*, 2008; Finneran and Crosson, 2013). However, it is usually the case that firms employ diverse technologies for a variety of reasons (Tsionas, 2002). Therefore the use of a single characteristic of the production technology might be challenging in the cases when heterogeneity is likely to arise from more than one factor, leading to an arbitrary or incomplete division of the sample (Alvarez *et al.*, 2012; Sauer and Morrison Paul, 2013). This is likely to happen in the Irish beef sector, which is characterised by the production of different types of animals, with different levels of intensity, in under various climatic and soil conditions, etc. Second, some authors allow for the consideration of multiple exogenous characteristics when splitting the sample into groups by using statistical techniques such as cluster analysis (Alvarez *et al.*, 2008). These two first approaches have in common that they use a two-stage approach (i.e. in a first step the sample is divided into groups and then separated regressions are performed in each of them), which has the shortcoming that the information contained in a given sub-sample cannot be used to estimate the technology of firms that belong to other sub-samples. This limitation is important because firms included in separated groups can often share some common features (Alvarez and del Corral, 2010).

More sophisticated methodologies that allow disentangling technology heterogeneity from firm technical inefficiency in a single stage are currently available, with the advantage that the limitations mentioned can be overcome. One option is to implement a random coefficients model, which accounts for firms' technology differences in the form of continuous parameter variation (Greene, 2005). Another possibility is to use latent class models in a stochastic frontier analysis (SFA) framework. Latent Class Models (LCM) have been increasingly recognised as a suitable way to deal with technology heterogeneity in a SFA framework. Several studies have applied LCM to different agricultural production systems in different countries, in order to answer diverse research questions. Kellermann (2014) implemented a LCM on a sample of Bavarian dairy farmers to explore differences in performance of farms using exclusively permanent grassland compared to farms which do not. Alvarez and del Corral (2010) and Alvarez and Arias (2013) also used a LCM to analyse the relation between increased intensity of milk production and farm technical efficiency for a sample of Spanish dairy farms. Sauer and Morrison Paul (2013) analysed differences in productivity, technical change and input biases among dairy farms in Denmark. Finally, examples of the LCM applied to crop sector can be found in Barath and Ferto (2015), who dealt with differences in performance and their relation to farm size in Hungary; and in Sauer *et al.* (2012) where the presence of heterogeneous technologies amongst small scale crop farms in Kosovo and its relation to land fragmentation and market integration was explored. In addition, Alvarez *et al.* (2012) explored how using a two-stage SFA approach versus a LCM affected the estimated parameters and concluded that the LCM provided a more satisfactory separation of technologies in the sample. Finally, all these papers found evidence that if technology heterogeneity was not taken into account when estimating technical efficiency, results could be misleading and therefore any policy recommendation arising from them would not be accurate.

III. Methodology

Since the work by Farrell (1957) the use of frontier estimation has been a popular approach for assessing firm efficiency. A production frontier is estimated in this study because it exploits input and output quantity data and does not require data on prices or behavioural assumptions on producers, which can be considered an advantage of this approach when compared to the estimation of a cost, profit or revenue functions (Kumbhakar and Lovell, 2000). SFA has been a widely implemented methodology for frontier estimation and technical efficiency measure in empirical research since it was firstly proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). When SFA is used in order to obtain an estimate of firm technical efficiency, it implicitly requires that the firms being compared share the same technology, represented by the frontier (Huang, 2004; Orea and Kumbhakar, 2004; Greene, 2005; Kumbhakar, 2006; Alvarez and del Corral, 2010). However, when analysing the agricultural sector, the assumption of technology homogeneity can be too strong. In these cases, the parameters of the single frontier estimated are not likely to represent the true technology (Kumbhakar, 2006). If technology heterogeneity is not correctly addressed, it is very likely to get subsumed into the producer specific inefficiency measure, leading to its overestimation (Orea and Kumbhakar, 2004). It could even be the case that farms that appear to be inefficient when compared to a common frontier are actually efficient when compared to their own respective frontier (Hassine and Kandil, 2009).

In a LCM framework, the researcher does not know which firms belong to which technology or how many different technologies there are in the sample. Therefore, it is a required assumption that farms being analysed operate under an unknown finite number of different technologies underlying the data, denoted by the subscript *J* in equation 1.

$$Y_{it} = f(X_{it}, t, \beta, \delta)|_j + v_{it}|_j - u_{it}|_j \tag{1}$$

The LCM model classifies the sample into several groups and each farm can be assigned to a particular group using the estimated probabilities (P_{ij}) of class membership. The farm *i* likelihood function (LF_i) is obtained as a weighted sum of their *j*-class likelihood functions, where the weights are the probabilities of class membership as shown in equation 2. The overall likelihood function is then obtained as the sum the individual likelihood functions (LF_i) as in equation 3, where θ_j are the frontier specific parameters to be estimated.

$$LF_i(\theta, \delta) = \sum_{j=1}^{J} LF_{ij}(\theta_j) * P_{ij}(\delta_j) \tag{2}$$

$$lnLF(\theta, \delta) = \sum_{n=1}^{N} ln\{\sum_{j=1}^{J} LF_{ij}(\theta_j) * P_{ij}(\delta_j)\} \tag{3}$$

The prior class probabilities (***P$_{ij}$***) are parameterised as a multinomial logit model, to ensure that $0 \leq P_{ij} \leq 1$ and $\sum_j P_{ij} = 1$.

$$P_{ij}(\delta_j) = \frac{exp(\delta_j Q_i)}{\sum_{j=1}^{J} exp(\delta_j Q_i)} \tag{4}$$

Since class probabilities might be a priori non-zero, the LCM allows for all the observations in the sample to be used to estimate the underlying technology for each class. In contrast, the two-stage procedures mentioned in the previous Section implicitly restrict the class probabilities to be equal to one for a particular class and to zero for the others, precluding using observations that were allocated to one particular group to estimate other class frontiers. Prior probabilities can be made depend on a vector of separating variables ($\boldsymbol{Q_i}$), defined to be farm specific and time invariant, that reflect differences in technologies used by farms (Sauer and Morrison Paul, 2013), with a corresponding vector of parameters ($\boldsymbol{\delta_j}$) to be estimated. One group is chosen as reference in the multinomial logit.

The overall likelihood function in equation 3 can be efficiently estimated using Maximum Likelihood. Once the likelihood function is maximised, the parameters can be used to obtain the posterior probabilities of class membership.

$$P(j|i) = \frac{LF_{ij}(\theta_j) * P_{ij}(\delta_j)}{\sum_{j=1}^{J} LF_{ij}(\theta_j) * P_{ij}(\delta_j)} \tag{5}$$

Both the coefficients of the production function to be estimated and the coefficients of the separating variables are used in the computation of the posterior probabilities. Note that posterior probabilities are modelled to be time invariant, which in practice implies that farms remain in the same class throughout the period being analysed[1].

Once the *J* production frontiers are defined, the distance from each firm observation to the frontier needs to be measured and it provides an estimate of the firms' technical efficiency, recovered from the estimated compound error:

$$TE_{it}|_j = exp(-u_{it}|_j) = exp(-E(u_{it}|_j|u_{it}|_j + v_{it}|_j) \tag{6}$$

Technical efficiency refers to the ability of the firm to produce an output using minimum inputs or to obtain the maximum level of output given a set of inputs. In LCM context, farm specific technical efficiency is computed for the frontier with the higher posterior probability for each farm in the sample (i.e. it is frontier specific).

[1] One way to allow posterior probabilities to vary over time is by estimating the LCM ignoring the panel structure of the data, and treating each observation as a cross sectional observation (Sauer and Morrison Paul, 2013). The panel data structure should not be ignored when present; however, estimating such model can give an idea of the amount of farms that would change class and therefore address how severe the assumption of time invariant posterior probabilities may be. In our case, almost 80% of farms did not change class when a model with no panel data specification was estimated, so such assumption should not have worrying implications for our results.

IV. Empirical Model and Data

In this analysis the functional form assumed for the production function estimated is the well-known and widely implemented trans-logarithmic, in order to avoid any a priori restrictions on the production technology specification.

$$\begin{aligned}\ln Y_{it} = \beta_0|_j + \sum_{k=1}^{K} \beta_k|_j \ln X_{itk} + \frac{1}{2}\sum_{k=1}^{K}\sum_{g=1}^{G} \beta_{gk}|_j \ln X_{itk} \ln X_{itg} \\ +\delta_t|_j t + \sum_{w=1}^{W} \alpha_w|_j dSOIL_{itw} + v_{it}|_j - u_{it}|_j\end{aligned} \tag{7}$$

In equation 7, Y_{it} is a single aggregated output produced by each farm, $\boldsymbol{X_{it}}$ is a vector of K inputs used by the farm on the production of output, t is a linear time trend that accounts for neutral technical change and $\boldsymbol{\beta_k|_j}$, $\delta_t|_j$ and $\boldsymbol{\alpha_w|_j}$ are parameters to be estimated. The subscript J refers to the different classes, meaning that a different set of parameters is estimated for each of the classes identified.

The main data source employed in this analysis is Irish Farm Accountancy Data Network (FADN) data which are collected through the Irish National Farm Survey[2] (NFS). An unbalanced panel for the years 2000 to 2013 is built including all farms classified as specialist cattle producers[3]. Here the total value of cattle output (in euros) includes the value of calves, weanlings, stores, finished cattle and other cattle sales produced on the farms in the sample, and excludes subsidies received. The NFS does not collect information on physical output of cattle production, however total output value is converted to a volume measure implementing the implicit volume methodology (O'Neill and Matthews, 2001; Newman and Matthews, 2007; Zhu and Lansink, 2010; Zhu et al, 2012). Following the mentioned literature, farm specific aggregated Tornqvist price indices are constructed using national price indices taken from the Irish Central Statistics Office. Implicit quantity indices are computed as the ratio of the sum of the value of all cattle outputs to this aggregate Tornqvist price index with base year 2010. Inputs used on farm are also aggregated into four categories, named area, labour, capital and variable costs. Land input measures cattle forage area in hectares, which is the total adjusted area under grass (including rough grazing) plus adjusted commonage area used by the farm cattle enterprise. In order to take into account differences in land quality, a set of dummy variables capturing the quality of the soil[4] in which the farm

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[2] The NFS is a member of the EU wide FADN, and has been collected and published by Teagasc on an annual basis since 1972. It fulfils Ireland's obligation to provide yearly data on farm output, costs and income to the European Commission as part of the Farm Accountancy Data Network (FADN) of the EU. Farms are classified into 6 farm systems according to the relative contribution of farms' different enterprises to its total Standard Gross Margin (SGM). It should be noted that the SGM was replaced with the Standard Output (SO) classification system in 2010.

[3] Farms are classified as specialist cattle producers when more than 60% of their SGM comes from a cattle enterprise. In this panel approximately 16% of farms abandon the survey each year and are replaced by new farms. Farms remain in the sample for 8.75 years on average and the total number of observations is 6323.

[4] Dummies for soil groups 2 and 3 are included, leaving out soil group 1 as the reference category. Group 1 includes soils that have no limitations which cannot be overcome by normal management practices or that have minor limitations, group 2 includes soils that have somewhat limited use possibilities for agricultural activities and group 3 includes soils with very and extremely limited agricultural use.

operates are also included in the production function estimated. Labour input is measured in total labour units working on the farm, including both unpaid and paid. One labour unit is defined in the NFS as at least 1800 hours worked on the farm by a person over 18 years of age. Capital aggregates the value in euros of machinery and buildings (calculated according to the end of year valuation based on a replacement cost methodology) and the value of the suckler cow herd, calculated as the average of the yearly opening and closing inventories. Variable costs aggregate feeding costs (including concentrates, pasture, winter forage, milk and milk substitutes), veterinarian costs, AI and service fees, transport expenses, casual labour and miscellaneous cattle specific variable costs. These last two aggregated inputs are built using the implicit volume methodology again, by dividing the value of each of them by an aggregate farm specific Tornqvist price index with base year 2010. Note that farms in the sample are classified as specialist cattle according to their dominant enterprise, however it does not exclude that they also engage in agricultural production other than cattle. In order to take this into account, inputs that are not specifically allocated to the cattle enterprise in the NFS (i.e. capital and labour) have been allocated using the share of cattle gross output to total gross output as weight. Output and input variables were divided by its geometric mean.

Variables proxying the technologies under which farms operate ($\boldsymbol{Q}_i$) are generally included as separating variables in the parameterisation of the prior probabilities. Farm specific mean values for the years in which they appear in the panel are used, making this set of variables farm specific but time invariant. Different levels of intensity of production are generally understood to imply the use of different production technologies (Alvarez and del Corral, 2010; Sauer and Morrison Paul, 2013; Teagasc, 2015) so in order to capture such differences the stocking rate, defined as the cattle livestock units per hectare, is included. In addition, Irish cattle farms are generally specialised in different beef production systems with suckler and finishing enterprises being the predominant types (Murphy and Meredith, 2014). Therefore the level of specialisation in breeding animals or in finishing cattle (defined as the share of calves and weanlings sold and finished cattle sold on total cattle sales respectively) are included as proxies. Finally, a dummy variable capturing whether a farm is located in a favourable soil type (soil class 1) or not is also included. Descriptive statistics for output, inputs and the separating variables included in the model are provided in Table 1.

Table 1. Descriptive statistics

	Mean	**Standard Deviation**
Output (euro)	22956.600	40085.920
Area (ha.)	26.438	19.834
Labour (labour units)	0.585	0.321
Capital (euro)	19125.140	22502.440
Variable costs (euro)	10112.650	10739.750
Time trend	7.207	3.942

Soil 1 (D)	0.435	0.496
Soil 2 (D)	0.474	0.499
Soil 3 (D)	0.092	0.288
Stocking rate (LU/ha)	1.158	0.432
Rearing specialisation	0.200	0.278
Finishing specialisation	0.357	0.362

Notes: (D) indicates a dummy variable. Monetary values are provided in 2010 prices. Time trend = 1, …, 14.

V. Results

A table with frontier estimates for the three classes LCM is included in the Appendix[5]. The first step is to determine the number of classes, which is unknown to the researcher. Orea and Kumbhakar (2004) and Greene (2005) advise against using a likelihood ratio test under these circumstances since the degrees of freedom are ambiguous. Therefore, the Akaike Information Criteria (AIC) and Bayes Information Criteria (BIC) are used in order to assess what model is preferred (Orea and Kumbhakar, 2004; Greene, 2005; Alvarez and del Corral; 2010)[6]. The LCM model with three classes is preferred over the LCM with two classes and the single frontier model, since it has the lowest AIC.

The majority of variables affecting prior probabilities are statistically significant, which is indicative of the information they contain being useful in classifying the sample[7]. In addition, the exclusion of separating variables was rejected by a Wald test at the 1% significance level. The constants are statistically significant, indicating that the production technologies of the different frontiers show differences among them (Sauer and Morrison Paul, 2013). The sign of the coefficient obtained point the direction of the effect of a given separating variable on the probability of a farm being classified in each class, with class 3 being the reference category. Higher stocking rate decreased the probability of being classified in class 2 whereas the level of specialisation in cattle rearing and being located in favourable soil type also decreased the probability of being classified under classes 1 or 2.

[5] A likelihood ratio test was performed in order to further assess the adequacy of the translog functional form as opposed to the more restrictive Cobb-Douglas functional form, but the latter was rejected at the 1% significance level.

[6] The formulas are $AIC = - 2 \times logLF(j) + 2 \times m$ and $BIC = - 2 \times logLF(j) + m \times log(n)$ respectively, where m is the number of parameters, n is the number of observations and *LF(j)* is the value of the *LF* for *J* groups. The AIC (and BIC) values for each of the single frontier, two and three class models are 1.68 (1.70), 1.45 (1.50) and 1.30 (1.39) respectively. The LCM model with four classes failed to converge, indication that such model could be over specified (Orea and Kumbhakar, 2004; Alvarez and del Corral, 2010).

[7] As an additional check, we compared the farm classification obtained from models where the separating variables were included and not. A large share of farms were classified in a different class when no separating variables were included, indicating that the separating variables have a strong influence in farm classification (Kellermann, 2014).

Elasticities and returns to scale estimates

Since output and input variables in the production function estimated are normalised by their means prior to estimation and are expressed in natural logarithms, it is possible to calculate output elasticities by partially differentiating the production function by each of the inputs as shown in equation 8.

$$E_k|_j = \beta_k|_j + \beta_{kk}|_j lnX_{kit} + \sum_{k \neq j} \beta_{kj}|_j lnX_{jit} \tag{8}$$

$$RTS|_j = \sum_{j=1}^{J} E_k|_j$$

The elasticities are computed for each observation with respect to their own frontier as indicated by the *J* subscript and they reflect the importance of each of the inputs in output production. Estimates obtained are provided in Table 2.

Table 2. Mean output elasticities

	Class 1	**Class 2**	**Class 3**	***Single Frontier***
Area	0.246***	0.170***	0.344***	*0.306****
	(0.038)	(0.062)	(0.023)	*(0.021)*
Labour	0.060**	0.189***	0.146***	*0.111****
	(0.030)	(0.065)	(0.022)	*(0.018)*
Capital	0.095***	0.159***	0.160***	*0.159****
	(0.020)	(0.034)	(0.013)	*(0.012)*
Variable costs	0.344***	0.265***	0.333***	*0.336****
	(0.025)	(0.060)	(0.018)	*(0.016)*
Returns to scale	0.745***	0.781***	0.983***	*0.912****
	(0.034)	(0.073)	(0.025)	*(0.021)*

*, **, *** indicate significance levels at the 10, 5 and 1% levels.

Notes: Standard errors are in parentheses, calculated using the delta method at the mean values.

All elasticities have positive signs at the means and are statistically significant at the 1% level, except for labour input in class 1 which is significant at the 5% level. Kruskal-Wallis tests for equality of populations are performed to test whether the populations are the same, which is rejected in all cases. Differentiated patterns in input importance can be observed in each of the three classes, suggesting that large differences exist between the three technologies identified. In classes 1 and 2, variable costs have a clear larger impact on output production than the rest of inputs, while for farms in class 3 forage area appears to have a larger impact. Farms in class 2 also obtain the highest returns for labour (and the lowest for forage area) when compared with the other two classes. Finally, the returns for labour and capital are remarkably low for farms in class 1. For illustrative purposes, the elasticities obtained when a single frontier model is estimated using the same pooled sample of cattle farms are provided in column 4 of Table 2. It can be seen how the average output elasticities obtained assuming an homogeneous technology for all farms are quite different than when the presence of multiple technologies is taken into account in the estimation. The sum of all input elasticities gives a measure of returns to scale for each farm in each class. Farms in classes 1 and 2 operate under decreasing returns to scale, while class 3 farms operate on average under close to constant returns to scale, meaning their scale is more adequate (Coelli *et al.*, 2005). Decreasing returns to scale in the Irish cattle sector were previously found in Finneran and Crosson (2013) and in Newman and Matthews (2007).

Class characteristics

In order to further examine the differences between classes, descriptive statistics for some farm characteristics such as dependence on subsidies, farm size, input use or intensity and type of production are provided in table 3[8].

Table 3. Average farm characteristics by class

	Class 1	**Class 2**	**Class 3**
Calf-to-weaner (D)	0	0.278	0.313
Calf-to-store (D)	0.035	0.339	0.378
Calf-to-finishing (D)	0.269	0.063	0.162
Weaner-to-finishing (D)	0.318	0.080	0.015
Store-to-finishing (D)	0.224	0.084	0.004
Total farm gross margin/ha.	826.088	555.711	665.007
Total farm net margin/ha.	1%	1%	1.1%
Variable costs/LU	285.767	253.646	263.048
Labour units/LU	0.450	0.337	0.284
Total subsidies dependence	0.492	0.551	0.478
SFP share (2005-2013)	0.724	0.531	0.620
Coupled premia share (2000-2004)	0.735	0.591	0.639
Pillar 2 share	0.212	0.349	0.293
Utilised Agricultural Area (ha.)	48.038	36.494	40.522
Cattle Units (LU)	61.837	29.460	41.550
Concentrate feed use per LU (kg/LU)	466.769	298.007	287.055
Stocking Rate (LU/ha.)	1.270	0.898	1.098
Observations	1672	1282	3369

Source: NFS, 2000-2013.

Notes: (D) Indicates a dummy variable. (LU) indicates livestock units.

[8] Again Kruskal-Wallis equality of populations tests are performed for each farm characteristic. The null hypothesis that the populations are the same is rejected for all variables.

Classes 2 and 3 group farms undertaking mainly cattle rearing production, defined as those specialised in the production of calves and weanlings that come from the suckler herd. However, class 3 farms seem to keep a higher amount of animals for fattening. These two groups of farms share some common characteristics. They are on average smaller in size (both in hectares and cattle livestock units) than class 1 farms and are also less profitable, since they obtain lower total gross margin per hectare. Class 2 and 3 farms also have differentiated characteristics. Class 2 farms obtain lower gross margin per hectare than class 3 farms and are also smaller in size, while class 3 farms are the least labour intensive. Class 1 includes farms specialised in fattening and finishing cattle, which obtain on average the highest gross margin per hectare. However, despite these differences in profitability between classes, the total net margin per hectare, which measures the percentage of revenue remaining after subtracting all operation expenses, is virtually the same for all classes. Class 1 groups significantly larger farms that also use a more intensive production system, which is generally associated with increased profitability on farm (Teagasc, 2015). Irish beef farms are very dependent on subsidies in order to support incomes, regardless of the class they are classified in, with total subsidies representing between 47% and 55% of total farm gross output on average. More variation between classes can be seen for the composition of total subsidies, with class 1 farms obtaining a much higher percentage of total subsidies from the SFP since its implementation in 2005, while class 2 farms obtain a the highest proportion of Pillar 2 payments.

Technical efficiency estimates

The LCM computes farm specific technical efficiency with respect to each farm's most likely frontier, based on the estimated posterior probabilities[9]. Total average technical efficiency level is higher when the LCM model is implemented and technology heterogeneity is taken into account (with an average total score of 0.653 in the LCM *versus* 0.448 in the single frontier model). Note that since technical efficiency in the LCM is computed for each farm using their respective frontier as reference, and therefore indicates how close on average they operate with respect to their frontier, the scores are not directly comparable across classes (Alvarez and del Corral, 2010; Kellermann, 2014). Farms in classes 2 and 3 are on average operating closer to their own frontiers, with technical efficiency scores of 0.643 and 0.713 respectively. These estimates imply that at the current level of input use they could, if fully efficient, obtain a 35.7% and 28.7% increase in output respectively. Farms in class 1 obtained the lowest score (0.541) on average, meaning these farms have the largest scope for improvement.

VI. Conclusions

The research objectives of this analysis were to explore the heterogeneity that exists among beef producers in Ireland; and also assess the implications of such heterogeneity for the

[9] In this case they are quite high, of 0.899, 0.933 and 0.906 for classes 1, 2 and 3 respectively suggesting that the LCM did a reasonably good job at splitting the sample.

estimation of technical efficiency and the technology parameters. For this purpose, a LCM was estimated in a SFA framework, using a rather long panel of farm level data for the sector.

Regarding the first research question, clear differences in the estimated output elasticities and returns to scale were observed among the three technologies identified by the LCM. These differences suggest the presence of clearly differentiated technologies among Irish beef producers. In addition, differences in a selection of farm characteristics across classes could also be observed. Regarding the second objective, significant differences in technical efficiency estimates obtained implementing both a single frontier model and a three class LCM were observed, with efficiency scores being higher when farms are compared to their own frontier as the LCM does. This result implies that, in line with previous research in the area, technical inefficiency estimates tend to be overestimated if technology heterogeneity is present in the sample but not accounted for in the estimation process. However, technical efficiency scores were on average low for each of the three classes, meaning there is a great scope for improvements at the current level of input use for the majority of farms in the sector. Overall, these results point out the importance of correctly addressing technology heterogeneity in order to make correct policy recommendations regarding the improvement of farm economic performance, and also point out to the need to take into account to certain extent farm differences in the design of subsidies and other policy measures.

Finally, a limitations of the model implemented can be highlighted. In latent class models, the true number of classes remains unknown in the sense that it is not a parameter that can be estimated by the model and cannot be tested. Class allocation is made as a function of probabilities, however for the model estimated here they were on average very high which is a satisfactory result. It is also left to future work a more detailed analysis of the sources of decreasing returns to scale in the sector, since Irish beef farms are on average quite small when compared to other farming systems inside Ireland or with EU counterparts.

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APPENDIX. LCM with 3 classes frontier estimates[10]

	Class 1	**Class 2**	**Class 3**
Constant	1.808***	0.304**	0.464***
	(0.049)	(0.133)	(0.035)
Area	0.290***	0.135**	0.333***
	(0.043)	(0.067)	(0.024)
Labour	0.057*	0.248***	0.150***
	(0.033)	(0.081)	(0.021)
Capital	0.098***	0.172***	0.159***
	(0.020)	(0.041)	(0.013)
Variable costs	0.307***	0.417***	0.338***
	(0.023)	(0.064)	(0.018)
$Area^2$	-0.157*	0.202	-0.001
	(0.095)	(0.163)	(0.063)
Area x Labour	-0.082*	0.252**	0.057*
	(0.045)	(0.100)	(0.034)
Area x Capital	0.061*	-0.124**	0.070***
	(0.034)	(0.054)	(0.023)
Area x Variable costs	-0.103**	-0.113	-0.058
	(0.046)	(0.115)	(0.038)
$Labour^2$	0.031	0.179*	0.007

[10] Limdep 9.0 software is used in the estimation.

	(0.049)	(0.100)	(0.030)
Labour x Capital	0.000	-0.022	-0.033*
	(0.021)	(0.050)	(0.018)
Labour x Variable costs	0.048	-0.007	-0.052*
	(0.032)	(0.093)	(0.032)
Capital^2	0.008	0.103**	0.053***
	(0.016)	(0.044)	(0.017)
Capital x Variable costs	-0.045*	-0.050	-0.032
	(0.025)	(0.054)	(0.019)
Variable costs^2	0.200***	0.478***	0.129***
	(0.041)	(0.128)	(0.043)
Time trend	-0.038***	0.000	-0.030***
	(0.004)	(0.015)	(0.003)
Soil type 2 (D)	-0.212***	-0.529***	-0.193***
	(0.036)	(0.083)	(0.026)
Soil type 3 (D)	-0.497***	-0.646***	-0.315***
	(0.107)	(0.136)	(0.046)
Variance parameters for the compound error			
Lambda	1.023	0.880***	0.278**
	(3.600)	(0.187)	(0.113)
Sigma	0.907***	0.298***	0.688***
	(0.009)	(0.052)	(0.036)
Sigma(u)	0.649	0.197	0.184
Sigma(v)	0.634	0.224	0.663
Estimated prior probabilities for class membership			
Constant	-1.543***	1.151***	*(Fixed*
	(0.464)	(0.360)	*Parameter)*
Stocking rate	0.065	-1.556***	*(Fixed*
	(0.343)	(0.295)	*Parameter)*
Specialisation rearing	-8.971***	-1.317***	*(Fixed*
	(2.623)	(0.474)	*Parameter)*
Specialisation finishing	3.562***	0.667	*(Fixed*
	(0.445)	(0.506)	*Parameter)*
Soil type 1 (D)	-0.550*	-0.562**	*(Fixed*
	(0.294)	(0.251)	*Parameter)*

*, **, *** indicate significance levels at the 10, 5 and 1% levels.

Notes: Standard errors in parentheses. (D) indicates a dummy variable