Measuring the technical efficiency of the Irish dairy sector using a generalised gamma distribution

Iordanis Parikoglou, Department of Economics, University of Southampton
(email: I.Parikoglou@soton.ac.uk)

Fiona Thorne, Teagasc - Agriculture and Food Development Authority
(email:fiona.thorne@teagasc.ie)

Contributed Paper prepared for presentation at the 96th Annual Conference of the Agricultural Economics Society, K U Leuven, Belgium

4 – 6 April 2022

Abstract

Technical efficiency is an important indicator of competitiveness and sustainability at the farm level. Inefficiency is usually assumed to stem from poor management and it is modelled in Stochastic Frontier Analysis (SFA) as a draw from the half-normal or exponential distribution. Although these assumptions are convenient, they may fail to capture accurately farmers' efficiency behaviour. This study measures the technical efficiency of the Irish dairy sector, using a generalized gamma (GG) for the inefficiency term (Griffin and Steel 2008). The GG can accommodate the possible multimodality and skewness of the efficiency behaviour, which may arises from the wider sustainability goals of farmers. We also use a generalized gamma mixture of two components (GG2), mainstream and very efficient farms. We allow the probability of farmers to be allocated to these components conditional on their stocking density, purchased concentrate feeds per milk output and ratio of total labour units to cows. We find that farms with higher stocking density are less likely to be in the very efficient group. Farmers who use more purchased feeds per milk output and more labour per cows are more likely to be in the very efficient group.

Keywords Stochastic frontier analysis, technical efficiency, Irish dairy sector, Bayesian inference

JEL code D24, Q12, O33

1 Introduction

The recent EU Green Deal and in particular the Farm to Fork Strategy aim overall to promote a more robust and resilient food system that will result in environmental, health and social benefits, and economic gains for citizens (European Commission 2020a; European Commission 2020c). The policy has (among others) a primary focus on the sustainable livelihood for primary producers, and their transition towards more sustainable practices, such as minimizing the use of pesticides, antimicrobials and fertilisation and improve animal welfare. The vision of Farm to Fork for promoting a more sustainable way of farming in EU will be supported by the Common Agricultural Policy (CAP) (European Commission 2020b).

The key element for the transition towards a more sustainable farming in CAP and Farm to Fork strategy is innovation: knowledge and advice are crucial innovation aspects that will enable all food chain actors to become sustainable. The Commission in cooperation with the EU Member States will strengthen the role of the European Innovation Partnership "Agricultural Productivity and Sustainability" (EIP-AGRI) in the Strategic Plans in order to accelerate the innovation and knowledge transfer; there will be a greater responsibility placed on Agricultural Innovation System (AIS) actors and Farm Advisory Services (FAS) for achieving the Farm to Fork objectives and targets (European Commission 2020c; European Commission 2018a; European Commission 2018b; EU SCAR 2019).

In Ireland, the AIS is one of the strongest and most integrated in EU, where the main mediator is the Teagasc FAS (EIP-AGRI 2018). One of the strongest points of the Irish AIS lies on the research and knowledge transfer in the dairy sector that creates considerable knowledge flows (Renwick et al. 2014; Läpple et al. 2016). The Teagasc FAS promote technologies that will allow Irish dairy to expand their production volume in a post quota environment, but in a more sustainable manner (O'Dwyer 2015; Läpple et al. 2019; Läpple et al. 2022): the economic, social and environmental dimensions of sustainability are deemed equally important.

The achieved production growth of the Irish dairy sector since since 2009 that was aligned with an expansion of the dairy herd and higher milk yields per cow, coupled with the entrance of some new dairy farmers (Kelly et al. 2020). However, given the low land mobility and availability in Irish agriculture (Kelly et al. 2020), the projected increased size of the national dairy herd implies an increase in stocking rate in the future (Teagasc 2020). Higher stocking rate in pasture-based systems is associated with increased chemical fertiliser and supplementary feed importation and labour shortages, resulting in further environmental and social (e.g. workload) pressures (Di and Cameron 2002; Teagasc 2021b; Kelly et al. 2020). Therefore, the Teagasc FAS aim to develop targeted advisory programmes (e.g. Teagasc 2021a) in order to ensure that the economic gains from optimal resource use are not at the expense of the environmental and social dimension.

This paper aims to understand the possible trade-offs between the economic, social and environmental sustainability dimensions, which arise from the more efficient use of production factors in the Irish dairy production. Instead of using the widely used Latent Class

Model (LCM), we use the generalized gamma (GG) distributions and a mixture of generalized gamma distribution with two components (GG2C) for the inefficiency term, proposed by Griffin and Steel (2008). The GG is a quite flexible distribution that can accommodate better the diverse efficiency behaviour of farmers (e.g. various sustainability goals) than the usual exponential and half-normal inefficiency models.

First, we measure the technical efficiency of the Irish dairy sector using a GG distribution, a half normal and exponential inefficiency distribution. We show that the latter overestimate the average technical efficiency and the returns to scale of farmers, while the flexible GG fits the data better. Second, we estimate a GG2C for the inefficiency term, and; we allow the components in GG2C to depend on farm characteristics, through the probability of belonging to either component. Hence, the paper makes two main contributions: 1) it informs policy making that aims to foster technical efficiency at the farm level, promoting a more sustainable way of farming, and; 2) it suggests an alternative, more flexible, way for measuring the technical inefficiency at the farm level and examining the dependency of inefficiency components on farms characteristics.

The remainder of the paper contains five more sections. Section 2 is divided into two subsections: the first subsection discusses the conceptual framework on the structural link between Decision Making Units' (DMUs) production characteristics and inefficiency used in empirical literature and its limitations; the second subsection discusses how the approach of Griffin and Steel (2008) can be used to address these limitations. Section 3 presents the specification of the empirical models employed in this paper and the estimation procedure details in Bayesian inference. Section 4 presents the summary statistics of the utilized dataset. Section 5 presents the results. Section 6 discusses the findings and concludes with key policy implications.

2 Background

2.1 Linking farmers' characteristics to efficiency behaviour

Technical efficiency is a relative measure of productivity and an indicator of resource waste in agricultural production and thus it has important for policy implications regarding the sustainability of agricultural production (Hansson et al. 2018). It reflects the maximal output given a certain level of input and technology and it is normalized usually (e.g. between 0 and 1) relative to some benchmark, such as the observed frontier outcome (Kumbhakar et al. 2018). There are two main approaches to approximate technical efficiency: Stochastic Frontier Model (SFM) and the Data Envelopment Analysis (DEA).

The main advantage of SFM compared to DEA, is that it can distinguish technical efficiency from the statistical noise component. The latter absorbs random shocks, such as extreme weather events, which often affects the agricultural production. A drawback of the SFM is that the inefficiency term lacks of any specific structural interpretation of why inefficiency exists (Kumbhakar et al. 2018). Inefficiency is seen as an outcome of poor management, which may arise from sub-optimal use of inputs such as less motivated workers or due to improper capital use (e.g. asymmetric information) or other reasons which are not observed by the researcher (Kumbhakar et al. 2018). Without a specific structural link it is difficult to know just how to treat inefficiency in empirical analysis (Kumbhakar et al. 2018).

A common assumption in agricultural productivity and efficiency analysis is that inefficiencies are conditional on farmers' production characteristics (e.g. Alvarez and del Corral 2010; Sidhoum et al. 2022). For instance, farmers at more extensive dairy production systems may be prone to make more production mistakes due to the diverse nature of production at extensive production decisions (planting, harvesting, silage, etc.) (Sidhoum et al. 2022). On the contrary, dairy farmers at more intensive production systems may make less production mistakes because they are relying more on purchased feeds, which results in less technical inefficiency (Sidhoum et al. 2022). As a consequence, more farmers at intensive dairy systems may be better managers, i.e. more efficient, than farmers in extensive dairy systems (e.g. Abdulai and Tietje 2007; Alvarez and del Corral 2010; Skevas et al. 2017; Ma et al. 2019). A suitable methodological approach in SFM that allows Decision Making Units (DMUs) to vary widely (e.g. intensive/extensive) is the Latent Class Model (LCM) (Kumbhakar and Orea 2004).

The LCM is a mixture model that classifies DMUs into a finite number of classes, while it allows the allocation of DMUs to the classes to be determined by their characteristics. In agricultural economics, the LCM is widely used for examining the differences in efficiencies and marginal productivities between classes; and the allocation of farmers to these classes conditional on their characteristics (Alvarez and del Corral 2010; Alvarez et al. 2012; Alvarez and Arias 2015; Sauer and Morrison Paul 2013; Kellermann and Salhofer 2014; Orea et al. 2015; Martinez-Cillero et al. 2019; Sidhoum et al. 2022; Dakpo et al. 2021a; Dakpo et al. 2021b; Grovermann et al. 2021). Some of the farmers' characteristics that are used as class membership determinants are feeds per cow, stocking density, labor per cow, capital per cow, agri-environmental subsidies, as an effort to inform better policy making (Sidhoum et al. 2022).

The major limitation in the LCM is that the efficiency behaviour of farms within classes might be more heterogeneous, which is not captured by the LCM. This may result in suboptimal policy implications (Sauer and Morrison Paul 2013).[1] Specifically, farmers, either in extensive or intensive dairy systems, may use production factors for wider sustainability goals other than purely economic gains (Lagerkvist et al. 2011; Howley 2015; Hansson and Lagerkvist 2015; Hansson et al. 2018). As a consequence, part of production decisions may be rational and may erroneously be attributed to poor management (e.g. farmers may prioritize other objectives over financial outcomes). Hence, inefficiency in empirical analysis does not always reflect poor management decisions. This is known as the "rational inefficiency hypothesis" (Bogetoft and Hougaard 2003). Hansson et al. (2018) provided empirical evidence to support the rational efficiency hypothesis on a sample of Swedish dairy farms, showing that lower efficiency levels are associated with relatively high levels of the Animal Welfare (AW) improving measures.

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[1] Alternatively, one could use a Random Coefficient Model (RCM) for capturing the individual farmer's heterogeneity in the sample (Emvalomatis 2012; Skevas 2019; Njuki et al. 2019). Nevertheless, the RCM does not allow for examining the probability of farmers' allocation to more or less efficient classes conditional on their characteristics.

In a relevant study, Sidhoum et al. (2022) used a number of Spanish crop farmers' characteristics in a LCM setting to separate farmers into two classes: environmental and social sustainable farms. They found that the average technical efficiency of the environmental sustainability class is lower than in the social sustainability class. The authors argue that while it is easier for farmers to combine social objectives with technical efficiency; farmers who put higher weight on environmental protection, may be more prone to production mistakes which leads to higher inefficiency. This finding is in line with Hansson et al. (2018), supporting the existence of rational inefficiency hypothesis in dairy farming. Nevertheless, even if the LCM is used to separate farmers into classes based on their objectives, such as social and environmental sustainability classes, the problem remains; farmers may have more diverse efficiency behaviour which cannot be captured from the inefficiency term due to the usual inefficiency specifications.

2.2 Generalized Gamma distribution for the inefficiency term

In general, inefficiency in SFM is usually specified as an unobserved term, that it is assumed to be a draw from a non-negative distribution. The most common choices for the distributional assumptions for the inefficiency term in agricultural production, including the LCM approaches, are the half normal and exponential distributional (e.g. Alvarez and del Corral 2010; Emvalomatis 2012; Martinez-Cillero et al. 2019; DeLay et al. 2021; McFadden and Rosburg 2021).[2] These distributional assumptions have a zero mode, which is aligned with an economic interpretation: the inefficiency of most of the DMUs will be close to zero (Stevenson 1980). This is a convenient theoretical and methodological assumption, justified by the forces of competition; and it links inefficiency to managerial competence, by imposing the assumption that inefficient behavior monotonically decreases at higher levels of inefficiency (Stevenson 1980; Papadopoulos 2021). However, these distributions have two (interrelated) limitations when it comes to describing the efficiency behaviour of DMUs.

First, DMUs might be quite diverse and their characteristics which are related to their management ability (e.g. training, intelligence etc.) in reality are unlikely to be distributed in a monotonic fashion (Stevenson 1980). In empirical analysis then, both distributions may tend to cluster to lead to a cluster of highly efficient firms (Griffin 2004; Griffin and Steel 2008; Kumbhakar et al. 2018; Steel 2020). This is relevant in the context of agricultural production, since the managerial ability of farmers differ in terms of their education, experience, motivation etc. Thus, inefficiency behavior of farmers may not decreases monotonically at higher levels of inefficiency. As a consequence, the exponential and half-normal distribution may overestimate the efficiency of farmers. One could relax this assumption by allowing inefficiencies distribution parameters to be a function of variables related to (e.g. the education of the farmer); but management abilities might be more complex than the available datasets would allow.

Second, and most important as deemed by the aims of this study, these distributions may fail to capture accurately possible multimodality and different skewness that might exist in the

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[2] Beyond the half normal (Aigner et al. 1977) and exponential distributional (Meeusen and van den Broeck 1977) inefficiency models, a few other alternative choices have been proposed in productivity and efficiency analysis of various sectors, such as the truncated normal (Stevenson 1980), gamma (Greene 1990), Weibull (Tsionas 2007), Rayleigh (Hajargasht 2015), and many more (e.g. Wheat et al. 2019; Feng et al. 2019).

data, (Griffin and Steel 2008; Bonanno et al. 2017). As explained before, even within classes, farmers may have diverse sustainability goals and put different weight on each of those. Thus, multimodality and various skewness may exist in the data due to the diverse inefficiency behaviour of farmers.

Thus, we aim to account for both limitations that come with the choice of the exponential of half-normal distribution for the inefficiency term in a LCM framework. For this reason, instead of using the LCM, we use the generalized gamma inefficiency model, following Griffin and Steel (2008). The GG is a flexible distribution, where the exponential and half-normal can be seen as its special cases (Griffin and Steel 2008). While efficiencies of farmers with classes in LCM are arbitrarily fit as negatively skewed with its mode at zero (as dictated by the restrictive exponential and half-normal distribution), the GG uses data information in order to draw inferences about the modality and skewness of the inefficiency.

We first estimate a GG, and Exp and HN inefficiency distribution model. We expect *a priori* that the average efficiency in the GG will be lower than in the Exp and HN. In addition, we would expect that production elasticities in Exp and HN of inputs such as feeds, labour, capital and livestock to be higher, compared to the GG. The main reason is that Irish dairy farmers have wider sustainability goals, which captured by the restrictive exponential and half-normal inefficiency distributions. We further estimate the mixture of generalized gamma distribution, GG2C, with two components: mainstream and very efficient farmers. The distinction of these two components takes place without estimating separate frontier such as in the LCM. We further examine the allocation of farmers into the mainstream and very efficient class conditional on selected farmers' characteristics.

3 Methodology

This section is divided into five subsections. The first section specifies the stochastic frontier model; no distributional assumptions for the inefficiency term are specified. The second subsection presents the half-normal and exponential distributional assumptions for a stochastic frontier. The third subsection presents the generalized gamma inefficiency model. The fourth subsection extends the generalized gamma inefficiency model into a mixture of two components.

3.1 Stochastic frontier specification

We use an output distance function to describe the multi-output nature of the production processes employed by Irish dairy farms (Newman and Matthews 2006):

$$D_o(\mathbf{x}, \mathbf{y}, t) = \min\left\{\theta : \frac{y}{\theta} \in \mathrm{productionpossibilitiessetinperiod} t\right\} \quad (1)$$

where the input and output vectors, $\mathbf{x} \in \mathbb{R}^N$ and $\mathbf{y} \in \mathbb{R}^M$ are implicitly defined as functions of time, t. The output distance function is measuring the distance of a producer to the boundary of the production possibilities set by determining the minimum amount, $\theta \leq 1$, by which the output vector should be deflated to reach this boundary. The combinations of $\mathbf{x}$, $\mathbf{y}$ and t for which the value of the distance function is equal to one define the boundary of the production possibilities set. Thus, the distance function itself can be used to define technical efficiency as a function of its arguments:

$$D_o(\mathbf{y}, \mathbf{x}, t) = \mathrm{TE} \quad (2)$$

The distance function itself is defined as an implicit function of observable quantities. Following Coelli and Perelman (1999), we impose the linear homogeneity of degree one in outputs, taking the natural logarithm of both sides of the resulting expression, rearranging and appending an error term we obtain:

$$-\log y_{it}^{m} = \log D_o\left(\mathbf{x}_{it}, \frac{\mathbf{y}_{it}}{y_{it}^{m}}, t\right) + v_{it} + u_i^{+} \quad (3)$$

where y_{it}^{m} is the amount of normalizing output for farm i in period t, v_{it} is a linear error term that accounts for statistical noise, assumed to be normally distributed with mean zero and variance σ_v^2, and $u_i^{+} \equiv -\log(\mathrm{TE}_i)$ is the one sided technical inefficiency term for the same observation.

Denoting the dependent variable in (3) by y_{it} and using a specification for the logarithm of the distance function that is linear in the parameters, the following empirical counterpart to the output distance function is obtained:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + v_{it} + u_i^{+} \quad (4)$$

where y_{it} is minus the logarithm of the normalizing output and $\mathbf{x}_{it}$ is a vector of covariates (functions of the arguments of $\log D_o$) and $\boldsymbol{\beta}$ is a vector of parameters to be estimated. Given that the normalising output is subtracted from the left side of the equation, then the parameters associated with outputs should be positive (*ceteris paribus*, increasing the amount of an output brings the farm closer to the frontier), while the parameters associated with inputs negative (*ceteris paribus*, increasing the amount of an input moves the farm away from the frontier). The distance function is specified as translog.

We use a a multivariate normal densities for $\boldsymbol{\beta}$ with means equal to zeros, while the prior covariance matrices, which diagonal elements equal 1000. Inverse gamma distribution is used for σ_ξ^2 with shape and scale hyper-parameters equal to 0.001 and 0.001. Model specification is complete once a distributional assumption is imposed on the inefficiency term in (4). We use three different distributional assumptions for the inefficiency term: 1) exponential, 2) half-normal, 3) generalised gamma, and 4) a mixture of two components of generalized gamma form.

3.2 Half-normal and exponential inefficiency assumptions

Exponential inefficiency model: $u_i \sim exp(\lambda)$ and $\lambda \sim G(\alpha_\lambda, b_\lambda)$ where $a_\lambda = 1$, $b_\lambda = -\log(r^*)$, where r^* is the prior median efficiency and equals 0.875. Half-normal inefficiency model: $u_i \sim N_+(0, \sigma_u^2)$ and $\sigma_u^{-2} \sim G(\alpha_u, b_u)$ where $a_u = 1$, $b_u = 1/37.5$, following van den Broeck et al. (1994).

3.3 Generalized gamma inefficiency model

The generalized gamma distribution (Stacy 1962), which is generated by assuming a gamma distribution for powers of the inefficiency u_i following Griffin and Steel (2008):

$$u_i^c \sim Gamma(\phi, \lambda) \quad (5)$$

where $G(\alpha, b)$ denotes a gamma distribution with shape parameter α and precision parameter b (i.e. with mean α / b) and the the following inefficiency density function:

$$p(u_i | c, \phi, \lambda) = \frac{c^{\phi}}{\Gamma(\phi)} u_i^{c\phi - 1} exp(-u_i^c \lambda) \qquad (6)$$

This three-parameter family includes a variety of simpler distributions, i.e. when $c = 1$ this simplifies to the gamma distribution, the exponential distribution when $\phi = c = 1$, the Weibull distribution for $\phi = 1$ and the half-normal distribution for $c = 2, \phi = 1/2$. A class of "half-exponential power distributions", i.e. univariate versions of exponential power distributions (Chapter 3, Box and G. C. 1973) truncated to the positive real line can be generated if $\phi = \frac{1}{c}$. By estimating a stochastic frontier model with a generalized gamma distribution, one can test all of these distributions (Hajargasht 2015). The distribution in (6) has a bellshaped density function for $c\phi > 1$ and the reverse J-shaped otherwise. The ability to generate negative skewness with this distribution contrasts with all the commonly used inefficiency distributions (Griffin and Steel 2008).[3]

Particular attention must be paid to the choice of the priors on the parameters (c, ϕ, λ) in order to have meaningful posterior inference. According to the elicitation procedure of Griffin and Steel (2008), the following priors are used:

- $\lambda \sim Ga(\phi, (-\log r^*)^c)$

- $\psi = \phi c \sim Ig(d_1, d_1 + 1)$ where $Ig(a, b)$ denotes the inverted gamma distribution with mode $b/(a+1)$ (Bernardo and Smith 1994)

- $c \sim Ig(d_2, d_2 + 1)$

In the generalized gamma inefficiency distribution, $r_j^* = 0.8$ and $d_1 = d_2 = 3$ (Griffin and Steel 2008).

The Deviance Information Criterion (DIC) is used for a comparison between the three distribution inefficiency models (Spiegelhalter et al. 2002). The DIC is a within sample measure of fit that can be used for comparison between SFA that are estimated in Bayesian inference (Griffin and Steel 2007). Defining the deviance of a model with parameters θ as $D(\theta) = -2 log f(y | \theta)$, where $\mathbf{y}$ are the data, then $DIC = \bar{D} + p_D$ where D is the expected deviance and p_D is a complexity term such that $p_D = \bar{D} - D(\bar{\theta})$, where $\bar{\theta}$ is the mean of the posterior parameter distribution.

3.4 Mixture of two components generalized gamma inefficiency model

The two groups could be associated with differences in how effectively a basically common technology is being used, for example by using different management structures: mainstream

[3] Carree (2002) showed that the estimated residuals of a stochastic production frontier are positively skewed in many empirical cases, while all the usually adopted inefficiency distributions induce negative skewness of the "composed error term" (inefficiency and error terms). See Bonanno et al. (2017) and Cho and Schmidt (2020) for a discussion on wrong skewness issue in stochastic frontier analysis. The flexible inefficiency distribution in this paper, can accommodate both positive and negative skewness in the estimated residuals.

farms may constitute the largest group of the Irish dairy sector, while there are a few very efficient firms. The mixture could be extended to three components, i.e. assume that there are a few laggard farms, but these would be forced out of the market due to competition (Skevas et al. 2017).

Denote by $p_{GG}(\,.\,|\,c, \phi, \lambda)$ the generalized gamma density function in eq. (6), the mixed inefficiency distribution is defined by

$$p(u_i\,|\,w, \theta) = w p_{GG}(u_i\,|\,c_1, \phi_1, \lambda_1) + (1-w) p_{GG}(u_i\,|\,c_2, \phi_2, \lambda_2) \qquad (7)$$

where $w \in [0,1]$ is a weight parameter and $\theta = (c_1, \phi_1, \lambda_1, c_2, \phi_2, \lambda_2)$, and the prior median efficiency for the component with very efficient farms is $r^* = 0.975$, and $d_1 = d_2 = 3$ (Griffin and Steel 2008). For the component with the mainstream farms, $r^* = 0.8$ and $d_1 = d_2 = 10$ (Griffin and Steel 2008). Furthermore, instead of imposing labelling restrictions in order to solve the identification problem associated with mixture modelling (e.g. O' Donnell and Griffiths 2006), we use a more structural approach following Griffin and Steel (2008). Specifically, we denote by ν_i the g-dimensional vector which groups the characteristics of the i-th firm, and we model the weight $w(\nu_i)$ as $w(\nu_i) = f(\nu'\gamma)$, where $f(\,.\,)$ is a monotonic function on (0,1) and γ a parameter vector. A convenient choice for $f(\,.\,)$ is the cumulative distribution function of a standard normal distribution, leading to a probit model for the weights:

$$w(\nu_i) = \Phi(\boldsymbol{\nu}'\boldsymbol{\gamma}) \qquad (8)$$

where $\boldsymbol{\gamma}$ is a vector of parameters to be estimated and $\boldsymbol{\nu}'$ is a vector of firm specific time invariant covariates, and $\gamma \sim N(0,1)$.

4 Data

The data used in this study are taken from the Teagasc's National Farm Survey (NFS) and cover a sample of Irish dairy farms and the period between 2008 and 2017. The dataset consists of a total of 3740 observations on 486 specialist dairy farms. Farms are usually reported between 1 and 10 years. We choose to keep only data from farms that are observed for at least five consecutive years. The reason is to ensure there is a sufficient number of observations per farm for estimating farm specific inefficiency scores. The final dataset then consists of an unbalanced panel of 2323 observations from 277 farms, in which farms remain in the sample for an average of 8.7 years.

Two categories of outputs are defined. The main output (y_1), which is measured as the total revenue from milk production. The second output (y_2) consists of aggregate revenues from beef, pigmeat, other meat products, crops and other minor commodities. Four input categories are defined. The capital (K) comprises of the value of machinery and buildings and total livestock value. Labor (L) is measured in total labour units working on the farm. Land (A) is the utilized agricultural area, measured in hectares (A). Materials (M) is measured in expenditures of the following subcategories: seeds and plants, fertilizers, crop protection, energy, contract work and purchased feed (includes purchased concentrates and bulky feed), upkeep of buildings, machinery hire and upkeep of land. We also account for three variables related to farm characteristics, which are related to three dimensions of sustainability, i.e. economic, social and environmental; each variable could be linked implicitly with one or more sustainability dimensions.

The first is the stocking density and is measured as the ratio of livestock units to hectare. Previous studies have suggested that increased stocking rate in pasture-based systems is linked to higher chemical fertiliser use, higher dependence on supplementary feed importation, larger nutrient surpluses and lower capacity of nutrient use, that result in higher environmental pressures (Di and Cameron 2002; Kelly et al. 2020). The environmental pressures can be reduced, if additional pasture is utilized, for given levels of feed and fertilizer use (Di and Cameron 2002; Kelly et al. 2020).

The second variable is the ratio of purchased concentrate feeds (kg) to milk output (litres). This variable was selected since the agricultural sector's sector greenhouse gas (GHG) emissions between 2003 and 2012 accounted for about 20% of total emissions caused by human activities; out of which, 70% of total GHGs from agriculture, forestry, and other land uses stem from the livestock sector (Tubiello et al. 2013). GHGs are a byproduct caused by the enteric fermentation of the ruminant livestock (Balaine et al. 2020; Läpple et al. 2022).

The third variable is measured as the ratio of total labour units to cows measured. This is to the working balance and overall social life of farmers (Buckley and Donnellan 2020). The variable can be seen also as an indicator of animal welfare. Specifically, similar to other EU dairy farms, family members mostly contribute to production (Ang and Oude-Lansink 2017). Given then the sluggishness of acquiring more workers and the projected increase number in livestock, animal welfare issues may occur.

We do not have available more variables which could provide a more accurate measurement of sustainability dimensions, such as GHG emissions, readily available within the standard dataset.

A Törnqvist index was constructed for each aggregate variable measured in monetary terms, using price indexes from EUROSTAT with 2010 as a base year. Then, each aggregate variable was deflated accordingly. Summary statistics for the utilized dataset are presented in Table 1.

Table 1:
Summary Statistics, Irish dairy farms 2008-2017

Variable	Mean	Std. Dev	Min	Max
Milk (€1000)	115.41	79.39	1.13	623.69
Other Output (€1000)	50.33	37.70	1.18	424.06

Labor (Units)	1.59	0.65	0.5	6.93
Capital (€1000)	252.91	178.37	8.80	1066.93
Materials (€1000)	69.10	47.89	4.67	383.43
Area (Ha)	54.01	28.97	3.7	222.61
Density (Cows per hectare)	1.88	0.51	0.57	3.54
Feeds per milk (kg/l)	0.26	0.11	0.08	0.95
Workload per cow (hours)	28.01	18.51	2.80	145.84

5 Results

5.1 Half-Normal, Exponential and Generalized Gamma inefficiency model results

The results are obtained from data augmentation techniques with 5 Markov Chain Monte Carlo (MCMC) chains. In each chain, 50,000 iterations were disregarded in order to reduce the influence of the initial values, and another 150,000 draws, 1 out of every 10 was retained to remove any potential autocorrelation. Table 2 presents the posterior summaries of key parameters at 95% credible interval of the SFA models with Half-Normal (HN), Exponential (Exp) and the Generalized Gamma (GG) inefficiency distributions.

Table 2:
Posterior means of key parameters at 95% credible interval with the HN, Exp and GG

Parameter	**HN**	**Exp**	**GG**
ε_K	-0.334*	-0.340*	-0.301*
ε_L	-0.041*	-0.039*	-0.048*
ε_A	-0.205*	-0.206*	-0.210*
ε_M	-0.391*	-0.394*	-0.383*
ε_{Y_2}	0.208*	0.207*	0.209*
ε_t	-0.018*	-0.018*	-0.019*
RTS	0.971	0.979	0.942
σ_u^2	0.15	-	-

σ_ν^2	0.012	0.012	0.12
λ	-	2.98	-
c	-	-	2.91
ψ	-	-	1.64
ϕ	-	-	1.91
Avg. TE	0.70	0.72	0.43
DIC	-2992.9	-2614.3	-3285.7

The data for inputs and outputs are normalized by their geometric mean allowing us to interpret the parameters associated with the first-order terms directly as distance elasticities, evaluated at the geometric mean of the data. The estimated distance elasticity ϵ_{Y_2} in the HN model shows that if the farmer produces 1% more of other output, *ceteris paribus*, then the value of the distance function is increased by 0.20%, moving the farmer closer to the frontier. The distance elasticity ϵ_L in the Exp shows that if a farmer increases L by 1% then the value of the farm's average distance function is decreased by 0.03%.

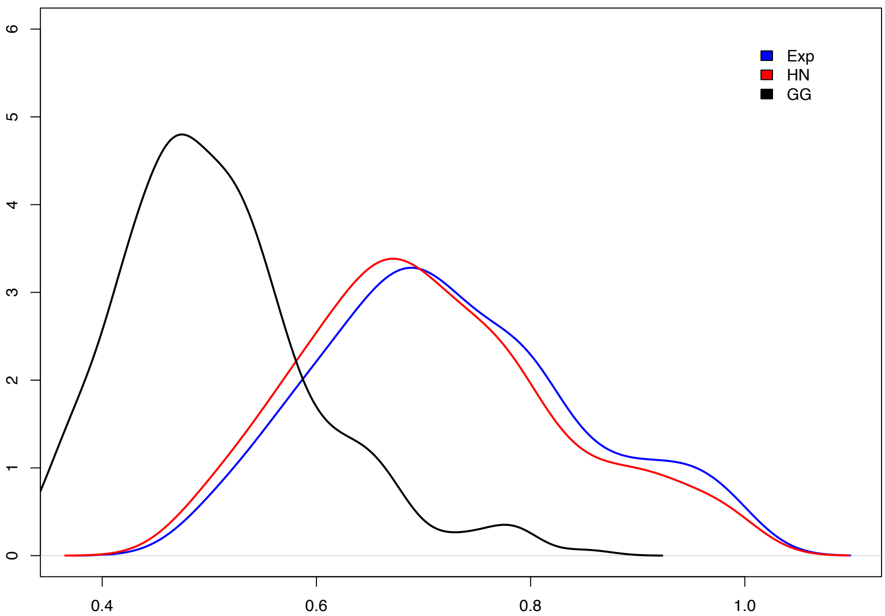
The GG has the lowest DIC value which indicates that it fits the data better compared to the half-normal and exponential model stochastic frontier model. This due to flexibility of the GG that allows for multimodality and various skewness in the efficiency behaviour: Irish dairy farmers have wider sustainability goals, and thus, the flexibility of the GG fits better their efficiency behaviour. This is evident also by the mean posteriors of c, ψ and ϕ, which differ from values that would correspond to an Exp, HN or Weibull model, as explained in the methodology section.

There are differences between the three models. In particular, the output elasticities of the three models are similar but differ slightly with respect to ϵ_K and ϵ_L. The lower estimated ϵ_K in the the flexible GG model than in the Exp and HN models, indicates that farmers make more production mistakes utilizing capital and livestock when the model is able to capture better the diverse efficiency behaviour (e.g. various sustainability goals) of farmers. Specifically, Irish dairy farmers may make production mistakes when they try to increase the feed requirements, given the fixed land, without relying in external inputs such as feeds etc. This finding is similar to Sidhoum et al. (2022) who suggest that farmers may be more inefficient when try to combine environmental and productivity objectives.

The ϵ_L in GG suggests that the Exp and HN underestimates the contribution of labour to production. This is in line with the findings Hansson et al. (2018), suggesting that a part of inefficiency is rational. Specifically, labour activities in the Irish dairy farming are possibly linked to achieve wider sustainability goals, and thus has higher impact on production in the inefficiency GG model that in the Exp and HN.

The most striking difference between the three models are related to the average efficiency scores. Specifically, the average efficiency in the GG is much lower than in the HN and Exp. The Figure 1 shows the kernel density of the efficiency scores at the farm level. As previous literature predicted, it can be seen that the restrictive Exp and HN distribution tend to produce a a left skewed cluster of efficiency scores (Griffin and Steel 2004; Griffin and Steel 2008). This drives the difference in the average efficiency score between the models.[4]

Figure 1: Kernel density of the farm level specific efficiency scores for Exponential (Exp), Half-Normal (HN), and Generalized Gamma (GG) inefficiency models



5.2 Generalized Gamma mixture results

The results from the generalized gamma mixture with two components are presented in Table 3. The posterior probability w is 0.27 which indicates that the data favour the mixture model over the GG model. The differences of between c_1, ψ_1, ϕ_1 and c_2, ψ_2, ϕ_2 are also interesting. In particular, c_1 is 1.1 which is very close to 1, i.e. the inefficiency distribution of the first component assimilates an exponential distribution. Nevertheless, Exp, HN (or Weibull) distribution would not fit well the efficiency behavior of the second component (according to the estimated c_2, ψ_2, ϕ_2). The estimated average efficiencies between GG and GG2C do not present any differences.

[4] The inefficiency specification is u_i, which implies that inefficiency is time invariant. This assumption can be relaxed by using its generalization, i.e. the Battese and Coelli (1992) time varying model.

Table 3:
Posterior means and credible intervals of key parameters at 95% credible interval

Parameter	Mean	Cred. Interval	
ε_K	-0.267*	-0.266*	-0.224*
ε_L	-0.054*	-0.065*	-0.201*
ε_A	-0.264*	-0.186*	-0.224*
ε_M	-0.393*	-0.543*	-0.412*
ε_{Y_2}	0.211*	0.254*	0.286*
ε_t	-0.018*	-0.015*	-0.017*
RTS	0.97	1.06	1.06
σ_ν^2	0.012	0.024	0.11
c_1	1.10	-	-
ψ_1	0.99	-	-
ϕ_1	1.23	-	-
c_2	3.67	-	-
ψ_2	2.06	-	-
ϕ_2	1.90	-	-
w	0.27	-	-
Avg. TE	0.48		

There are some discrepancies in the estimated input elasticities between the GG2C and the GG. Specifically, the elasticities ϵ_K and ϵ_L are lower and higher respectively in GG2C compared to GG. These discrepancies are due to the fact that GG2C incorporates more information regarding farmers' behaviour, i.e. distinguishes for two components; and the allocation of farmers to those depends on the three selected variables related to their production characteristics. Hence, the difference in the elasticities reinforces the view that a more flexible inefficiency distribution is able to capture more accurately the contribution of particular inputs to production, as discussed in the previous subsection. Table 4 below shows the estimated coefficients for the explanatory variables in the weight of GG2C.[5]

[5] We tried to include more sustainability indicators of farm level performance as explanatory variables in the weight of GG2C; but we encountered convergence issues possibly due to the correlation among the explanatory variables.

Table 4:
Coefficients for explanatory variables in the weight of GG2C

Parameter	Mean	Cred. Interv.
Stocking Density	-1.707*	[-2.402 , -0.905]
Feeds per milk	0.987*	[0.485 , 1.427]
Workload per cow	0.073*	[0.026 , 0.155]

The negative sign of the stocking density elasticity shows farmers with higher stocking density are more likely to be in the less efficient group. This finding is in contrast with the findings of other studies that focused on dairy sectors in other countries (e.g. Abdulai and Tietje 2007; Alvarez and del Corral 2010; Skevas et al. 2017; Ma et al. 2019). The grass based feed system though in the Irish dairy sector is the main source of competitiveness. Given the low land mobility, farmers at higher stocking density may face more difficulties in achieving the necessary feeding requirements for producing more milk output per cow in a sustainable manner, i.e. without increasing purchased feeds, the use of fertilisers etc. This results in higher technical inefficiency. Previous empirical studies have also found that higher stocking rates have a negative effect on technical efficiency at the Irish dairy farm level (Carroll et al. 2008; Kelly et al. 2013; Bradfield et al. 2021).

We also report a positive sign for the amount of concentrate feeds per milk output. In the same manner, this shows that farmers who use more purchased feeds per cow are more likely to be in the more efficient group. This is because farmers who (perhaps are more profit oriented) and rely more on purchased feeds in order to achieve the feeding requirements, are more efficient (e.g. Sidhoum et al. 2022).

Finally, farmers who allocate more labour per cow are also more likely to be in the more efficient group. This is similar to Bradfield et al. (2021), who found that higher hired to family labour ratio has a negative effect on technical inefficiency in the Irish dairy sector. Dakpo et al. (2021a) found that the share of hired labour in total labour has a negative impact for French dairy farms in a pooled model, but insignificant in a LCM. The share share of hired labor is positively associated with efficiency in French dairy farming when selection bias is accounted for (Dakpo et al. 2021b).

6 Conclusions

This paper aims to understand the possible trade-offs between the economic, social and environmental sustainability dimensions, which arise from the more efficient use of inputs in the Irish dairy production. Instead of using a Latent Class Model (LCM), we use generalized gamma mixture of two components (GG2C) for the inefficiency term. GG2C does not require the estimation of separate frontiers such as in in the Latent Class Model (LCM). More importantly, it can accommodate for possible skewness and multimodality of the data, which may arise from the diverse sustainability goals of dairy farmers. For instance, Hansson et al. (2018) showed that Swedish dairy farming, part of inefficiency is linked to rational production decisions, i.e. farmers have wider goals than productivity improvements. In this regard, GG2C is more flexible for describing the farmers' efficiency behaviour compared to the Exponential (Exp) and Half-Normal (HN) distributions.

We first estimate an Exp, HN and a Generalized Gamma (GG) inefficiency model to test the fitness in our data. We found that Exp and HN frontier models overestimate technical efficiency compared to the GG. It is also interesting that the elasticity with respect to capital (which consists of capital and livestock value) and labour is lower and higher respectively in the GG. These differences are attributed to the flexibility of GG that captures possible multimodality and various skewness. We further estimated the GG2 with the two components, mainstream and very efficient group of farmers. We allow the allocation of farmers to these two groups to be dependant on their stocking rate, feeds per milk output and labour per cow. We found that farmers who use more feeds per milk output and allocate more labour per cow are more likely to be in the very efficient component.

The results of the paper highlight again the importance of the grass based feed system to the Irish dairy sector. Advisors should continue to promote innovations that will enhance farmers to use more efficiently the pasture based system and be less reliant to harmful inputs such as feeds. Regarding the results with respect to labour per cow: Bradfield et al. (2021) argue that potential expansion beyond current family labour would overall improve rural employment. We further argue that the adoption of innovations at the farm level is essential for reducing the demand for labour. In this way, farmers would have a better working-life balance, particularly amid the projected increase in the national dairy herd.

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