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Farm technical and environmental efficiency and subsidy redistribution in Ireland: A simulation approach of possible performance and equity effects

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Abstract

We investigate the relationship between EU Common Agricultural Policy environmental payments, and dairy and beef farm level competitiveness and environmental performance. We use an Irish panel of farm level financial data for the years 2000–2017 and apply stochastic frontier analysis. Our estimates identify a positive relationship between technical efficiency and the Green, Low-Carbon, Agri-Environment Scheme for dairy farms, in contrast with the negative relation identified for previous payments of this kind such as the Rural Environment Protection Scheme for both beef and dairy. We then simulate increases in the first type of environmental payments financed through reductions in decoupled payments. We use alternative scenarios for payment redistribution such as flat allocation, allocation to farms with low stocking rates or proportional reallocation of payments. We find that under the second scenario, marginal environmental gains can potentially be achieved for dairy farms. For beef farms, the proportional allocation performs best regarding environmental gains. We also find that under this scenario, the impacts on income inequality can be smoothed for both farm types.

KEYWORDS
agricultural subsidies, income inequality, methane emissions, simulation, stochastic frontier analysis, technical efficiency

JEL CLASSIFICATION
Q12, Q18, Q52

1 | INTRODUCTION

The Common Agricultural Policy (CAP) in the European Union (EU) is broadly structured into two main groups of payments, or Pillars (Hill, 2012). Payments granted under Pillar I relate to direct income support and market measures, whereas those under Pillar II relate to rural development. Under the current CAP design, there is a range of environmental obligations in both Pillars I and II, although most of the environmental policy falls under Pillar II. When designing a new CAP post-2020, the transition towards more sustainable agricultural production systems as part of the EU's European Green Deal (European Commission, 2019a) took centre stage in the negotiations. In June 2021, the European Parliament and the Council reached a provisional agreement, to be implemented in January 2023. The agreement included important environmental provisions such as compulsory eco-schemes, increased conditionality, or the allocation of 35% of rural development funds to agri-environment commitments.[1] Eco-schemes are policy instruments based on conditionality, meaning that failing to implement the environmental obligations they impose results in a reduction of payments (European Commission, 2019b).[2] These schemes will be funded by member states' direct payment (i.e., CAP Pillar I) budgets (European Commission, 2019b). This redistribution and balance between Pillar I and II funding is a major focus of our empirical analysis.

Agricultural subsidies influence both farm income (Bonfiglio et al., 2020 and Ciliberti & Frascarelli, 2018) and farm competitiveness (Latruffe, 2010). Research on the effects of subsidies on farms' income distribution and competitiveness is not new. However, the quantification of changes in the distribution of income, and in economic and environmental performance due to changes in agri-environmental subsidies has received limited academic attention. Existing empirical research finds mixed results of different types of agri-environmental payments on technical efficiency. A negative impact was shown by Areal et al. (2012) for English and Welsh dairy farms, Kumbhakar et al. (2014) for Norwegian crop farms; Lakner et al. (2014) for organic farms in Germany; and Latruffe and Desjeux (2016) for dairy, beef and crop French farms. However, other analyses have found a positive relationship (see Mamardashvili & Schmid, 2013 for Swiss dairy farms; Manevska-Tasevska et al., 2013 for dairy, beef and pig farms in Sweden; Lakner et al., 2014 for organic farms in Switzerland; and Martinez Cillero et al., 2018 for Irish beef farms). Regarding the analysis of the distributional effects of changes in farm subsidies, Ciliberti and Frascarelli (2018) find that the reform in the Single Payment Scheme in Italy in 2013 limited the reduction in farm income inequality. They argue that it has increased the share of farm income that is dependent on increased market exposure, leading to higher risks of price volatility and increasing pressure on income. Bonfiglio et al. (2020) analyse the effects of the same reform on both technical efficiency and income inequality. They find that while a redistribution based on the number of worked hours reduces technical efficiency, inequality is also reduced.

We investigate the relationship between farm level competitiveness, proxied by farm level technical efficiency estimates (Latruffe, 2010), and past and present CAP agri-environmental

[1] https://ec.europa.eu/commission/presscorner/detail/en/IP_21_2711

[2] See *List of potential agricultural practices that eco-schemes could support*, prepared by the European Commission and available at https://ec.europa.eu/info/news/commission-publishes-list-potential-eco-schemes-2021-jan-14_en

subsidies. Using an unbalanced panel of National Farm Survey (NFS) farm level financial data, for Irish farms classified as specialist dairy or beef producers, we apply standard stochastic frontier analysis (SFA) to estimate farm level technical efficiency scores and the effect of subsidies and other farm characteristics on these estimates. In addition to this traditional economic performance measure, we also explore farm level environmental efficiency, by computing an environmental efficiency score as the ratio of minimum feasible to observed levels of methane emissions, for a given farm production technology and given levels of inputs used, based again on a frontier approach and estimated using SFA (Jin & Kim, 2019). We also relate the environmental efficiency measure to the same set of subsidy and farm characteristic variables as the technical efficiency scores. We estimate these scores using data for Irish dairy and beef farms. We focus on methane production, produced by ruminants since this accounts for 58% of Irish emissions from agriculture in 2019.[3] We then perform a series of simulations of a decrease in decoupled payments, which would be used to finance an increase in the Green, Low-Carbon, Agri-Environment Scheme (GLAS) payments, a type of environmental scheme granted in recent years to Irish farmers. We contemplate three different scenarios where the additional payments are allocated: (a) equally to those farms that receive the GLAS payment; (b) to those farms with a stocking rate below the sample median (i.e., extensive farms); and (c) proportionally to the already received GLAS payments. For each scenario, we attempt to quantify changes in farm level technical and environmental efficiency, as well as in income distribution.

The paper is organised as follows: Section 2 provides a description of the system of CAP payments in place in Ireland. Section 3 describes the data and variables used in the empirical analysis; and Section 4 outlines our approaches for the estimation and the simulation. Section 5 contains the main econometric results, and Section 6 the results for the simulations. Section 7 concludes.

2 | CAP SUBSIDIES IN IRELAND BETWEEN 2000 AND 2017

Before the implementation of the 2003 reform, known as the Mid-Term Review, the system of direct income support granted to Irish farmers was very complex, consisting primarily of a series of direct payments coupled with production (i.e., given per head of animal produced or hectare farmed). The 2003 Mid-Term Review introduced decoupled direct support, defined as not linked to current prices, factor use or production (Burfisher & Hopkins, 2003). Decoupled payments were implemented in Ireland through the Single Farm Payment (SFP) in 2005,[4] replacing all the previous types of livestock coupled support. Although there was no requirement to produce to receive the SFP, farmers were required to maintain the land in Good Agricultural and Environmental Condition (GAEC).[5] Decoupled payments were maintained, albeit restructured in the 2013 CAP Reform. This Reform introduced the Basic Payments Scheme (BPS) to replace the SFP in 2015. It consisted of a basic payment (European Commission, 2016a) and a series of compulsory and optional top-ups (European Commission, 2016b). The basic payment was also granted based on the possession of entitlements, established by the 2014 SFP received by each farmer. The greening component required farmers to follow certain beneficial practices for the environment, such as crop diversification and the maintenance of permanent

[3]https://www.epa.ie/our-services/monitoring--assessment/climate-change/ghg/agriculture/

[4]The implementation guidelines of the SFP were outlined in Regulation (EC) No. 1782/2003 (EUR-LEX, 2003).

[5]These conditions covered compulsory and optional standards concerning soil protection, water management, and so on. Failing to comply led to a reduction in the payments.

pastures and ecological focus areas (European Commission, 2011), to encourage sustainable use of natural resources.

Apart from income support payments, Irish farmers were also eligible for a number of Pillar 2 payments between 2000 and 2017, the most important being agri-environmental payments. Farmers participate in agri-environmental payments on a voluntary basis. The Rural Environment Protection Scheme (REPS) was implemented in four rounds, starting in 1994, and was closed to new entrants in 2009. REPS paid farmers to maintain and improve the environmental conditions of their land. The Agri-Environment Options Scheme (AEOS) replaced REPS in 2010 and was implemented in three rounds, and it was closed to new entrants in 2012. Finally, the Green, Low-Carbon, Agri-Environment Scheme (GLAS) was introduced in three rounds between 2015 and 2016, when it was closed to new entrants. All three types of payments were undertaken under 5-year contracts, therefore GLAS is the current payment. Agri-environmental payments share the common feature of being supposed to compensate farmers for the adoption of practices that mitigate the negative impacts of farming activities on the environment, promote conservation of high value environments and enhance rural landscapes (DAFM, 2007). These payments were co-financed between the EU and the Irish National Exchequer and were implemented through successive Rural Development Plans.[6] They consisted (mainly of) payments per hectare. A timeline of the agri-environmental payments granted to Irish farmers between 2000 and 2017 can be found in Table S1 in Appendix S1 (online).

3 | DATA AND VARIABLE DESCRIPTION

We obtained a sample of the NFS dataset through the Irish Social Science Data Archive (ISSDA, An Teagasc. National Farm Survey, 2019).[7] The NFS, compiled by Teagasc annually since the 1970s, includes a random stratified sample of farms, and contains a detailed panel of farm level financial data built to be representative of the Irish farming population. We select specialist dairy and beef farms for our analysis,[8] and include data between 2000 and 2017. We select these two farming systems for several reasons. First, dairy production constitutes the largest Irish farming system in terms of economic output. The beef system generates remarkably low family farm income (FFI)[9] (€333 per hectare, according to 2019 NFS data), whereas dairy farms record the highest (€1118 per hectare in the same year; Donnellan et al., 2020). Second, despite the greater economic importance of dairy, beef farming occupies the greatest number of farms (58% of Irish farms, while the dairy system comprises 17% of farms—Donnellan et al., 2020). Third, beef farms are most reliant on subsidies for their survival, with direct payments representing 162% and 129% of FFI for specialist cattle rearing and specialist cattle other farms, respectively, in 2019 (Donnellan et al., 2020). It is likely that changes in the configuration of direct support will affect this group of farms in particular. Finally, it is likely that these two sectors will be the target of policy measures aimed at reducing emissions from the agricultural sector in Ireland. For example, in a MACC (Marginal Abatement Cost Curve)

[6]REPS3 was implemented as part of the Rural Development Programme 2000–2006; AEOS and REPS4 were part of Ireland's Rural Development Programme 2007–2013; and GLAS payments were implemented in the Rural Development Plan 2014–2020.

[7]Teagasc NFS data accessed via the Irish Social Science Data Archive at www.ucd.ie/issda

[8]The NFS classifies farms in systems depending on their dominant enterprise, based on production specialisation defined according to the Standard Gross Margin (until 2008) and the Standard Output (SO) (since 2009) of the farm (Donnellan et al., 2020).

[9]Defined in the NFS as total farm gross output minus direct and overhead costs (Donnellan et al., 2020).

analysis, Teagasc pointed out the need for the development of policy measures to encourage the uptake of mitigation technologies on farm, such as genetic and feeding improvements (Teagasc, 2019).

For each specialist group, we compute a single aggregated output category and four input categories. The output variable is computed as the sum of the annual values of the farm total livestock and total crops gross output.[10] Livestock gross output includes the value of output obtained by the farm from the dairy, beef, sheep, pigs or poultry enterprises, and crops gross output includes the value of all cash crops and fodder crops sold. Since the production of livestock is not an annual process, the value of the opening and closing inventories of livestock (dairy, beef animals and sheep) are subtracted and added, respectively, to the value of gross output. Our output measure excludes subsidies.

The four input categories included are land, labour, capital and intermediate inputs. Land is measured in hectares, and includes the utilised agricultural area (UAA) of the farm. This is defined as the area under crops and pasture plus the area of rough grazing (including area owned and rented, and excludes area let). Labour is measured as the total amount of labour units, and includes both paid and unpaid.[11] The capital input category aggregates the monetary value of machinery, buildings and livestock. Due to the prevalence of part-time farming among Irish beef producers (Donnellan et al., 2020), we include a dummy variable indicating whether a beef farm is considered part-time[12] or not in the production function estimated for this system. This inclusion takes account of the potential structural differences between part-time and full-time farms, which may arise from differences in labour intensity or production technology capabilities, for example. Machinery and building values correspond to the end of year valuation of each based on the replacement cost methodology, while the value of livestock corresponds to the opening plus closing valuation of livestock divided by two. Finally, the intermediate input category aggregates the value of the farms' direct (i.e., purchased feeds, artificial insemination and veterinarian costs, fertilisers, crop protection costs, transport, hired machinery, and other costs directly incurred in the production of the farm enterprises) and overhead costs (i.e., interest payments, depreciation, repairs, etc.).

The NFS also contains detailed and disaggregated information regarding the level of subsidies received by each farm. We use this rich information to analyse the link between different types of subsidies and farm technical efficiency. We build the subsidy variables as ratios of the amount of each type of subsidy received (in euros) over farm livestock units (LU).[13] We include five subsidy ratios: (i) decoupled direct payments (we group both the SFP, and posterior BPS, in a single ratio); (ii) REPS; (iii) AEOS; and (iv) GLAS. Table S2 in Appendix S2, online, provides details regarding the timelines of each of this type of payment. We also include the share of pasture hectares on total farm hectares in order to

[10]The SO of an agricultural product is defined as the average value of the product at farm-gate price, with regional SO coefficients being calculated for each product as average values over a reference period. Farms are classified as specialist beef, or dairy, producers if more than 60% of their total SO comes from beef/dairy products. This threshold implies that these are all highly specialised dairy/cattle producers; therefore, the importance of the other farm output is minor.

[11]Hired labour is included in the model as part of the labour input category. In the NFS, the total number of labour units working on the farm is the sum of labour units unpaid and labour units paid. Therefore, it includes the number of paid labour units working on the farm, accounting for both regular and casual labour. In our sample, the importance of paid labour on total labour input is not high (2.7% of total of cattle farms, and 10.8% of total dairy farms).

[12]A farm is considered part-time if it requires <0.75 standard labour units to operate, as calculated on a standard man-day basis (Donnellan et al., 2020).

[13]A dairy cow is taken as the basic grazing LU, with other grazing stock given equivalents based on pre-established coefficients (see Donnellan et al., 2020, p. 85, for details). Using these ratios helps remove the confounding effects of farm size.

explore the relationship between using a grass-based feeding system and technical efficiency. We account for the quality of the soil in which farms operate by including a dummy that equals one if the farm is located in land defined as more favourable for agricultural production, and zero otherwise (see Donnellan et al., 2020, p. 87, for details on this classification). The use of a soil quality dummy has limitations in terms of its ability to capture variation across environmental conditions of farms in detail (such as the impact of extreme uncharacteristic weather events, biodiversity or detailed soil composition and water availability). Some recent literature has used environmental information, such as rainfall and the growing season length (Gadanakis & Areal, 2020), highlighting that incorporating these aspects affects technical efficiency estimates and farm rankings, but no suitable proxy is available for our NFS data. Finally, we include two dummies in the inefficiency effects model that capture the income tercile for each farm. We first normalise the FFI using farm total LU, in order to avoid confounding effects due to differences in farm size, and generate dummies that equal 1 for farms in each of the income ratio terciles (i.e. farms in the first tercile have the lowest income per LU, while farms in the third tercile have the highest). Since we are interested in exploring the redistribution effects of shifting payments between CAP Pillars across farms with different levels of income, these variables allow the establishment of the relationship between farm income and technical and environmental efficiency.

We use the yearly price indices series published by the Central Statistics Office (CSO) to deflate the monetary values of output and inputs in the NFS (with base year 2010), in order to approximate volume measures. The CH_4 enteric fermentation emissions are obtained using the Irish Environmental Protection Agency (EPA) emission factors published for different types of cattle (Duffy et al., 2016, 2017, 2018 and Duffy et al., 2019). These factors are multiplied by the yearly average number of animals reported by the farmers in the NFS to compute a farm specific measure of CH_4 enteric fermentation emissions.

Table 1 shows the descriptive statistics for the main variables included in our model. Dairy farms are on average much larger than beef farms, both in terms of total farm output generated, hectares of land farmed and value of capital input. Dairy farms also employ more labour and have higher total costs. Dairy farms have on average a higher share of pasture area in the total farm area, and are located on better quality soils. Beef farms received on average more REPS and GLAS and decoupled payments, per LU.

4 | METHODOLOGY

4.1 | Stochastic frontier analysis

We apply SFA to obtain estimates of farm level technical efficiency, as well as assess the effect of several farm specific characteristics on this estimate, since SFA accommodates external shocks (disease, weather etc.) through the inclusion of a random error in the production function (Coelli et al., 2005). SFA also has an advantage over the DEA alternative since it estimates the relationships between exogenous variables and farm level technical efficiency in one step.[14] Farm production technology is represented using a production function:

$$ln Y_{it} = f\left(ln\boldsymbol{X_{it}}, t\right) + v_{it} - u_{it} \tag{1}$$

[14]The advantages of this one step approach are well established in the applied technical efficiency literature—see, for example, the discussion in Wang and Schmidt (2002).

TABLE 1 Average values of main variables in the model

	Dairy farms	Beef farms
Production function variables		
Total output (€)	133,241 (88,340)	25,907 (26,332)
Land (hectares)	58.89 (31.41)	42.92 (27.92)
Labour (labour units)	1.65 (0.66)	1.09 (0.42)
Capital (€)	234,433 (164,400)	93,875 (79,821)
Variable costs (€)	82,667 (55,830)	23,692 (20,693)
Part-time farm (D)	0.06 (0.23)	0.74 (0.44)
Efficiency drivers		
REPS/LU (2000–2014)	26.54 (56.67)	72.26 (123.52)
GLAS/LU (2015–2017)	4.13 (16.68)	24.84 (53.79)
AEOs/LU (2011–2017)	7.98 (6.49)	7.83 (35.17)
Decoupled subs./LU (2005–2017)	181.75 (78.95)	301.03 (179.16)
Soil type 1 (D)	0.58 (0.49)	0.44 (0.50)
Pasture share	0.91 (0.14)	0.89 (0.18)
Observations	6615	7004
Average FFI\LU by FFI ratio tercile dummy		
First FFI ratio tercile (D)	212.44 (126.17)	44.44 (150.12)
Second FFI ratio tercile (D)	461.15 (60.08)	291.44 (52.10)
Third FFI ratio tercile (D)	768.76 (175.76)	602.42 (254.73)

Notes: Standard deviation in parentheses. (D) indicates a dummy variable, LU indicates livestock units. The averages refer to the 2000–2017 period, unless stated otherwise.

where Y_{it} is farm output, $\boldsymbol{X_{it}}$ represents a vector of k inputs, t is a time trend capturing technical change, and i and t denote the ith farm ($i = 1,\ldots,n$) and the tth time periods ($t = 1,\ldots,T$), respectively. Equation (1) displays the double error term that characterises SFA, with a stochastic random error v_{it} and the inefficiency term u_{it} (Meeusen & Van den Broeck, 1977; Aigner et al., 1977; see Kumbhakar & Knox Lovell, 2000 for further details of the method).

We use a translog functional form:

$$ln\,Y_{it} = \beta_0 + \sum\nolimits_{k=1}^{K} \boldsymbol{\beta_k} ln\boldsymbol{X_{itk}} + \frac{1}{2}\sum\nolimits_{k=1}^{K}\sum\nolimits_{g=1}^{K} \boldsymbol{\beta_{gk}}\, ln\,\boldsymbol{X_{itk}}\, ln\,\boldsymbol{X_{itg}} + \beta_e E_{it} + \sum\nolimits_{k=1}^{K} \boldsymbol{\beta_{ek}}\, ln\boldsymbol{X_{itk}} E_{it} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum\nolimits_{k=1}^{K} \boldsymbol{\beta_{tk}}\, ln\,\boldsymbol{X_{itk}}\, t + v_{it} - u_{it} \tag{2}$$

Since the Cobb–Douglas is nested in the translog functional form, we test the preferred specification using a likelihood ratio test. In Equation (2), β_0, $\boldsymbol{\beta_k}$, $\boldsymbol{\beta_{gk}}$, β_e, $\boldsymbol{\beta_{ek}}$, β_t, β_{tt} and $\boldsymbol{\beta_{tk}}$ are parameters to be estimated. It also includes non-neutral technical change, by allowing for the interaction of the inputs and the time trend t. We incorporate further flexibility to the specification in Equation (2) by including interactions of the four inputs and a dummy variable (E_{it}) that equals one if the farm is in the top quartile of methane emissions, calculated based on the methane emissions variable outlined in the data description section (Morrison Paul et al., 2000 estimated a similar specification, albeit using policy dummies instead of emission dummies).

Regarding the distribution of the two error terms in Equations (1) and (2), we make the following distributional assumptions:

$$u_{it} \sim N^{+}\left(0,\sigma_{itu}^2\right), \text{with } \sigma_{itu}^2 = exp\left(\boldsymbol{\gamma_m Z_{it}}\right)$$
$$v_{it} \sim N\left(0,\sigma_{itv}^2\right) \tag{3}$$

The inefficiency term, u_{it}, is modelled with constant mean 0 and variance σ^2_{itu}, which is made dependent on a vector of m inefficiency drivers $\boldsymbol{Z_{it}}$. In Equation (3), $\boldsymbol{\gamma_m}$ is a set of parameters to be estimated. This model corresponds to the heteroscedastic specification of the inefficiency term proposed in Caudill et al. (1995). The farm specific technical efficiency estimates are recovered post-estimation using the approach outlined in Battese and Coelli (1988) as:

$$Technical\,efficiency_{it} = E\left[exp\left(-u_{it}\right) \mid e_{it}\right] = E\left[exp\left(-u_{it}\right) \mid v_{it} - u_{it}\right] \tag{4}$$

We apply the True Fixed Effects (TFE) and True Random Effects (TRE) estimation approaches proposed in Greene (2005). In the TFE estimation, the limitation of a common intercept (β_0) in Equation (2), which may bias the results in the presence of time invariant farm specific unobserved heterogeneity, is relaxed by including farm specific intercepts (i.e., β_i instead of β_0). In TRE estimation, the time invariant farm specific unobserved heterogeneity is accommodated through the inclusion of a random (across farms) constant term β and a time invariant farm specific random term α_i (i.e., $[\beta + \alpha_i]$ instead of β_0).

4.2 | Methane efficiency

The factors defining the methane efficiency frontier are the level of inputs used by farms, and the state of the production technology used on the farms in our sample, and it reflects the resulting maximum methane emissions level that farms can potentially produce. As a result, $\ln Y_{it}$ in Equation (1) is replaced by $\ln M_{it}$, which is the log of our measure of farm specific methane emissions:

$$lnM_{it} = f\left(ln\boldsymbol{X_{it}}, t\right) + v_{it} - u_{it} \tag{5}$$

As in Equation (1), $\boldsymbol{X_{it}}$ is a vector of k inputs used in the farm, that contribute to methane production, t is a time trend, and i and t denote the individual farm and time periods, respectively. As it is estimated using a production function, it does not rely on a specific farmer's behaviour. It merely exploits input and emissions data and does not require behavioural assumptions about producers (such as profit maximisation or cost minimisation), which can be considered an advantage of this approach when compared to the estimation of cost, profit or revenue functions (Kumbhakar & Knox Lovell, 2000). Equation (5) also includes the double error term typical of SFA, with v_{it} being the stochastic random error. We again assume a translog functional form[15] for $f(.)$ in Equation (5), and the same error distribution already outlined in Equation (3) for u_{it} and v_{it}. We link this methane efficiency measure to the same subsidy and farm characteristics drivers rather than technical efficiency.

In this specification, the output oriented SFA model estimates the maximum possible level of farm methane emissions, keeping input use unchanged, represented by the frontier. The methane efficiency ME_{it} score represents the gap between each farm observation and the emissions frontier, as estimated by this modified SFA framework. In this case, the gap is interpreted as the emissions shortfall (Jin & Kim, 2019). The emissions–input ratio represents a farm's methane efficiency score: $ME_{it} = \frac{M_{it}}{f(X_{it})e^{v_{it}}} = e^{-u}_{it}$ determined as the ratio of farms' observed methane (M_{it}) and maximum possible methane (in the denominator). A caveat of this approach

[15]In Equation (2), we included dummies for emission levels. In Equation (5), we follow a similar approach and include dummies for highly productive farms (defined again based on the top quartile of the total farm output distribution), as well as interactions with the inputs included, instead of the emissions dummy in Equation (2).

is that the resulting ME_{it} measure should not be interpreted as an environmentally corrected technical efficiency measure, such as those proposed by Dakpo et al. (2017), as we do not model production and emissions simultaneously. The measure we estimate is simply an indication of how observed methane emissions of dairy and beef farms compare to the maximum emissions possible, with lower ME_{it} values indicating better environmental performance in terms of methane emissions. The ME_{it} measure is recovered post-estimation, equivalent to technical efficiency in Equation (4):

$$ME_{it} = E\left[exp\left(-u_{it}\right) \mid e_{it}\right] = E\left[exp\left(-u_{it}\right) \mid v_{it} - u_{it}\right] \tag{6}$$

Finally, note that although it is possible to include our measure of environmental pollution (methane emissions) as a negative output within the SFA framework (as done for example in Dakpo et al., 2017), we choose to estimate methane efficiency separately as outlined in this section, both because our emissions measure is directly related to the animal input, and also to facilitate our simulation of changes in both technical and environmental efficiency due to a reallocation of funds across different types of subsidies.

4.3 | Simulating changes in subsidies

We simulate increases in the payments received by Irish farmers under the GLAS, since it is the largest and currently used environmental payment,[16] with an increase of one subsidy exactly compensated by a decrease of another. This revenue neutrality[17] is kept in our simulation by reducing the total decoupled subsidies received by 1% (Creedy & Hérault, 2012). This simulation mimics the current CAP proposals to use direct payments (i.e., Pillar I) to finance new payments for environmental purposes (see European Commission, 2019b). In our simulated scenarios, reduced decoupled subsidies keep the original distribution, and we only affect the size of the subsidy. Consequently, the ratio of the received subsidy to the total subsidy across farms in the sample is kept fixed across the simulations. However, a caveat of this approach is that it only allows for small changes in the simulated payments.[18] The reallocation of the 1% of the decoupled subsidies is distributed to GLAS recipients using three alternative mechanisms. In the first, the additional resources are allocated equally to those farms that receive the GLAS payment (a 'flat allocation'). In the second mechanism, the resources are allocated to those farms with a stocking rate below the sample median (the 'stocking rate allocation'). In the third, we allocate the additional revenues in direct proportion to the observed share of the subsidy in the sample (i.e., $Subsidy_h / \sum_{h=1}^{H} Subsidy_h$; 'proportional allocation'). In this third mechanism, we also simulate an alternative scenario in which decoupled subsidies are untouched. While this scenario might not be feasible because it requires additional funds, it helps to disentangle the effects of GLAS subsidies. We called this scenario 'Non-financed proportional allocation'. Table 2 provides an overview of the three mechanisms (and four scenarios) we simulate in this study.

Following Bonfiglio et al. (2020), we estimate changes in technical efficiency using a two-stage procedure. In the first step, the simulated value of the farm output ($\ln Y^{S}$) is computed.

[16]The number of recipients of the rest of the current payments is very small. In our simulation, reallocation of the additional resources to these small numbers of recipients results in very inflated values of farm efficiency. The Bonfiglio et al., 2020 approach can only be used for relatively small changes in the simulated subsidies and output, hence our choice of a 1% transfer.

[17]Revenue neutrality implies that the simulated allocation does not require an increase or decrease in taxes.

[18]One important consequence of simulated large changes in the payments is that in the second stage when the new efficiency is estimated, convergence in the estimation when using the ML method might not be achieved.

TABLE 2 Overview of the scenarios

Mechanism	Scenario name	Subsidy treatment: Decoupled subs./LU	Subsidy treatment: GLAS/LU
1	Flat	Reduced	Flat allocation
2	Stocking rate	Reduced	Stocking rate allocation
3	Proportional	Reduced	Proportional
3	Non-financed	Original	Non-financed proportional allocation

In the second step, Equation (2) is re-estimated using the simulated output $\ln Y^{s}$ and subsidy levels. Focusing only on subsidies, the logarithm of the inefficient term u_{it}, associated with farm i at time t can be written as:

$$u_{it} = \rho_0 + \rho_1 * Subsidy_1 + \ \dots \ + \rho_p * Subsidy_p + \tag{7}$$

where u_{it} is defined in Equation (3), Subsidy_1 is the subsidy of type 1 with an associated parameter ρ_1 to be estimated (with p number of subsidies). In addition, the observable output can be expressed using the following expression:

$$ln\,Y_{it} = \widehat{ln\,Y}_{it} - u_{it} \tag{8}$$

where $\widehat{ln\,Y}_{it}$ is the estimated output using Equation (2). Consequently, we can derive the logarithmic distance of observable output of farm i under scenario S as follows:

$$D_i^s = \widehat{ln\,Y}_{it} - ln\,Y_{it}^s = u_{it} + \rho_1{}^*\left(Subsidy_{it1}^s - Subsidy_{it1}\right) + \ \dots \ + \rho_p{}^*\left(Subsidy_{itp}^s - Subsidy_{itp}\right) \tag{9}$$

Using Equations (8) and (9), the logarithm of observable output of farm i under scenario S can be thus obtained as follows:

$$ln\,Y_{it}^s = \widehat{ln\,Y}_{it} - D_i^s = ln\,Y_{it} - \rho_1{}^*\left(Subsidy_{it1}^s - Subsidy_{it1}\right) + \ \dots \ + \rho_p{}^*\left(Subsidy_{itp}^s - Subsidy_{itp}\right) \tag{10}$$

$ln\,Y_{it}^s$ and Subsidy_{it}^s are used to re-estimate the parameters from Equation (2). We simulate the environmental and distributional effects of allocating the additional resources to those farms that receive the GLAS payment. In our simulation, farm income is estimated using the following expression:

$$Income_{it}^s + \sum_{k=1}^{p} Subsidy_{itk} \tag{11}$$

In Equation (11), $Income_{it}^s$ is the farm output value less the production cost: $Y_{it}^{s*}q_i - Cost_{\text{it}}$, where Y_{it}^s and q_i are the output under scenario S and the monetary value of a unit of production for farm i at time t, respectively. Note that when modelling changes in the farm income distribution using Equation (11), the output Y_{it}^s is estimated with Equation (10), and then it is used to estimate the simulated level of farm income in Equation (11). After this, income inequality is measured using the Gini coefficient.

5 | ESTIMATION RESULTS

The Cobb–Douglas functional form was rejected in favour of the more flexible translog in all cases.[19] This section focuses on the technical and environmental efficiency estimates and their drivers, together with the income distribution analysis.[20]

5.1 | Technical efficiency and efficiency drivers

Table 3 presents the average technical efficiency estimates between 2000 and 2017 obtained for the dairy and beef models (as described in Equation 4). These scores, which take values from 0 to 1, indicate the distance from each farm observation to the production frontier. Note that, since they have been estimated separately for each farming system, they are not directly comparable (i.e., they do not allow establishing which system is more efficient, but only how close each group of farms operates in relation to their respective frontier). The average technical efficiency score obtained for the 2000–2017 period for dairy farms is 0.87, while beef farms had an average score of 0.63 in the same period. The standard deviation is larger for beef farms, suggesting there is more heterogeneity present in the sector.

Table 3 also displays the coefficients obtained through the estimation of the inefficiency effects model (Equation 3). These coefficients indicate the direction of the impact of each variable on farm technical inefficiency (i.e., a negative coefficient for a given variable means a positive effect on technical efficiency and vice versa). Note that the magnitude of the coefficients has no direct interpretation; therefore, we will focus the discussion below on the coefficients' sign and significance alone.

Our variables of interest are those capturing the impact of CAP subsidies received by Irish beef and dairy farmers in the period analysed, and in particular, we are interested in the relationship between agri-environmental payments and technical efficiency. Recall that the payments are divided by LU,[21] in order to avoid confounding effects with farm size (Minviel & Latruffe, 2017).

In their meta-analysis, Minviel and Latruffe (2017) pointed to an overall negative relationship between subsidies and farm technical efficiency. In our case, the impact of higher environmental subsidies (per LU) is statistically insignificant for beef farms, except for REPS payments, which had a negative and statistically significant effect on technical efficiency. For the case of dairy farms, the impact of receiving higher REPS (per LU) is also negative and statistically significant, however the impact of receiving higher GLAS is positive, and statistically significant. Mixed positive and negative relationships between different types of environmental payments and farm technical efficiency have also been found in the literature (Minviel & Latruffe, 2017), as already noted in Section 1. This is not surprising, given that environmental payments are varied in their implementation across countries and agricultural production systems. In addition, differing results might also be obtained depending on how environmental subsidies are included in the model[22] (Minviel & Latruffe, 2017). Past literature has theorised that the relationship between agri-environmental payments and technical efficiency is likely to be negative, linked to more extensive production techniques (Mamardashvili & Schmid, 2013) or reduced input use

[19]Appendix S3, online, provides specification tests.

[20]Appendix S4, online, shows the output elasticities estimated.

[21]However, in reality they are not linked to LU.

[22]For example, Mamardashvili and Schmid (2013) treated these subsidies as outputs to production, while most other papers incorporate them as efficiency drivers (Areal et al., 2012; Latruffe & Desjeux, 2016).

TABLE 3 Mean technical efficiency and coefficients of technical inefficiency drivers

	Dairy	Beef
Average technical efficiency	0.87 (0.10)	0.63 (0.21)
Inefficiency effects model		
REPS/LU	0.68*** (0.07)	0.20*** (0.02)
GLAS/LU	−0.59* (0.34)	0.04 (0.09)
AEOs/LU	−1.91 (1.76)	−0.03 (0.09)
Decoupled subs./LU	0.49*** (0.03)	0.03*** (0.01)
Soil type 1 (D)	−0.03 (0.07)	−0.24*** (0.05)
Pasture share	1.39*** (0.28)	0.06 (0.12)
First FFI ratio tercile (D)	3.40*** (0.14)	1.10*** (0.06)
Second FFI ratio tercile (D)	1.88*** (0.12)	0.41*** (0.05)
Constant	−7.49*** (0.34)	−1.37*** (0.13)

Notes: Standard deviations are displayed in parentheses below the average technical efficiency score. In the inefficiency effects model results, standard errors are in parentheses. ***Significant at 1%, **Significant at 5%, *Significant at 10%.

(Latruffe & Desjeux, 2016) that these payments generally require. Lakner (2009) noted that these payments could also induce market distortions. Areal et al. (2012) also found a negative link between environmental payments and technical efficiency of dairy farms in England and Wales, which the authors attributed to more efficient farms not taking up high amounts of environmental payments. However, other research has noted the positive impacts of agri-environmental payments as compensation for the disadvantages of reduced agricultural potential (Manevska-Tasevska et al., 2013) or overcompensation compared to the environmental good incentivised (Lakner et al., 2014).[23]

Receiving higher decoupled (per LU) support appears to be negatively associated with the technical efficiency of Irish beef and dairy farms from 2005 onwards. This is in line with the general negative impacts in previous analyses, Minviel and Latruffe (2017). For the case of beef farms, Iraizoz et al. (2005) and Hadley (2006) also found negative relationships between direct support and efficiency in Spain, and England and Wales, respectively, using data for a period when direct payments were still coupled (1989 to 1999 for the case of Spanish beef farms; and 1982 and 2002 for the case of English and Welsh beef farms). Hadley (2006) also found a negative relationship between direct support and efficiency of English and Welsh dairy farms. Negative impacts of decoupled support could be linked to the continuation of distorting effects on production caused by previous coupled income support (Rizov et al., 2013).

In terms of the rest of the controls in the inefficiency effects model, a greater proportion of pasture is linked to lower efficiency levels for dairy farms. Predominantly grass-based feeding systems, implying additional grazing and grass management requirements, may mean that farmers are more prone to managerial mistakes, translating to lower farm efficiency (Álvarez et al., 2008). Finally, better quality soil types are linked to higher technical efficiency levels, although the relationship appears to be statistically significant only for beef farms. The coefficients obtained for the first and second income ratio tercile dummies suggest that farms in the higher income tercile have larger technical efficiency scores than farms in these two lower terciles.[24] These estimates suggest that the gap between the current production level and its maximum

[23]However, note that since these are voluntary schemes that require additional management guidelines or data recording, selection bias might potentially be present.

[24]Recall that farms in the first tercile of the distribution of the income ratio have lower income per LU, with farms in the third tercile having higher income per LU (this is the excluded reference category).

TABLE 4 Average methane production across income quintiles of FFI per LU (hundred tonnes/year)

	Dairy		Beef	
Quintile	**Methane**	**CV (%)**	**Methane**	**CV (%)**
First	0.15	0.87	0.14	0.77
Second	0.13	0.79	0.17	0.79
Third	0.11	0.77	0.18	0.89
Fourth	0.10	0.77	0.17	0.82
Fifth	0.08	0.80	0.14	0.88
Total sample	0.11	0.86	0.16	0.84

potential output (as indicated by the estimated frontier) could be reduced for farms in the lower income terciles in particular, for instance by better targeting subsidies to these farms. For example, Table 3 showed a positive and statistically significant relationship between efficiency and GLAS support for dairy farms. Therefore, dairy farms in the lowest income tercile (i.e., less technically efficient) could theoretically benefit more from increased support of this type.

5.2 | Methane efficiency analysis

Table 4 displays the average methane production (computed as outlined in Section 3) across different levels of FFI (the first quintile corresponds to lower income, and the fifth quintile to higher income). Methane production level is driven by the farm production level and by the composition of the livestock. For dairy, higher income quintiles have the highest levels of methane production whereas beef farms show the opposite pattern. Dairy farms in the first quintile have the greatest heterogeneity as indicated by the higher coefficient of variation (CV). For beef farms, the opposite holds.

Following Jin and Kim (2019), we also model methane production using the SFA framework outlined in Section 4.2. The average ME_{it} scores for each group of farms are shown in Table 5. Note that the methane efficiency estimates measure the distance between observed farm emissions and the potential levels of methane emissions represented by the frontier. Under this modified SFA framework, ME_{it} (defined by Equation 6) measures how much emissions farms could potentially produce at the current level of inputs used in the production of agricultural outputs. Therefore, smaller ME_{it} signifies larger environmental gains, as farms are producing less methane than the potential.

Table 5 shows that the mean methane efficiency is 0.76 for dairy farms, and 0.84 for beef. This indicates that dairy farms are situated on average further from their respective emissions frontier,[25] suggesting better environmental performance in terms of methane emissions. As in the case of the technical efficiency estimates, beef farms' methane efficiency estimates show greater heterogeneity. We also computed the correlation between the technical efficiency and methane efficiency scores estimated for both types of farms. The Spearman rank correlation coefficients indicate that there is a small negative correlation between both efficiency measures for dairy farms (−0.11), while the correlation is larger and positive for beef farms (0.24). The negative, albeit small, correlation observed for dairy farms suggests that more technically efficient dairy farms are also more environmentally efficient (i.e., higher technical efficiency is linked to lower methane efficiency); while the opposite is true for beef farms (since the correlation is positive, and also

[25]Note that the estimation of two separated frontiers for dairy and beef precludes direct comparison of the efficiency scores estimated for each group of farms.

TABLE 5 Methane efficiency and drivers

	Dairy	Beef
Average methane efficiency	0.76 (0.14)	0.84 (0.15)
Inefficiency effects model		
REPS/LU	0.07* (0.04)	0.09*** (0.02)
GLAS/LU	0.46 (0.29)	0.37*** (0.08)
AEOs/LU	0.86 (0.57)	0.05 (0.11)
Decoupled subs./LU	0.17*** (0.02)	0.28*** (0.01)
Soil type 1 (D)	−0.28*** (0.06)	0.18*** (0.06)
Pasture share	−0.89*** (0.19)	−0.51*** (0.14)
First FFI ratio tercile (D)	−0.66*** (0.06)	0.55*** (0.06)
Second FFI ratio tercile (D)	−0.49*** (0.06)	0.08 (0.06)
Constant	−0.69*** (0.19)	−3.73*** (0.16)

Notes: Standard deviations are displayed in parentheses below the average methane efficiency score. In the inefficiency effects model results, standard errors are in parentheses. ***Significant at 1%, **Significant at 5%, *Significant at 10%.

higher). Some environmental inefficiencies might be linked to sub-optimal use (waste or overuse) of farm inputs (Picazo-Tadeo et al., 2011) or managerial deficiencies by farmers. Therefore, they could arise from the lack of modern or innovative production technologies, or alternative farm practices, on some of these farms. In this case, technical progress (i.e., such as the implementation of optimal feeding practices) may make it possible to reduce emissions while maintaining input levels.

The coefficients obtained after the estimation of the inefficiency effects model in the modified SFA framework are also displayed in Table 5. In this model, receiving higher normalised GLAS (and previously REPS) and decoupled subsidies are linked to a larger gap between the maximum level and observed level of methane production for beef farms (i.e., better emissions efficiency). For dairy farms, normalised REPS and decoupled payments are also associated with improved methane efficiency. Our methane measure is driven by the farm specific output level and the composition of the livestock portfolio, therefore the payments included in the model are not directly conditioned on the levels of these factors. Consequently, we do not expect a reverse causality between methane production and the level of environmental subsidies.[26] Increased pasture share for both types of farms is associated with more inefficient methane pollution, which might be related to deficient pasture management practices or technologies. The negative sign for the first and second tercile dummies (relative to the highest) for dairy farms suggests that dairy farms in lower income terciles have more room for environmental performance improvement. The positive and statistically significant coefficient is only observed for the first tercile FFI ratio dummy, suggesting that beef farms with lower FFI per LU operate further from the maximum methane emissions level (i.e., have better environmental performance).

6 | SIMULATION RESULTS

We simulate a 1% decrease in total decoupled subsidies and then use these resources to increase the GLAS payments. Recall, that for the reallocation of these additional resources, we simulate three mechanisms (outlined in Table 2). In the first, the allocation of the additional revenue

[26]We employed the Hausman test for endogeneity between methane production and environmental payments (see Wooldridge, 2010), and we did not find evidence of it for dairy or beef farms.

follows a flat allocation; in the second, farms receive additional payments when their stocking rate is below the sample median; and in the third, the additional funds are allocated proportionally to the share of the GLAS subsidy in the sample (in this third case, both reducing and without reducing decupled subsidies). Figure 1 displays the mean stocking rate at different quintiles of the FFI per LU distribution (quintile 1 corresponds to lower income levels, and quintile 5 corresponds to higher income levels). It suggests that a policy allocating the extra funds to farms with lower stocking rates is potentially regressive, as lower income households would receive smaller payments.

In Tables S5.1 (for dairy) and S5.2 (for beef) (in Appendix S5, online), we show the changes in technical efficiency estimates resulting from the simulation exercise, and the four alternative reallocation of funds approaches. Scores above 100 indicate that increasing GLAS would induce a generalised increase in technical efficiency for farms. For dairy farms, the reallocation of the subsidies across all the mechanisms has marginally better results for the highest income levels as indicated by the FFI per LU quintile breakdown. For beef farms, the flat allocation keeps the levels of efficiency at the levels of the base scenario. In the rest of the scenarios, the average efficiency reduces.

In Tables S5.3 (for dairy) and S5.4 (for beef) (in Appendix S6, online), we show the changes in methane efficiency estimates resulting from the same simulation exercises. A score of more than 100 indicates again that the methane efficiency score increases because of increasing GLAS payments, that is, resulting in worsening methane emissions. Again, the simulated changes are marginal, though mostly in the right direction (improved emission performance on average), with the stocking rate allocation performing best for dairy, though the proportional allocation is better for the beef farms.

Finally, we present results regarding changes in income distribution. Table 6 displays the estimated changes in the Gini coefficient across the simulated mechanisms. For beef farms, income distribution improves as shown by the reduction in the Gini coefficient across all the four analysed scenarios, with the most improvement shown with the stocking rate allocation. On the other hand, all allocations increase income inequality, with the stocking rate allocation (mechanism 2) showing the worst performance.

7 | POLICY DISCUSSION AND CONCLUSIONS

The changes in the environmental payments through time in Ireland started with the Rural Environment Protection Scheme (REPS) in 1994, followed by the Agri-Environment Options Scheme (AEOS) in 2010, and finally evolved into the Green, Low Carbon, Agri-environment Scheme (GLAS) in 2015, capture the evolution in the policy focus and strategies for environmental protection. The AEOS introduced specific measures to promote biodiversity, encourage water management and quality and combat climate change. Under GLAS, participants are required to prepare nutrient management plans and actions for greater biodiversity protection. We explore empirically the relationships between these environmental payments with both technical efficiency and environmental performance (measured by methane emissions). Proposals for the new CAP Pillar I payments include the implementation of eco-schemes, aimed at promoting aspects such as increases in the space per animal and low intensity grass-based livestock systems, further shifting Pillar 1 towards environmental objectives. Therefore, we also simulate the distributional, efficiency and environmental performance of a reallocation of payments across Pillars in the spirit of the new CAP payments reform. We use farm level accountancy data for Irish beef and dairy farms between 2000 and 2017 to analyse two main research questions. First, we explore the link between the historical set of environmental payments granted under Pillar II and farm level technical efficiency and environmental performance. Second, we simulate a reduction in decoupled support combined with an increase in GLAS subsidies, using three mechanisms to reallocate these funds: a 'flat' allocation where

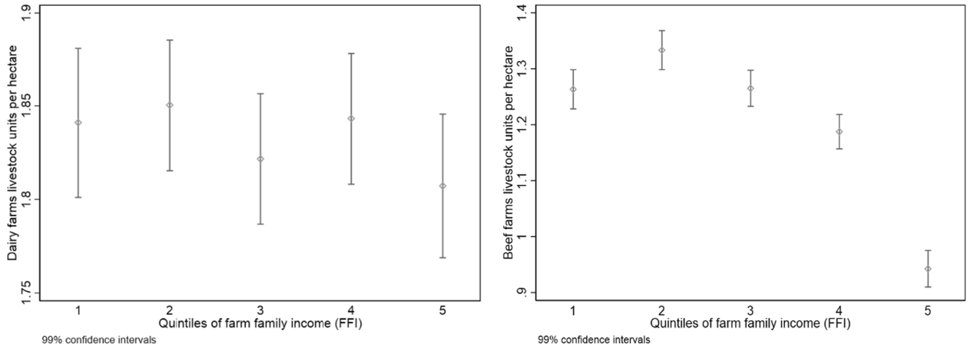

FIGURE 1 Stocking rate across farm family income per LU quintiles (2000–2017)

TABLE 6 Changes in the income distribution relative to the base scenario

		Change compared to base scenario (%)			
		Mechanism (1)	Mechanism (2)	Mechanism (3)	
System	Gini (base scenario)	Flat	Stocking rate	Proportional	Non financed
Dairy	0.30	0.29	0.73	0.20	0.28
Beef	0.47	−1.80	−1.79	−1.77	−1.76

each recipient of the GLAS payment receives the same amount from the additional funds; allocation to those farmers with stocking rates below the sample median; allocation in direct proportion to current GLAS subsidy receipts. Under these scenarios, we compute changes in technical efficiency, methane efficiency, and income inequality associated with this hypothetical transfer of funds across Pillars.

Our estimates suggest that GLAS payments have a positive and statistically significant relationship with farm level technical efficiency of Irish dairy farms, and are also linked with improved methane efficiency of Irish beef farms. In addition, our simulation results show that increases in GLAS financed by decoupled payments can potentially improve environmental performance (i.e., methane efficiency). Regarding improvements in technical efficiency, we find that the flat allocation of additional GLAS payments performs slightly better for both types of farms. However, for reduced methane emissions, the stocking rate allocation performs best for dairy, and the proportional allocation is better for the beef farms. As for the effects on income inequality, increasing GLAS payments can potentially decrease income inequality under the analysed scenarios for beef farms. In the case of dairy farms, the proportional allocation has the lowest impact on income inequality. Our findings highlight the importance of considering the heterogeneous effects of changes in environmental payment schemes across different farm types. Our simulation results suggest that there is a trade-off between improving competitiveness (measured by technical efficiency) and environmental gains (measured by methane efficiency). These estimates point to the need for designing schemes where instruments consider the structural differences in dairy and beef production, as well as income differences. Accounting for these inequalities would also benefit the design of future policy instruments for environmental protection, aimed to improve social acceptability and unlock the potential of the sector to contribute towards a more sustainable economy.

Finally, some limitations of our analysis should be noted. In terms of the emissions data used, we focus on emissions generated by animal production and ignore other sources such as input use (i.e., energy, nitrate fertiliser use), as this information is not available in the dataset we use. Therefore, our measure is likely to under-represent total farm emissions. Should more detailed environmental externality data become available as part of the NFS in the future, more sophisticated methodologies to model farm total GHG emissions (such as the approach in Dakpo et al., 2017) could be fruitful. Despite this limitation, this analysis offers interesting and relevant empirical evidence in light of the newly designed CAP.

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