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Technical efficiency and equity effects of environmental payments in Ireland

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Abstract: We investigate the relationship between farm level competitiveness and environmental performance using Stochastic Frontier Analysis (SFA). We use an Irish panel of farm level financial data for the years 2000-2017 to analyse the link between EU Common Agricultural Policy environmental payments, and dairy and beef production from economic and environmental views. Our estimates identify a positive relationship between technical efficiency and environmental payments in place in recent years, although not for early versions of these payments. We simulate increases in the Green, Low-Carbon, Agri-Environment payments targeted to farms with low stocking rates, financed through reductions in decoupled payments. We find that under this stylised scenario, competitiveness and environmental gains are achieved for dairy farms. However, under this scenario, we do not identify gains for beef farms. We also find a reduction in income inequality under this scenario for both farm types.

Keywords: Stochastic Frontier Analysis, emissions, income inequality, agricultural subsidies, technical efficiency, simulation.

JEL codes: Q12-Micro Analysis of Farm Firms, Farm Households, and Farm Input Markets; Q18-Agricultural Policy - Food Policy; Q52-Pollution Control Adoption and Costs - Distributional Effects - Employment Effects.

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1. Introduction

The Common Agricultural Policy (CAP) in place in the European Union (EU) is broadly structured along with two main groups of payments, or Pillars (Hill, 2012). Payments granted under Pillar I relate to direct income support and market measures, while those under Pillar II relate to rural development. In the current CAP design, there is a range of environmental obligations in both Pillars I and II, although most of these measures are in Pillar II. Under the current plans for designing a new CAP post-2020, transit towards more sustainable agricultural production systems as part of the EU's European Green Deal (European Commission, 2019a) has taken centre stage in the negotiations. A new range of different measures is being discussed (European Commission, 2021). For example, eco-schemes are policy instruments that members of the European Union are expected to implement. These schemes are typically designed to be voluntary and are based on conditionality, meaning that failing to implement the environmental obligations results in a reduction of payments (European Commission, 2019b). It is planned that these schemes will be funded by Member States' direct payment (CAP Pillar I) budgets (European Commission, 2019b). It is this re-distribution and balance between Pillars I and II funding that is of particular interest for our empirical analysis. In June 2021 the European Parliament and the Council reached a provisional agreement to be implemented starting in January 2023. The agreement included important environmental provisions, such as making eco-schemes compulsory, increased conditionality, or allocating 35% of rural development funds to agri-environment commitments[1].

Agricultural subsidies affect factors important to farm survival, such as income (Bonfiglio et. Al, 2019 and Ciliberti and Frascarelli, 2018) and farm level competitiveness (Latruffe, 2010). While research on either the distributional effects and competitiveness effects of subsidies in the agricultural sector is not new, the quantification of changes in the distribution of the farmer income and farm level economic and environmental performance due to changes in agri-environmental subsidies has received limited attention in the existing literature. Regarding changes in farm level performance linked to receiving agri-environmental subsidies, past literature uncovered mixed results. The impact of different types of agri-environmental payments on technical efficiency in several European countries is explored in few previous analyses and is found to be mostly negative (for example, Kumbhakar, Lien, and Hardaker (2014) for Norwegian crop farms; Lakner et al. (2014) for organic farms in Germany; or Latruffe and Desjeux (2016) for dairy, beef and crop French farms). A positive relationship is found for example in Mamardashvili and Schmid (2013) for Swiss dairy farms; Manevska-Tasevska, Rabinowicz, and Surry (2013) for dairy, beef, and pig farms in Sweden; Lakner et

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

al. (2014) for organic farms in Switzerland; or Martinez Cillero et. al (2017) for Irish beef farms. As to 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 (2019) analyse the effects of the same reform in both technical efficiency and income inequality. They find that technical efficiency is negatively correlated with direct payments for arable farms and positively correlated for farms specialised in livestock. They also find that using workforce size rather than the number of hectares as a criterion of redistribution has the best redistributive properties.

In this paper we investigate the relationship between farm level competitiveness, proxied by farm level technical efficiency estimates (Latruffe, 2010), and past and present CAP agri-environmental subsidies. In order to explore this relationship, we first apply standard Stochastic Frontier Analysis (SFA) to estimate farm level technical efficiency scores and the effect of subsidies on these estimates. Second, we also analyse environmental efficiency by applying a modified SFA approach (Jin and Kim, 2019). Under this alternative specification, a policy maker will seek to keep observed levels of methane production under the maximum (i.e., frontier) level computed through SFA. We focus on methane production since 58% of Irish emissions from agriculture in 2019 corresponded to this gas, produced by the rumen of cattle animals.[2] We use an unbalanced panel of National Farm Survey (NFS) farm level financial data, and include farms classified as specialist dairy and beef producers. We find mixed evidence regarding the relationship between agri-environmental payments and farm efficiency. Our SFA estimates show that payments under the Rural Environment Protection Scheme (REPS) had a negative impact on the efficiency of both types of farms, however more recent schemes had a positive impact on the efficiency of dairy farms only. We also find evidence that the Green, Low-Carbon, Agri-Environment Scheme (GLAS) can increase the gap between the maximum possible levels of methane production and the observed ones.

We then simulate decreases in decoupled payments to finance an increase in payments under the GLAS and quantify resulting changes in competitiveness, environmental performance, and changes in income inequality. We find that when the additional payments under the GLAS mechanism are allocated to farms with low stocking rates, there is a trade-off between competitiveness and goals for environmental protection. Regarding changes in income distribution, our simulated scenario shows that income inequality measured by the Gini coefficient can be reduced in both farm types.

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

Under the new CAP reforms, it is foreseen that while a big proportion of direct payments under Pilar I will be still used for income support, a proportion will be used to promote voluntary pro-environmental actions (see IEEP, 2020). We simulate additional transferences of resources from Pilar I to actions previously financed by Pillar II. The paper is organized as follows. Section 2 provides a description of the system of CAP payments in place in Ireland in the period we analysed. Section 3 describes the data and variables used in the empirical analysis; and section 4 outlines the approaches followed for the estimation of efficiency and its drivers, as well as for the simulation performed. Section 5 contains the main results for the baseline specification, and section 6 the results for the simulations performed. Section 7 concludes.

2. CAP policy framework between 2000 and 2017

Since its inception in the 1957 Treaty of Rome, the EU CAP has included an ever-changing system of subsidies granted to European farmers. The bulk of agricultural support in the EU has traditionally been in the form of market support mechanisms, followed by direct income support (i.e. Pillar I payments). 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 to production (i.e. given per head of animal produced or hectare farmed), that included several specific livestock and arable premia granted between 1993 and 2004. The 2003 Mid-Term Review introduced decoupled direct support as part of the CAP for the first time. A subsidy can be considered decoupled if it is not linked to current prices, factor use, or production (Burfisher and Hopkins, 2003). Decoupled payments were implemented in the CAP through the Single Farm Payment (SFP). It was implemented in Ireland in 2005[3] and replaced all the previous types of livestock coupled support outlined above. Ireland opted for the implementation of full decoupling, which meant that coupled support was entirely removed, therefore, the direct link between agricultural production and direct payments was also removed. Note that although there was not a requirement to produce in order to receive the SFP, farmers were required to maintain the land in Good Agricultural and Environmental Condition (GAEC)[4]. Decoupled payments were maintained, albeit re-structured 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, calculated with relation to the entitlements owned

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

[4] These conditions covered a group of compulsory and optional standards concerning soil protection, water management, etc. Failing to comply led to a reduction of part of the payment received by the farmer.

by a farmer under the SFP in 2014. For the case of Ireland, the top-ups consisted of a greening top-up (compulsory) and a top-up for young farmers (also compulsory)[5] (European Commission, 2016b). The greening component required farmers to follow certain beneficial practices for the environment, such as crop diversification and the maintenance of permanent pastures and ecological focus areas (European Commission, 2011). The idea behind this design was to further enhance the purpose of direct payments as a useful tool to achieve a sustainable and efficient use of natural resources in agriculture (European Commission, 2011).

Apart from income support payments for Irish farmers, they also received a number of Pillar 2 payments between 2000 and 2017, the most important being agri-environmental payments. Farmers' participation in agri-environmental payments is on a voluntary basis. The Rural Environment Protection Scheme (REPS) was implemented in 4 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 3 rounds between 2015 and 2016, when it closed to new entrants. Priority was given to farmers with environmental assets and to farmers who undertake GLAS actions. Access is on the basis of tiers. If oversubscribed within a tier, a ranking system will apply. Note however, that all these three types of payments were undertaken under 5-year contracts. Agri-environmental payments share the common feature that they intend to compensate farmers for the adoption of farming practices that help to mitigate the negative impacts of farming activities on the environment, promote the conservation of high value environments and the enhancement of rural landscapes (DAFM, 2007). Finally, organic payments were implemented in 2015 in order to incentivize organic production. These payments were co-financed between the EU and the Irish National Exchequer, and they consist of (mainly) payments per hectare, and are implemented through successive Rural Development Plans[6]. A timeline of the agri-environmental payments granted to Irish farmers between 2000 and 2017 can be found in Table A1 in Appendix 1.

3. Data and variable description

We obtained a sample of the NFS dataset through the Irish Social Science Data Archive (ISSDA, 2020). 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

[5] Ireland also opted for the implementation of voluntary coupled support for protein crops.

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

population. We select specialist dairy and beef farms for our analysis[7], and include data between 2000 and 2017. We select these two farming systems for several reasons. First, dairy production constitutes the largest farming system in terms of economic output. The beef system obtained remarkably low family farm income (€333 per hectare, according to 2019 NFS data), while dairy obtained the highest (€1,118 per hectare in the same year) (Donnellan et al., 2020). Second, despite the larger economic importance of dairy production, beef farming constitutes the largest category in terms of the number of farms. The beef system comprises 58 per cent of Irish farms, while the dairy system comprises 17 per cent of farms (Donnellan et al., 2020). Third, beef farms have the highest reliance on subsidies for their survival, with direct payments representing 162 per cent of family farm income for the case of specialist rearing farms in 2019 (Donnellan et al., 2020). It is likely, that changes in the configuration of direct support will impact 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) analysis Teagasc pointed out the need for development of policy measures to encourage uptake of mitigation technologies on-farm, such as genetic and feeding improvements (Teagasc, 2019). In the same line, Ireland's 2019 Climate action Plan calls to "*accelerate the assessment of feed additives […] to mitigate methane emissions from enteric fermentation, including identification of their abatement potential in grazing-based systems*" (Department of the Environment, Climate and Communications, 2019; page 105).

For each specialisation 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. 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 in hours, and includes both hours paid and unpaid. The capital input category aggregates the monetary value of machinery, buildings and livestock.

[7] 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 (since 2009) of the farm (Donnellan et al., 2020).

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[8] or not in the production function estimated for this system. 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, casual labour and other costs directly incurred in the production of the farm enterprises) and overhead costs (i.e. hired labour, interest payments, depreciation, repairs, etc.).

In addition to farm level financial information, 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)[9] . 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; (iv) GLAS; and finally (v) organic farming payments. Table A2 in Appendix 2 provides details regarding the timelines of each type of payment in the dataset. We also include the share of pasture hectares on total farm hectares in order to explore the relationship between using a grass based feeding system and technical efficiency. Finally, we account for the quality of the soil in which farms operate by including a dummy which equals 1 if the farm is located in land defined as more favourable for agricultural production, and zero otherwise (see Donnellan et al., 2020, page 87, for details on this classification).

We complement this database through two external data sources. We use 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 of each of them. The CH_4 enteric fermentation emissions are obtained using the Irish Environmental Protection Agency (EPA) emission factors published for different types of cattle animals (Duffy et al., 2016, 2017, 2018 and 2019; see Table 5.4). 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.

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

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

Descriptive statistics for the variables described in this section can be found in Table 1. Due to the low number of beef farms receiving organic subsidies in our sample, this variable is not included in the inefficiency effects model estimated for beef farms. 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 hours and have higher total costs. Dairy farms have on average a higher share of pasture area in total farm area, and are located in better quality soils. Beef farms receive on average a higher amount of both types of payments, decoupled and agri-environmental, per livestock unit.

Table 1. Average values of main variables in the model

	Dairy farms	Beef farms
Production function variables		
Total output (€)	131,242	24,780
	(82,325)	(22,954)
Land (hectares)	58.25	42.17
	(29.40)	(26.01)
Labour (hours)	3,065.32	1,810.25
	(1,216.44)	(721.29)
Capital (€)	230,460.96	91,072.06
	(152,957.56)	(71,334.82)
Variable costs (€)	86,680.18	23,771.38
	(58,733.43)	(19,758.69)
Part-time farm (D)	0.06	0.74
	(0.23)	(0.44)
Efficiency drivers		
REPS/LU (2000-2014)	26.50	72.30
	(56.60)	(123.50)
GLAS/LU (2015-2017)	4.10	24.80
	(16.70)	(53.80)
AEOs/LU (2011-2017)	0.80	7.80
	(6.50)	(35.20)
Organic subs./LU (2016-2017)	1.50	-
	(12.20)	
Decoupled subs./LU (2005-2017)	181.89	301.10
	(79.43)	(179.11)
Soil type 1 (D)	0.58	0.44
	(0.49)	(0.50)
Pasture share	0.92	0.89
	(0.14)	(0.18)
Observations	6,149	6,390

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.

4. Methodology

4.1 Stochastic Frontier Analysis

In this analysis we apply SFA in order to obtain estimates of farm level technical efficiency, as well as assessing the effect of several farm specific characteristics on this estimate. In the context of our analysis, SFA is preferred to alternative methodologies to estimate technical efficiency such as Data Envelopment Analysis (DEA) or semi-parametric approaches due to its capacity to accommodate external shocks through the inclusion of a random error in the production function estimated (Coelli et al., 2005). Accounting for these factors is important when using agricultural data, since farm production can be often affected by disease or adverse weather conditions (Irz and Thirtle, 2004; Zhu and Lansink, 2010). Farm production technology is represented using a production function:

$$lnY_{it} = f(lnX_{it}, t) + v_{it} - u_{it} \tag{1}$$

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 i-th farm ($i = 1,\ldots,n$) and the t-th time periods ($t = 1,\ldots,T$) respectively. Equation (1) displays the double error term that characterizes SFA, with a stochastic random error v_{it} and the inefficiency term u_{it}, proposed in the seminal papers by Meeusen and Van den Broeck (1977) and Aigner et al. (1977). A detailed and didactic description of the standard SFA methodology can be found in Kumbhakar and Knox Lovell (2000).

Since SFA is a parametric estimation approach that relies on Maximum Likelihood (ML) estimation, we need to make assumptions about the functional form of the production function outlined in equation (1) as well as about the distribution of the two error terms it includes. In this analysis we assume a translog functional form for the estimated production function:

$$LnY_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k lnX_{itk} + \frac{1}{2}\sum_{k=1}^{K}\sum_{g=1}^{K} \beta_{gk}\, lnX_{itk} lnX_{itg} + \beta_t t + \frac{1}{2}\beta_{tt}t^2 + \sum_{k=1}^{K} \beta_{tk} lnX_{itk}\, t + v_{it} - u_{it} \tag{2}$$

This functional form is commonly assumed in related literature, as it offers flexibility in the representation of the production technology (for example, see previous SFA analyses of Irish agricultural sector in O'Neill and Matthews, 2001; Newman and Matthews, 2007; or Carroll et al., 2001). Another common, albeit less flexible, functional form also found in the literature is the Cobb-Douglas specification. Since the Cobb-Douglas is nested in the translog functional form, we will test the preferred specification using a likelihood ratio test. In equation (2), β_0, β_k, β_{gk}, β_{tt} *and* β_{tk} are parameters to be estimated. It also includes non-neutral technical change, by allowing for the interaction of the inputs and a time trend t.

Regarding the distribution of the two error terms in equation (1), we make the following assumptions:

$$u_{it} \sim N^{+}(0, \sigma^2_{itu}), \text{ with } \sigma^2_{itu} = exp(\gamma_m Z_{itm}) \quad (3)$$
$$v_{it} \sim N(0, \sigma^2_{itv})$$

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 heteroskedastic 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:

$$Technical\ efficiency_{it} = E[exp(-u_{it})|e_{it}] = E[exp(-u_{it})|v_{it} - u_{it}] \quad (4)$$

Since we are using panel data, 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 imposed in the model described in equation (2), which may bias the results in the presence of time invariant farm specific unobserved heterogeneity (likely to arise from differing production conditions and farmers' attitudes, such as climatic conditions, educational levels or risk preferences), is relaxed by allowing farm specific intercepts β_0 in the model as described in equation (2).

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.[10] In this specification, as in the typical random effects panel estimator, α_i and the variables in equation (6) are assumed to be uncorrelated (Greene, 2005).

4.2 Methane inefficiency

Jin and Kim (2019) apply a modified version of the classic SFA methodology for frontier estimation outlined in Section 4.1. They apply an alternative SFA model where lnY_{it} in equation (1) is replaced by lnM_{it}, which is the log of farm specific computed methane emissions:

$$lnM_{it} = f(lnX_{it}, t) + v_{it} - u_{it} \quad (5)$$

As in equation (1), $\boldsymbol{X_{it}}$ is a vector of k inputs used in the farm, that also contributes to methane production, t is a time trend, and i and t denote the individual farm and time periods, respectively. Equation (7) also includes the double error term typical of SFA. We assume a translog functional form

[10] $LnY_{it} = (\beta + \alpha_i) + \sum_{k=1}^{K} \beta_k lnX_{itk} + \frac{1}{2}\sum_{k=1}^{K}\sum_{g=1}^{K} \beta_{gk}\, lnX_{itk} lnX_{itg} + \beta_t t + \frac{1}{2}\beta_{tt}t^2 + \sum_{k=1}^{K} \beta_{tk} lnX_{itk}\, t + v_{it} - u_{it}$

for *f(.)* in equation (7), and the same error distribution outlined in equation (3) for u_{it} and v_{it}. In this framework, v_{it} is also the stochastic random error. The gap between each observation and the frontier is measured in this modified SFA framework by the methane efficiency score (ME_{it}), which is recovered post-estimation, in an equivalent way as technical efficiency in equation (4):

$$ME_{it} = E[exp(-u_{it})|e_{it}] = E[exp(-u_{it})|v_{it} - u_{it}] \quad (6)$$

In this case the gap is interpreted as the emissions shortfall (Jin and Kim, 2019). Under this view, environmental gains imply maintaining the observed level of methane under the maximum possible level represented by the frontier (i.e. the larger the gap, or shortfall, from the frontier the better).

4.3 Farm income distribution

Farm income is estimated using the following expression:

$$Income^{s}_{it} \; + \sum_{k=1}^{p} Subsidy_{itk} \quad (7)$$

$Income^{s}_{it}$ is the farm output value less the production cost: $Y^{s}_{it} * q_{i} - Cost_{it}$, where Y^{s}_{it}, q_i are the output under scenario S and the monetary value of a unit of production for farm *i* at time *t.* To measure changes in income distribution we use the Gini coefficient. In addition, we follow Lopez-Feldman (2006) to decompose the factors affecting this metric. The methodology follows Lerman and Yitzhaki (1985) who show that the Gini coefficient can be represented as follows:

$$G = \sum_{k=1}^{K} S_k G_k R_k$$

Where S_k is the share of the income source *k* in the total income, I_k is a metric of inequality regarding the income source *k*, and R_k is a metric of the correlation between the income source *k* and the distribution of total income. In other words $R_k = Cov\{Income_k, F(Income_k)\} / Cov\{Income_k, F(Income)\}$, where F(Income) and F($Income_k$) are the cumulative distribution of total income and income from source $_k$. While the income source $_k$ is equally distributed, G_k will be equal to zero, R_k is positive and large if the income source is unequally distributed and its distribution benefits those at the top of the income distribution.

4.4 Simulating changes in subsidies

We simulate increases in the payments under the Agri-Environment Scheme (GLAS). We concentrate on this payment because it is the largest and currently used environmental payment[11]. Revenue neutrality[12] is kept in our simulation by reducing total decoupled subsidies by 1%. Note that the additional revenue is raised from all recipients of decoupled subsidies. Note that one caveat of this approach is that it only allows for small changes in the simulated payments[13]. The re-allocation of the 1% of the decoupled subsidies is distributed to GLAS recipients by using two mechanisms. In the first mechanism, the additional resources are allocated equally to those farms that receive the GLAS payment. We refer to this scenario as *"flat allocation"* in the paper. In the second mechanism, the resources are allocated to those farms with a stocking rate below the sample median. We refer to this scenario as *"stocking rate allocation".*

Following Bonfiglio et. al (2019) we estimate changes in technical efficiency using a two stage procedure. In the first step, the simulated value of the farm output is computed (i.e. LnY^s). In the second step, Equation (2) is re-estimated using the simulated output and subsidy levels. According to Bonfiglio et. al (2019), the logarithm of the inefficient term associated with farm *i* at time *t* can be written as:

$$u_{it} = \rho_0 + \rho_1 * Subsidy_1 + \ldots + \rho_p * Subsidy_p \tag{8}$$

Where u_{it} is defined in equation (5), $Subsidy_1$ is the subsidy of type 1, ρ_1 is the parameter to be estimated. In addition, the observable output can be expressed using the following expression:

$$LnY_{it} = \widehat{LnY}_{it} - u_{it} \tag{9}$$

Where $\widehat{LnY}_{it}$ is the estimated output using expression (5). Consequently, we can derive the logarithmic distance of observable output of farm *i* under scenario *S* as follows:

$$D^s_i = \widehat{LnY}_{it} - LnY^s_{it} = u_{it} + \rho_1 * (Subsidy^s_{it1} - Subsidy_{it1}) + .. + \rho_p * (Subsidy^s_{itp} - Subsidy_{itp}) \tag{10}$$

Using expression (10), the logarithm of observable output of farm *i* under scenario *S* can be thus obtained as follows:

$$LnY^s_{it} = \widehat{LnY}_{it} - D^s_i = LnY^s_{it} - \rho_1 * (Subsidy^s_{it1} - Subsidy_{it1}) + .. + \rho_p * (Subsidy^s_{itp} - Subsidy_{itp}) \tag{11}$$

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[11] The number of recipients of the rest of the current payments is very small. In our simulation, re-allocation of the additional resources to these small numbers of recipients results in very inflated values of farm efficiency. The Bonfiglio et. al (2019) approach can only be used for relatively small changes in the simulated subsidies and output, hence our choice of a 1% transfer.

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

[13] 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 maximum likelihood method might not be achieved.

$LnY^s{}_{it}$ and $Subsidy^s{}_{it}$ are used to re-estimate equation (5). We simulate the environmental and distributional effects of allocating the additional resources to those farms that receive the GLAS payment. When modelling changes in the farm income distribution we replace Equation (12) to estimate the new farm income under the analysed scenarios.

5 Results

5.1 Elasticities, returns to scale and technical change

Specification tests can be found in Appendix 3. The Cobb-Douglas functional form was rejected in favour of the more flexible translog in all cases. A Hausman test rejected the TRE estimation for dairy farms in favour of TFE, while for beef farms TFE estimation did not converge, therefore TRE is used. The dummy variable capturing technology differences between beef farms operated part-time is statistically significant, which indicates that technological differences exist between part-time farms and those operated full-time. The sign of the coefficient is negative, indicating that farms operated part-time obtain less output than full-time farms, using the same inputs[14].

The estimated coefficients of the first order terms of the translog production function are provided in Table 2. Since the inputs are expressed in natural logarithms and were divided by their arithmetic means before estimation, the first order coefficients displayed can be interpreted as output elasticities (at the sample means).

[14] Almost three quarters of beef farms are operated on part-time basis, while only 6 per cent of dairy farms are considered to be part-time.

Table 2. Estimated coefficients

	Dairy	Beef
Output elasticities		
Area	0.154***	0.201***
	(0.028)	(0.048)
Labour	0.090***	0.007
	(0.026)	(0.043)
Capital	0.128***	0.261***
	(0.024)	(0.048)
Variable costs	0.187***	0.384***
	(0.027)	(0.046)
Part-time dummy		-0.099***
		(0.021)

Notes: Standard errors are in parentheses. ***Significant at 1%, **Significant at 5%, *Significant at 10%.

All elasticities in both models have positive signs and are statistically significant at the 1% level, except for the elasticity of labour in the model estimated for beef farms. This finding could be linked to the prevalence of part-time farmers in this sector, where the number of working hours presents less variability. Moreover, labour input has the smallest contribution to output production in both models. Variable costs input has the highest elasticities in both models. The higher coefficient of land input for beef farms compared to dairy is not surprising, since beef production in Ireland is predominantly grass-based; therefore, the availability of grazing area is of great importance in the production of output. Capital input has a substantially smaller contribution to output production for dairy compared to beef farms.

5.2 Technical efficiency and efficiency drivers

Table 3 displays the coefficients obtained through the estimation of the inefficiency effects model described in 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.

Table 3. Coefficients of technical inefficiency drivers

	Dairy	Beef
REPS/LU	0.118**	0.076***
	(0.050)	(0.020)
GLAS/LU	-0.419*	-0.073
	(0.251)	(0.086)
AEOs/LU	-2.801**	-0.067
	(1.341)	(0.086)
Organic subs./LU	-6.768	-
	(6.970)	
Decoupled subs./LU	0.002***	-0.029***
	(0.000)	(0.011)
Soil type 1 (D)	-0.392***	-0.252***
	(0.058)	(0.047)
Pasture share	0.804***	0.142
	(0.222)	(0.128)
Constant	-3.689***	-0.753***
	(0.224)	(0.123)

Notes: Standard errors are in parentheses. ***Significant at 1%, **Significant at 5%, *Significant at 10%.

The key 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.

Note that the payments are divided by LU; however, in reality they are not linked to livestock units. This normalization using LU is used in order to avoid confounding effects with farm size. This is a standard procedure in the literature when using dairy or beef farms (see for example discussion in: Minviel and Latruffe,2016).

The impact of receiving higher normalised environmental subsidies is statistically insignificant for beef farms, with the exception of REPS payments which had a negative and statistically significant effect on technical efficiency. For the case of dairy farms, the impact of receiving higher normalised REPS is also negative and statistically significant, however the impact of receiving higher GLAS or AEOs is positive, and also significant. Finally, the impact of organic subsidies is statistically insignificant. Past literature has theorized that the relationship between agri-environmental payments and technical efficiency is likely to be negative, linked to more extensive production techniques (Mamardashvili and Schmid 2013) or reduced input use (Latruffe and Desjeux 2016) these payments generally impose. Lakner (2009) noted these payments could also induce market distortions. However, some research has noted that positive impacts of agri-environmental payments to successful compensation of the disadvantages originated by the reduced agricultural potential (Manevska-Tasevska, Rabinowicz, and

Surry 2013) or to overcompensation compared to the environmental good incentivized (Lakner et al. 2014)[15].

Receiving higher normalised decoupled support appears to be positively associated with technical efficiency of Irish beef farms from 2005 onwards[16]. The opposite relationship however is estimated for dairy farms. Theory suggests that decoupled payments can benefit farm technical efficiency through several channels. First, positive effects can indirectly arise from increased investment on farm due to the relaxation of farmers' financial constraints (Zhu et al., 2012), by facilitating access to credit, which would in turn increase on-farm investment and it would improve performance (Rizov et al., 2013; Kazukauskas et al., 2014). It is also possible that Irish farms are benefiting from the reduced need for external credit by using decoupled payments directly to increase investment (Breen et al., 2006). A second possible source of efficiency improvements is linked to reduced farmers' risk aversion arising from the increased income associated with decoupled payments (Hennessy, 1998; Zhu et al., 2012), resulting also in increased investment on farms. Finally, other positive effects could be linked to the removal of the link between the payment and production enterprises, leading to incentives to engage in more efficient farm practices and productive farm activities by adapting their production decisions to market signals (Rizov et al., 2013). Negative impacts of decoupled support; however, could be linked to the continuation of distortionary effects on production that were caused by previous income support that was linked (i.e. coupled) to farm production levels (Rizov et al., 2013).

In terms of the rest of farm characteristics included as controls in the inefficiency effects model, higher share of pasture over total farmland is linked to lower efficiency levels for dairy farms. Having more pasture area is likely to imply farms use a predominantly grass-based feeding system, therefore the are also likely to perform additional activities on-farm that relate to pasture growth and management, resulting in farmers being more prone to managerial mistakes that translate in lower farm efficiency (Alvarez et al., 2008). Finally, being located in better quality soil types is unsurprisingly linked to higher technical efficiency levels for both types of farms.

Table 4 presents yearly and overall descriptive statistics for the technical efficiency estimates 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,

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

[16] Decoupled payments are not linked to livestock units; however, the normalization of decoupled payments using LU is used in order to avoid confounding effects with farm size. This is a standard procedure in the literature when using dairy or beef farms (see for example discussion in: Minviel and Latruffe,2016).

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 operate in relation to their respective frontier). The closer the scores are to 1, the closer farms operate to the frontier.

Table 4. Technical efficiency estimates

	Dairy		Beef	
	Mean	S.D.	Mean	S.D.
2000	0.825	0.090	0.632	0.204
2001	0.852	0.087	0.580	0.235
2002	0.862	0.087	0.594	0.208
2003	0.876	0.084	0.600	0.217
2004	0.884	0.080	0.620	0.208
2005	0.820	0.101	0.618	0.211
2006	0.798	0.105	0.626	0.201
2007	0.869	0.093	0.612	0.213
2008	0.832	0.098	0.632	0.194
2009	0.755	0.121	0.607	0.216
2010	0.838	0.106	0.586	0.221
2011	0.873	0.071	0.712	0.167
2012	0.806	0.094	0.692	0.182
2013	0.835	0.080	0.613	0.188
2014	0.854	0.071	0.623	0.178
2015	0.863	0.071	0.704	0.165
2016	0.840	0.080	0.695	0.172
2017	0.873	0.084	0.637	0.177
Total	0.843	0.096	0.631	0.203

Notes: S.D. indicates standard deviation.

The average technical efficiency score obtained for the 2000–2017 period for dairy farms is 0.843, while beef farms had an average score of 0.631 in the same period. These scores indicate that both beef and dairy farms have scope for efficiency improvement, particularly beef farms. Figures 1 and 2 display the distribution of the technical efficiency scores estimated for the dairy and beef farms samples separately, between 2000 and 2017. They show that the dispersion is higher in the beef farms sample, suggesting there is more heterogeneity present in the sector.

Average yearly estimates of technical efficiency displayed in Table 4 show a slightly positive trend between 2000 and 2017, with the comparison of technical efficiency at the beginning and at the end of the time frame show an overall improvement. A deterioration of average efficiency scores can be observed in 2009 and 2010 for dairy and beef farms, respectively. Average technical efficiency then recovered afterwards.

Figure 1. Dairy farms technical efficiency distribution (2000-2017)

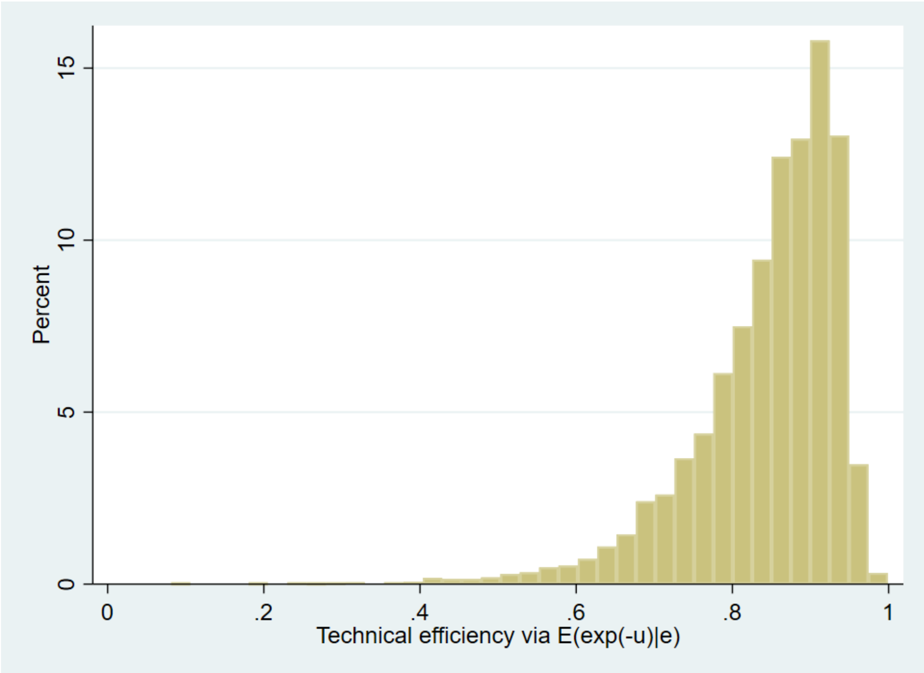


Figure 2. Beef farms technical efficiency distribution (2000-2017)

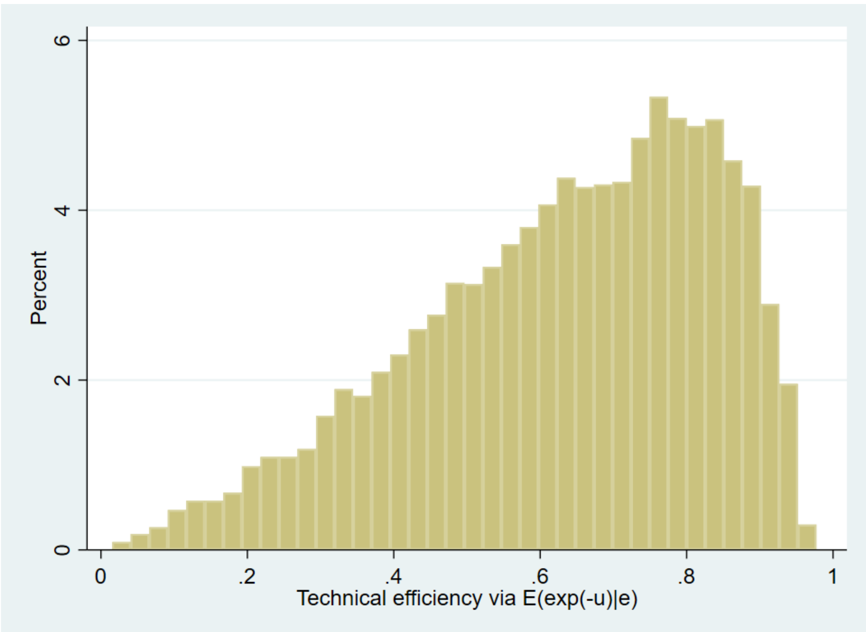
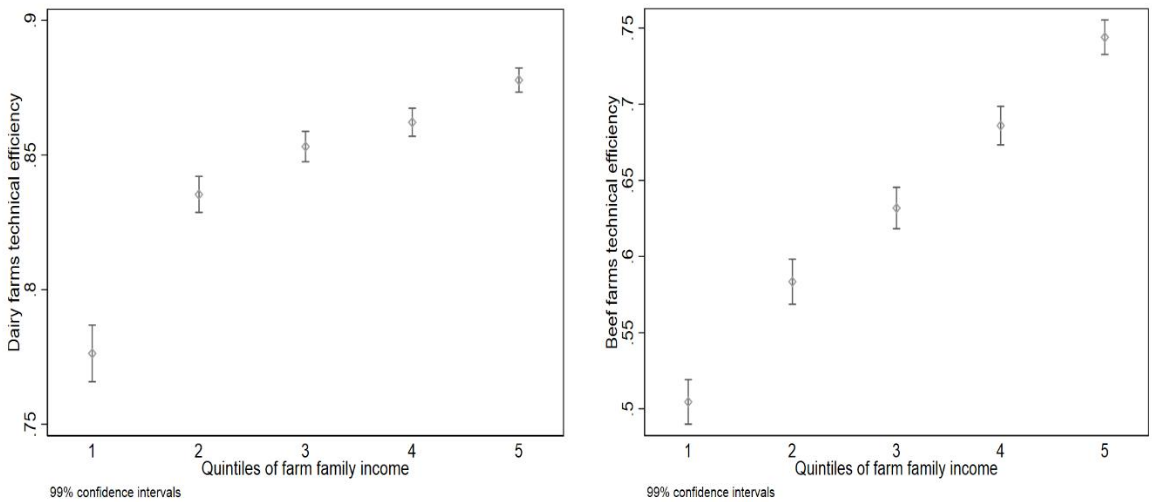


Figure 3 displays the technical efficiency scores across the distribution of family farm income, for dairy farms in the right hand side figure, and for beef farms on the left. Technical efficiency displayed is the average technical efficiency estimated for each income quintile. Quintiles 1 corresponds to lower income, and quintiles 5 corresponds with higher income.

Figure 3 suggests that farms in the higher income quintile have larger average technical efficiency scores than farms in the lower quintiles. The gap between the current production level and its maximum potential output (as indicated by the estimated frontier) could be reduced for farms in the lower income quintiles in particular, if certain subsidies targeted these groups of farms better. For example, Table 3 showed a positive and statistically significant relationship between efficiency and decoupled support for beef farms only (i.e. the relationship was negative for dairy farms). Therefore, beef farms in lower income quintiles (i.e. less technically efficient) would theoretically benefit more from increased decoupled support. Decoupled payments have been found to have positive indirect effects on efficiency, arising from several channels. Decoupling can encourage efficient farm practices by allowing farmers to follow market signals when making production decisions (Carroll et al., 2008; Kazukauskas et al., 2014). In addition, they contribute to the relaxation of credit constraints by making it easier to access credit or reducing the need for external financing (Rizov et al., 2013). The alleviation of financial constraints may induce an increase in investment in newer and more efficient farm technology (Zhu et al., 2012), leading to technical efficiency improvements. For the case of dairy farms in lower income quintiles (i.e. also less technically efficient), could benefit from increased targeting environmental support to this group of farms, as suggested by the positive and statistically significant relationship between these payments and efficiency for dairy farms shown in Table 3.

Figure 3. Technical efficiency across farm family income quintiles (2000-2017)



5.3 Methane production

Table 5 displays the average methane production (computed as outlined in Section 3) across different levels of the farm family income. Farms in higher income quintiles have higher average levels of methane production in both dairy and beef systems. However, note that higher heterogeneity in methane production can be found in low income levels. Methane production level is driven by the farm production level and by the composition of the livestock.

Table 5. Average methane production across income quintiles of fam income (tonnes per year)

	Dairy		Beef	
	Methane	**CV (%)**	**Methane**	**CV (%)**
First quintile	0.760	1.058	1.032	0.716
Second quintile	0.871	0.922	0.958	0.626
Third quintile	1.109	0.776	1.232	0.563
Fourth quintile	1.277	0.760	1.659	0.513
Fifth quintile	1.654	0.672	3.049	0.651
Sample	1.134	0.856	1.586	0.847

Following Jin and Kim (2019), we also model methane production following the SFA framework outlined in Section 4.4. The average ME_{it} scores for each group of farms are displayed in Table 6. Note that these efficiency estimates have a different interpretation to the ones discussed in Table 5, since in this case they measure the distance between observed farm emissions and the potential levels of methane emissions represented by the frontier (Jin and Kim, 2019). Under this modified SFA framework, ME_{it} (recall, defined according to equation (8)) measures how much output (emissions) farms could obtain at the current level of inputs they use on farms. Therefore, the smaller ME_{it} is, the larger the environmental gains, as farms are producing less methane than they could. Table 6 shows that the mean methane efficiency is 0.756 for dairy farms, and 0.843 for beef. This indicates that dairy farms are situated on average further from their respective "methane frontier", suggesting that their observed emissions are lower than frontier emissions, relative to beef farms[17]. As in the case of the technical efficiency estimates, beef farms' methane efficiency estimates are more dispersed, suggesting again greater heterogeneity in the sector.

The coefficients estimated using the modified SFA framework are displayed in Table 6. As in the production case, the contribution of the variables included in the efficiency terms is indicated by the inverse of the sign of the coefficients displayed in Table 6. In this model, receiving higher normalized GLAS and decoupled subsidies is linked to a larger gap between the maximum level of methane production and the observed one for beef farms. For dairy farms, normalized REPS, GLAS and decoupled payments increases the gap between the frontier and the observed levels of methane production. We interpret this as improvements in environmental performance. The level of methane production in our estimation is driven by the output level (i.e. y_{it} in Equation (1)) and the composition of the livestock portfolio. Note that the environmental payments are not directly conditioned on the

[17] 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.

levels of these factors. Consequently, we do not expect a reverse causality between methane production and the level of environmental subsidies[18].

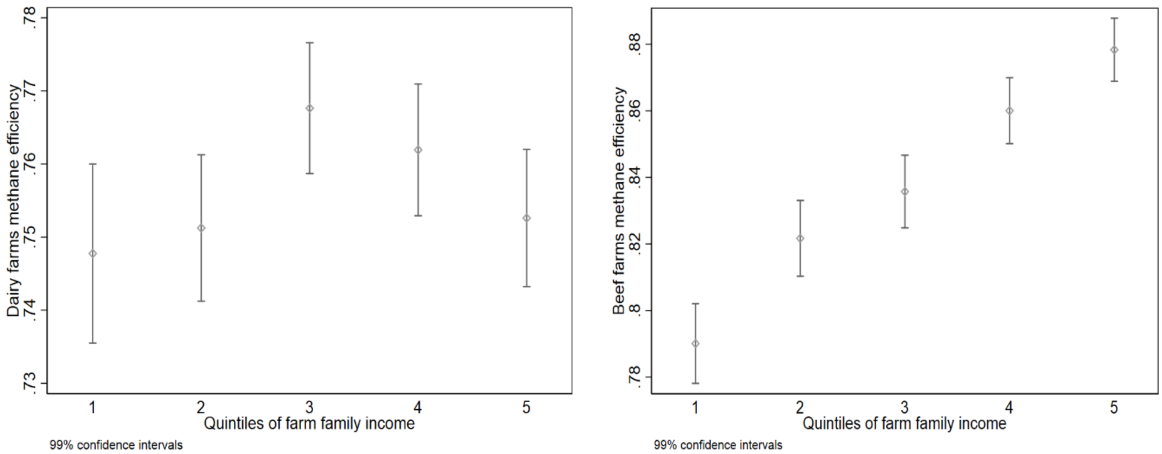
Table 6. Methane inefficiency model output

	Dairy	**Beef**
Methane efficiency	0.756	0.843
	(0.135)	(0.152)
Inefficiency effects model		
REPS/LU	0.122**	0.020
	(0.049)	(0.020)
GLAS/LU	0.662**	0.341***
	(0.290)	(0.082)
AEOs/LU	0.746	-0.006
	(0.576)	(0.106)
Organic subs./LU	1.152**	-
	(0.544)	
Decoupled subs./LU	0.002***	0.236***
	(0.000)	(0.013)
Soil type 1 (D)	-0.136**	0.067
	(0.056)	(0.055)
Pasture share	-1.037***	-0.436***
	(0.190)	(0.146)
Constant	-1.074***	-3.306***
	(0.186)	(0.146)

Figure 4 displays the average methane efficiency scores calculated based on the methane frontier estimated, for each quintile of family farm income distribution. Farms in higher income quintiles have more room for environmental improvement than low income farms. Figure 4 also shows that the gap between farms in lower and farms in higher income quintiles is more visible in the case of beef farms.

[18] We employed the Hausman test for endogeneity between methane production and environmental payments (see Wooldridge 2002), and we did not find any evidence for it in daily and beef farms.

Figure 4. Methane efficiency across farm family income quintiles (2000-2017)



5.4 Income distribution

Table 7 and Table 8 display the current effect of the subsidies in the income distribution. Note that the first panel shows the effect of REPS and AEOS and the second panel the effect of GLAS and AEOS. The metrics displayed in the table are explained in the methodological section. The column "Change" displays the elasticity of changes in the Gini coefficient for a 1% change in the analysed income source.

The tables are presented in this way to represent the fact that REPS and GLAS were not implemented jointly across the time in the sample (see Table A2 in the appendix). The first panel of Table 8 shows that that decoupled support represents around 18% of daily farm family income. We can see that while REPS and GLAS, which have the largest shares after the decoupled supports (S_k), are unequally distributed (i.e. G_k is not zero). However, compared with other sources of income, their contribution towards income inequality is among the smallest compared with the other income sources (i.e. R_k is around 0.5). Regarding beef farms, Table 8 shows that decoupled support has a more important contribution towards total farm income than for daily farms. Consequently, changes in this payment will considerably impact income inequality. Concerning the REPS and GLAS payments, G_k and R_k show similar patterns to the ones found for dairy farms.

Table 7. Subsidies and income distribution of dairy farms

	S_k	G_k	R_k	Change(%)
		REPS & AEOS		
Farm income	0.7758	0.3014	0.9343	-0.0276
Decoupled support	0.1868	0.5012	0.6315	0.0157
REPS	0.037	0.8362	0.4599	0.0117
AEOS	0.0004	0.9958	0.4554	0.0002
		GLAS & AEOS		
Farm income	0.8049	0.3014	0.9438	-0.0192
Decoupled support	0.1938	0.5012	0.6358	0.0181
GLAS	0.0009	0.9923	0.5379	0.0008
AEOS	0.0004	0.9958	0.4920	0.0003

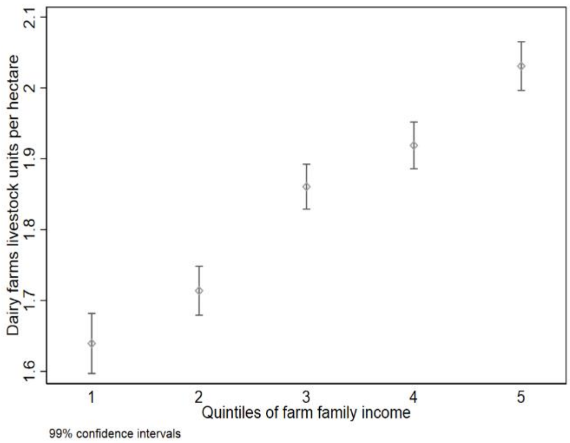
Table 8. Subsidies and income distribution of beef farms

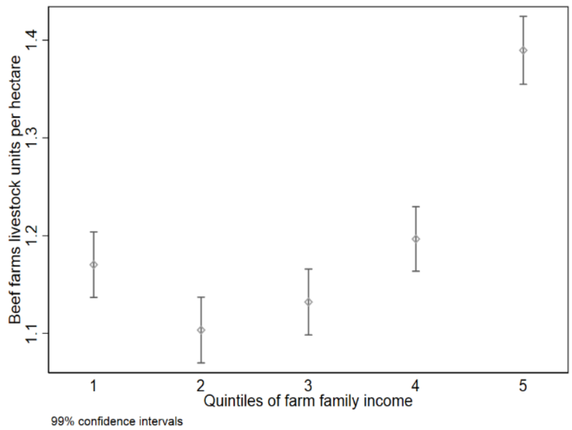
	S_k	G_k	R_k	Change(%)
		REPS & AEOS		
Farm income	0.5225	0.4746	0.8938	0.0252
Decoupled support	0.369	0.4729	0.7544	-0.0437
REPS	0.104	0.7697	0.6198	0.0186
AEOS	0.0045	0.9839	0.4102	0
		GLAS & AEOS		
Farm income	0.5795	0.4746	0.8966	0.0299
Decoupled support	0.4092	0.4729	0.788	-0.0324
GLAS	0.0063	0.9767	0.5214	0.0016
AEOS	0.005	0.9839	0.4832	0.0009

6. Simulation results

We simulate a 1% decrease in total decoupled subsidies and then use these resources to increase the GLAS payments. For the re-allocation of these additional resources, we follow two mechanisms. In the first scenario (labelled as *"Flat allocation"* in Tables 9 to 11), the allocation of the additional revenue follows a flat allocation and in the second scenario farms receive additional payments when their stocking rate is below the sample median (labelled as *"Stocking rate allocation"* in Tables 9 to 11). Figure 5 displays the mean stocking rate at different quintiles of the farm income distribution. One can see that a policy allocating the extra funds to farms with lower stocking rates is potentially progressive, lower income households would receive larger payments. Recall, quintiles 1 corresponds to lower income levels, and quintiles 5 corresponds to higher income levels.

Figure 5. Stocking rate across farm family income quintiles (2000-2017)





6.1 Changes in technical efficiency

In Table 9, we display the changes in technical efficiency estimates resulting from the simulation exercise, and the two alternative re-allocation of funds approaches described above. Scores above 1 indicate that increasing GLAS would induce a generalised increase in technical efficiency for dairy farms. The re-allocation of the subsidies using the second mechanism (i.e. stocking rate allocation) has slightly better results (i.e. the sample mean of this score under these scenarios are 1.007 and 1.009). Note that in general the largest improvements in technical efficiency come from farms at the bottom of the income distribution. The largest level of heterogeneity in changes in technical efficiency can be found in lower income quintiles farms, as indicated by the Coefficient of Variation (CV). As for beef farms, we do not see significant changes. Note that in our SFA model for beef farms (see Table 3), GLAS is not statistically significant.

Table 9. Changes in technical efficiency relative to the base scenario

	Flat allocation		Stocking rate allocation	
	Dairy			
	Technical efficiency	**CV**	**Technical efficiency**	**CV**
First quintile	1.012	0.037	1.016	0.046
Second quintile	1.007	0.018	1.010	0.027
Third quintile	1.006	0.014	1.008	0.018
Fourth quintile	1.006	0.020	1.007	0.023
Fifth quintile	1.003	0.013	1.004	0.017
Sample	1.007	0.022	1.009	0.028
	Beef			
	Technical efficiency	**CV**	**Technical efficiency**	**CV**
First quintile	1.000	0.000	1.000	0.000
Second quintile	1.000	0.002	1.000	0.004
Third quintile	1.000	0.003	1.000	0.006
Fourth quintile	1.000	0.002	1.000	0.004
Fifth quintile	1.000	0.002	1.000	0.003
Sample	1.000	0.002	1.000	0.004

In Table 10, we display the changes in methane efficiency estimates resulting from the same simulation exercise. A score of more than 1 indicates that the methane efficiency score increases as a result of increasing GLAS. Note that such increase would not represent an environmental gain, given that higher methane efficiency implies that the farm is closer to the methane frontier. In the case of dairy farms, the re-allocation of the GLAS payments via low stocking rates produces the largest environmental gains. These gains come mainly from farms at the bottom of the income distribution. Note also that these farms have the largest heterogeneity as indicated by the coefficient of variation. In the case of beef farms, the two mechanisms reduce environmental gains similarly. Note that for these farms the largest heterogeneity in the score is found in farms at the top of the income distribution.

Table 10. Changes in methane efficiency relative to the base scenario

	Flat allocation		Stocking rate allocation	
	Dairy			
	Methane efficiency	CV	Methane efficiency	CV
First quintile	1.000	0.021	0.999	0.032
Second quintile	0.999	0.027	0.998	0.039
Third quintile	1.000	0.013	1.000	0.020
Fourth quintile	0.999	0.020	0.998	0.029
Fifth quintile	1.000	0.010	1.000	0.013
Sample	1.000	0.019	0.999	0.028
	Beef			
	Methane efficiency	CV	Methane efficiency	CV
First quintile	1.009	0.000	1.008	0.000
Second quintile	1.007	0.029	1.006	0.033
Third quintile	1.008	0.029	1.007	0.035
Fourth quintile	1.010	0.029	1.010	0.032
Fifth quintile	1.006	0.026	1.007	0.029
Sample	1.008	0.028	1.008	0.031

6.2 Changes in income distribution

Table 11 displays the estimated changes in the Gini coefficient across the simulated scenarios. The analysed scenarios reduce income inequality in dairy and beef farms. A flat allocation of additional resources via the GLAS payment financed by a reduction in the decoupled payments has a slightly larger reduction in income inequality than an allocation based on the stocking rate. This is due to the fact that in the second scenario only a subsample of the population receives the additional payments.

Table 11. Changes in income distribution relative to the base scenario

		Changes in Gini (%)	
	Gini	Flat allocation	Stocking rate allocation
Dairy farms	0.292	-0.801	-0.534
Beef farms	0.404	-1.319	-1.287

7. Policy discussion and conclusions

The European Green deal sets out the strategies to ensure a sustainable and inclusive economic growth in the EU. The Farm to Fork Strategy is central in the Green Deal and it addresses the challenges arising from transiting towards a more sustainable food system. The CAP payments are foreseen to play an important role under this new road map. Under this proposal, one of the key measures are the 'eco-schemes', with compulsory implementation for Member States but of optional adoption for farmers, which will aim at addressing the requirements in the EU environmental agenda. Another novelty of the proposals is to implement the new CAP through national strategic plans in which every

Member State would choose the policy instruments justifying how their strategy will help in achieving goals regarding environmental protection. An important criticism of these new proposal is the lack of transparency and data on environmental performance (see Pe'er et al. 2019).

The evolution of the environmental payments, which started with the REPS and transformed into the AEOS, and finally evolved into the GLAS describes an evolution in the strategies for agri-environmental protection. GLAS collects the experience from previous schemes regarding farmers participation and targeted actions for environmental protection. REPS was designed to establish farming practices and controlled production methods for conservation and wider environmental problems. 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. Our results add to the narrow literature on quantifying the effects of these payments in competitiveness and environmental performance. We find evidence that GLAS has positive effects on both efficiency and environmental performance.

The promotion of the eco-schemes is covered under the proposals for the new CAP payments in Pillar I. The eco-schemes actions promote increases in the space per animal and low intensity grass-based livestock systems[19]. In order to investigate the distributional, competitiveness and environmental performance of these reforms, we use farm level NFS data from Ireland to analyse the link between the historical set of environmental payments granted under Pillar II and farm level competitiveness, environmental performance, and income inequality, for Irish beef and dairy farms between 2000 and 2017. We carry out a simulation exercise where we reduce decoupled support and increase GLAS subsidies. We use two mechanisms to re-allocate these resources. Under the first scenario, we use a flat allocation mechanism where each recipient of the GLAS payment receives the same amount from the additional revenue. Then under a second scenario, GLAS recipients obtain additional resources when they have a stocking rate below the sample median. In both cases, we compute changes in technical efficiency, environmental gains (i.e. methane efficiency), and income inequality induced by this hypothetical transfer of funds across Pillars.

Our simulated results show that increases in GLAS financed by decoupled payments can potentially improve competitiveness (i.e. technical efficiency) and environmental performance (i.e. methane efficiency) of dairy farms under the second scenario for the re-allocation of funds. The largest

[19] 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*

improvements in our metrics are located at the bottom of the farm income distribution. Regarding beef farms, under both of our scenarios, competitiveness does not change. However, environmental gains are reduced under both scenarios. As for the effects on income inequality, increasing GLAS can potentially decrease income inequality under the two analysed scenarios. Our findings highlight the importance of considering the heterogeneous effects in changes of environmental payment schemes. It shows that neglecting these effects across farm production types and farm income levels could cause conflicting results regarding competitiveness, environmental gains, and income inequality. 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 of designing a scheme where instruments consider the structural differences in dairy and beef production, as well as income differences. We find that while farms in the lowest quintiles of the income distribution have more room to improve competitiveness (i.e. they display lower average technical efficiency) than farms in higher income quintiles, they also have lower average methane efficiency estimates, which suggest that they operate further from the emissions frontier. 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 toward a more sustainable economy.

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Appendix 1

Table A1. Agri-environmental payments received by Irish farmers (2000-2017)

	REPS1	REPS2	REPS3	REPS4	AEOS1	AEOS2	AEOS3	GLAS		
								Tranche1	Tranche2	Tranche3
2000										
2001										
2002										
2003										
2004										
2005										
2006										
2007										
2008										
2009										
2010										
2011										
2012										
2013										
2014										
2015										
2016										
2017										

Note: The cells shared in grey indicate the years when farmers could enter the contracts as part of each payment and round/tranche.

Appendix 2

Table A2. CAP payments (2000-2017) in the data

	Direct payments (Pillar 1)			Pillar 2 payments			
	Premia	SFP	BPS	REPS	GLAS	AEOs	Organic payments
2000	x						
2001	x						
2003	x						
2004	x						
2005		x		x			
2006		x		x			
2007		x		x			
2008		x		x			
2009		x		x			
2010		x		x			
2011		x		x		x	
2012		x		x		x	
2013		x		x		x	
2014		x		x		x	
2015			x		x	x	
2016			x		x	x	X
2017			x		x	x	x

Note: SFP: single Farm Payment BPS: Basic Payment Scheme; REPS: Rural Environment Protection Scheme; AEOs: Agri-Environment Options Scheme; GLAS: Green, Low-Carbon, Agri-Environment Scheme.

Appendix 3

Table A3-1. Likelihood ratio tests for functional form of the production function

	LR value	p-value	Decision
Dairy data	169.15	0.000	Reject CD
Beef data	54.94	0.000	Reject CD

Table A3-2. Hausman test FE vs. RE

	Chi^2 value	p-value	Decision
Dairy data	431.20	0.000	Reject TRE
Beef data	For the case of beef farms, the TFE specification failed to converge, therefore TRE is used to estimate their frontier		

Note

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