Heterogeneity in the effect of GHG mitigation strategies on Irish dairy farms

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Abstract

The agricultural sector is increasingly under pressure to participate in the greenhouse gas (GHG) emission reduction effort. At the farm level, significant improvements can be achieved through the adoption of new technologies. This study explores the heterogeneity in the effect of GHG mitigation strategies across the distribution of GHG emissions on Irish dairy farms. The econometric analysis is performed on an unbalanced panel dataset by using fixed effects (FE) unconditional quantile regression models. The preliminary results reveal that GHG mitigation strategies have a differential effect across the distribution of GHG emissions, with two main implications. First, the findings suggest that relying on estimations of a technology's effect at the mean can be somewhat misleading as this does not reflect the effect of heterogeneity. Second, the study shows that the effect of GHG mitigation strategies is larger for high emitting farms than for low emitting farms.

Keywords: Heterogeneity; technology effect; GHG mitigation; unconditional quantile regressions; Irish dairy farms.

1 Introduction

Over the last couple of decades, global awareness of environmental issues associated with greenhouse gas (GHG) emissions and notably their contribution to climate change has grown. The 2015 Paris Agreement marked a significant milestone in terms of international cooperation as 192 parties (including 191 countries and the European Union (EU)) committed to limit global warming to 2 degrees Celsius (or even 1.5 if possible) relative to pre-industrial levels (UNFCCC, n.d.). This international agreement generated the necessary political will to incorporate to a greater extent GHG reduction targets into country-specific policy agendas. In 2021, the Energy & Climate Intelligence Unit counted that 139 countries have either pledged for or are currently discussing mid-century carbon neutrality (Energy & Climate Intelligence Unit, 2023). Within this context, food production contributes to approximately a third of global GHG emissions and is thus expected to participate in the GHG reduction effort (Clark et al., 2020; Xu et al., 2021). This is challenging as the world population and hence global food demand continues to grow (Godfray et al., 2010; United Nations, 2017). Moreover, increased wealth in developing countries is anticipated to cause a larger shift towards animal-based diets (Godfray et al., 2010). Currently, it is estimated that animal-based foods are responsible for about 57% of food-related GHG emissions, which is twice as much as plant-based products (Xu et al., 2021). Hence, the need to reduce GHG emissions from livestock production is becoming increasingly urgent (Lynch et al., 2021).

Incentives to prevent or at least restrain the global increase in the consumption of animal-based products can be implemented as a means to stabilise GHG emissions associated with livestock production (Lynch et al., 2021). Nevertheless, technological mitigation strategies are also required to further contribute to the achievement of GHG reduction targets. Given the 30-year timeframe under which carbon neutrality has been aimed for, it is unlikely that ground-breaking innovations will provide sufficiently large improvements in GHG emissions (Cassman and Grassini, 2020). It is thus important to continue working on the adoption of readily available technologies, which have potential for GHG mitigation and are not yet optimally used. Technology adoption has long been a popular topic of interest to researchers and policy makers because of its role in agricultural productivity growth and farming incomes (Feder et al., 1985; Foster and Rosenzweig, 2010; Macours, 2019). A common finding in the literature is that at the farm level, producers can be slow to adopt technologies, even those with proven economic benefits and public support (Pannell and Claassen, 2020; Takahashi et al., 2020; Weersink and Fulton, 2020). Technology diffusion generally follows an S-shaped curve, whereby farmers do not adopt all at once, notably due to differences in individual and farm characteristics, as well as heterogeneity in technology returns (Rogers, 1995). When promoting the uptake of environmentally sound technologies, the adoption challenge can be even stronger, as farmers are more likely to be sensitive to economic, productive, or lifestyle arguments rather than wider, environmental claims (Pannell et al., 2006; Vanclay, 2004).

Despite the wide body of literature on technology adoption, public policies still build on the assumption that the adoption process will be relatively quick and promoted technologies will provide the expected returns at the farm level. However, delays in achieving desired policy outcomes can be caused by slow adoption rates and underperforming technologies. These issues can be particularly concerning in the instance that farmers for which promoted technologies would have the highest return are the slowest to adopt. Hence, it is important to better understand how the effect of promoted technologies can vary across farms. To date, very few studies have investigated the heterogeneity in technology returns (Foster and Rosenzweig, 2010; Weersink and Fulton, 2020). This article fills this gap in the literature and specifically explores the heterogeneity in the effect of GHG mitigation strategies on specialised dairy farms in Ireland.

The need to reduce GHG emissions is particularly salient for Ireland's livestock-based agricultural sector. The Irish government has recently committed to achieving a 51% decrease in GHG emissions by 2030 and carbon neutrality by 2050 (Government of Ireland, 2021). To reach these targets, five-year carbon budgets were introduced for the agricultural sector (Government of Ireland, 2022). These are likely to limit future growth in the Irish dairy sector, which has been rapidly expanding and intensifying for the last decade (Balaine et al., 2022b). Encouraged by national agri-food strategies, Irish milk production increased by 67.5% in 2020 relative to the 2007-2009 average (Central Statistics Office, 2020). Dairy growth was largely driven by higher cow numbers and enhanced reliance on inputs (Dillon et al., 2022). Such structural changes made it difficult to concurrently reduce agricultural GHG emissions during that time period (Balaine et al., 2022b). In fact, the Irish Environmental Protection Agency (EPA) estimates that agricultural GHG emissions increased by 9.6% (Environmental Protection Agency, 2022). Overall, Ireland did not achieve the 2020 targets of a 20% decrease in GHG emissions from non-Emission Trading Scheme (ETS) sectors[1] relative to 2005 levels (Environmental Protection Agency, 2021). These targets were set out in 2009 as part of the EU effort sharing decision (European Commission, n.d.). Failure to achieve them will have financial implications for the Irish government.

The achievement of future GHG reduction targets in the Irish agricultural sector heavily relies on farmers' adoption of GHG mitigation strategies, especially if animal numbers remain unchanged. In December 2020, the Department of Agriculture, Food and the Marine (DAFM) published the 'Ag Climatise' roadmap towards climate neutrality, which details actions to be implemented by sub-sector (Department of Agriculture Food and the Marine, 2020). These are mainly based on previous research that has identified GHG mitigation strategies using the Teagasc[2] Marginal Abatement Cost Curves (MACCs) (Department of Agriculture Food and the Marine, 2020; Lanigan et al., 2018). Among proposed changes, there exist some low-hanging fruit; that is, scope for incremental improvements in four 'win-win' areas of farm management that would be cost saving for farmers while providing wider GHG benefits. For the predominant grass-based milk production systems, these are input utilisation, breeding for better production efficiency, feeding system, and animal health (Department of Agriculture Food and the Marine, 2020). Hence, such aspects of farm management are focused upon in Irish agricultural extension (Department of Agriculture Food and the Marine, 2020; Teagasc, 2016, 2015).

In this study, we specifically examine whether changes in farm management practices have a heterogeneous effect across Irish dairy farms and, more precisely, across the distribution of their agricultural GHG emissions. To do so, we focus on GHG mitigation strategies in the areas of input utilisation, breeding, feeding, and animal health (Department of Agriculture Food and the Marine, 2020; Lanigan et al., 2018). GHG emissions are estimated at the farm level using a cradle-to-farm gate life cycle assessment (LCA) method developed by O'Brien et al. (2014, 2010). We report emissions by unit of output (i.e., kilogram (kg) of Fat-Protein-Corrected-Milk (FPCM)) as an indicator of milk GHG

[1] Non ETS-sectors include agriculture, transport, residential, commercial, waste, and non-energy intensive industries.
[2] Teagasc is the Irish Agriculture and Food Development Authority.

efficiency, and by hectare (ha) as a measure of milk GHG pressure (Balaine et al., 2022b; Buckley and Donnellan, 2022). Using 2013-2019 panel data from the Teagasc National Farm Survey (NFS), we estimate two-way fixed effects (FE) unconditional quantile regression models at the 25th, 50th, and 75th percentiles (Borgen, 2016; Firpo et al., 2009). In this way, we assess differences in the effect of GHG mitigation strategies across low, middle, and high emitting farms, respectively. We then compare estimation results with findings from two-way FE ordinary least squares (OLS) regression models (estimated at the mean).

The remainder of the article is structured as follows. In the second section, we describe econometric models used in this study. In the third section, we present the data and descriptive statistics. In the fourth section, we detail results, followed by a discussion and conclusions in the fifth section.

2 Econometric models: Unconditional quantile regression models

We are interested in analysing the heterogeneous effects of GHG mitigation strategies across the distribution of GHG emissions. To do so, we use unconditional quantile regression models developed by Firpo et al. (2009) and implemented with a FE setting in the Stata software by Borgen (2016). Unlike conditional quantile regression models, these unconditional models have the advantage of allowing for the estimation of the effect of mitigation strategies on the *th* percentiles of the unconditional distribution of GHG outcomes. In other words, percentiles are defined pre regression and thus not determined by the values taken by control variables in the model (Asfaw et al., 2020). As a consequence, with unconditional regression models, changes in control variables do not alter the interpretation of the effects of GHG mitigation strategies. As previously mentioned, we also estimate a two-way OLS regression model for comparison purposes (Allison, 2009).

The FE OLS model is as follows:

$$GHG_{it} = \beta_0 + \beta_1 M_{it} + \beta_2 X_{it} + \alpha_i + \varepsilon_{it} \quad [1]$$

where i indexes farms and t indexes time. β_0 is the constant term. β_1 is the effect of GHG mitigation strategies, M. β_2 is the effect of other control variables, X. α_i are the farm fixed effects. ε_{it} is the error term.

As for the unconditional quantile regression models, the estimation is a two-step process (Borgen, 2016). First, we obtain the recentered influence function (RIF) (Firpo et al., 2009). Second, we replace the outcome variable in equation [1] with this RIF. Specifically, the RIF is defined as follows:

$$RIF(GHG; q_\tau, F_{GHG}) = q_\tau + \frac{\tau - 1\{GHG \leq q_\tau\}}{f_{GHG}(q_\tau)} \quad [2]$$

where q_τ is the value of the outcome variable, GHG, at the percentile τ. F_{GHG} is the cumulative distribution function of GHG. $f_{GHG}(q_\tau)$ is the density of GHG at q_τ. The indicator function, $1\{GHG \leq q_\tau\}$, identifies whether or not the value of the outcome variable is below q_τ. The models are estimated at the 25th, 50th, and 75th percentiles.

Finally, in all models, we cluster standard errors at the farm level.

3 Data and descriptive statistics

The data used in this study is collected through the Teagasc NFS, which is carried out on a yearly basis as part of the EU Farm Accountancy Data Network (FADN). The data is gathered on a representative sample of about 900 Irish farms by a team of professional data recorders. Sampled farms are classified into six farming systems according to their main source of gross output: dairy, cattle rearing, cattle other, sheep, arable, and mixed livestock. In this analysis, we focus solely on specialised dairy farms over the 2013-2019 time period. Our sample constitutes an unbalanced panel dataset, and contains a total of 1,905 observations accounting for 340 specialised dairy farms. Farms remain on average 5.6 years in the panel.

The key variables of interest include GHG emissions (as dependent variables) and a set of GHG mitigation strategies promoted through Irish extension (as independent variables) (Department of Agriculture Food and the Marine, 2020; Teagasc, 2016, 2015). Other farm and farmer characteristics are also accounted for in the analysis. All variables are defined in Table 1, where their sample averages are also reported. Additional summary statistics at the 25th, 50th, and 75th percentiles of the GHG emission distributions are presented in the Appendix in Table A.1 for GHG emission efficiency and Table A.2 for GHG emission pressure.

Table 1: Variable definition and summary statistics, 2013-2019 pooled sample (n = 1,905)

Variable name	Definition	Unit	Mean (standard deviation)
GHG emission variables			
GHG efficiency	GHG emissions emitted per unit of output	g of CO_2e / kg of FPCM	1126.86 (217.37)
GHG pressure	GHG emissions emitted per hectare	kg of CO_2e / ha	12112.41 (4222.36)
GHG mitigation variables			
N surplus	Nitrogen surplus per hectare	kg / ha	177.04 (70.23)
NUE	Nitrogen use efficiency	%	22.64 (6.70)
Milk yield	FPCM produced per dairy cow	kg of FPCM / cow	5275.09 (1048.92)
Homegrown grass	Share of homegrown grass (including grazed grass and grass silage) in the diet of dairy cows	%	76.97 (11.32)
Grazing season	Length of the grazing season	days	238.88 (27.95)
BTSCC	Bulk tank somatic cell count	'000 cells / ml	182.14 (77.77)
Other farm and farmer characteristics			
Herd size	Average size of the dairy herd	cows	83.20 (47.46)
Stocking rate	Dairy stocking rate	cows / ha	2.06 (0.51)
Specialisation	Degree of specialisation in dairy production (ratio of dairy cows to total livestock units)	%	64.57 (12.31)
Discussion group	Length of participation in a farmers' discussion group	years	5.48 (7.53)
Age	Age of the main farm holder	years	55.42 (10.57)
Gross margin	Gross margin per hectare	€ / ha	2395.32 (971.63)

As previously mentioned, GHG emissions associated with dairy production are estimated based a cradle-to-farm gate LCA method developed by O'Brien et al. (2014, 2010). This LCA approach is internationally standardised (International Organization of Standardization, 2006a, 2006b), and follows specific guidelines for dairy production (British Standards Institute, 2011; Carbon Trust, 2010; International Dairy Federation, 2015). More specifically, the model was developed according to the publicly available specification 2050:2011 from the British Standards Institute (2011) and validated by the Carbon Trust, an accredited third party (O'Brien et al., 2014). On- and off-farm emissions are estimated using emission factors either based on the Intergovernmental Panel on Climate Change guidelines or coming from other sources in the literature (Dong et al., 2006; Duffy et al., 2019; O'Brien et al., 2014). They are then converted to kg of carbon dioxide equivalent (CO_2e) using the 100-year global warming potential (Forster et al., 2007). GHG emissions are used as dependent variables in two different ways (Balaine et al., 2022b; Buckley and Donnellan, 2022). On the one hand, in order to represent environmental efficiency, emissions are reported per unit of output as kg of FPCM[3]. On the other hand, in order to represent environmental pressure, emissions are reported on a per-hectare basis.

The effect of improving the four 'win-win' areas of farm management described in the DAFM 'Ag Climatise' report (i.e., input utilisation, breeding for better production efficiency, feeding system, and animal health) is tested through different GHG mitigation strategies (Department of Agriculture Food and the Marine, 2020). These are presented by area of farm management in Table 2, as well as their expected effect on GHG efficiency and pressure. First, because improving input utilisation can be achieved by reducing input application and enhancing response, this aspect is represented by nitrogen surplus and use efficiency in this analysis (Buckley et al., 2016, 2015). Nitrogen surplus gives an estimation of nitrogen management and pressure within the farm gate. It is calculated following an input-output accounting method, by subtracting all farm nitrogen outputs (e.g., nitrogen contents in milk and livestock sold off farm) from nitrogen inputs (e.g., nitrogen contents in concentrate feed and fertilisers). The measure is reported on a per-hectare basis to account for farm size. Nitrogen use efficiency (NUE) is calculated as the ratio of nitrogen outputs to nitrogen inputs, and is reported as a percentage. It represents how efficient the conversion of inputs into outputs is at the farm level.

[3] According to the International Dairy Federation (2015), milk must be converted into FPCM to compare farms with different dairy cow breeds and diet composition. The formula to calculate FPCM is as follows:
$FPCM = Milk\ produced * (0.1226 * Fat\% + 0.0776 * Protein\% + 0.2534)$
where both $FPCM$ and $Milk\ produced$ are measured in kg per year.

Table 2: GHG mitigation strategies under study

'Win-win' areas of farm management	GHG mitigation strategies	Expected effect on GHG emissions	
		GHG efficiency	GHG pressure
Input utilisation	Reduce nitrogen surplus	+	-
	Improve NUE	+	-
Breeding for production efficiency	Increase milk yield	+	-
Feeding system	Increase the share of homegrown grass in cow diet	+	-
	Lengthen the grazing season	+	-
Animal health	Decrease BTSCC	+	-

Second, since dairy cows are selected to improve genetic merit and ultimately increase production efficiency, this area of farm management is represented by FPCM produced per dairy cow.

Third, due to the temperate climate and grass-based nature of Irish milk production, the feeding system mainly relies on the growth and intake of grazed grass and grass silage (Hanrahan et al., 2017; O'Brien et al., 2018). Thus, two indicators of grassland management are used in this study: the share of homegrown grass in cow diet and the length of grazing season (Läpple et al., 2012; O'Brien et al., 2018). Homegrown grass is estimated through a back calculation based on cow energy demand requirements (O'Brien et al., 2018). More precisely, kg of dry matter fed from grazed grass are calculated as total energy demand minus energy supply coming from other sources of feed than grass (mainly homegrown and brought-in forage and concentrate feeds). Energy demand includes energy used for maintenance and activity, milk production, pregnancy, and body weight change and growth. The share of homegrown grass in cow diet is then deduced by dividing the sum of dry matter fed from grazed grass and grass silage by total kg of dry matter fed. As for the length of grazing season, it is directly recorded in the Teagasc NFS as the number of days that dairy cows spend at grass (Läpple et al., 2012). When cows spend only the day at pasture and come indoors at night, this counts only for half a day of grazing in the variable.

Fourth, improvements in herd health status are measured in terms of bulk tank somatic cell count (BTSCC), which is an indicator of milk bacterial contamination and risk of mastitis incidence (Dillon et al., 2018; Geary et al., 2012). A threshold of 200,000 cells per ml is generally accepted as an indicator of mastitis occurrence (International Dairy Federation, 1997).

Other farm characteristics that are accounted for in this study include herd size, stocking rate, and the degree of specialisation in dairy production (as measured by the ratio of dairy cows to total livestock units). Moreover, we control for farmer age and participation in extension, represented by years of participation in a farmer discussion group. In Ireland, farmer discussion groups are a predominant means of transferring knowledge to the farming community (Balaine et al., 2023, 2022a). About 50% of Irish dairy farmers participate in this form of extension services.

4 Results

In a first step, we examine the heterogeneity in the effect of GHG mitigation strategies through FE unconditional quantile regressions (Borgen, 2016; Firpo et al., 2009), and compare our findings with results of FE OLS regressions (i.e., estimations at the mean) (Allison, 2009). Quantile regressions are estimated at the 25th, 50th, and 75th percentiles of the GHG emission distributions. Table 3 reports the estimation results for the GHG efficiency outcome, while Table 4 summarises the findings for GHG pressure. Due to space constraints, we only focus on the effect of GHG mitigation strategies in results interpretation.

Overall, the findings reveal that reductions in N surplus and improvements in the length of grazing seasons are effective GHG mitigation strategies both in terms of GHG efficiency and pressure. Inversely, despite showing some GHG efficiency benefits, increases in NUE and milk yield would be detrimental for GHG pressure. As for homegrown grass, it does not have a significant effect in any of the regressions, thereby showing no GHG benefits. Finally, reducing BTSCC does not constitute a suitable mitigation strategy, as the variable has either no significant effect or an unexpected negative association with GHG pressure at the 25th percentile.

When delving deeper into the estimation results for the GHG mitigation variables, both tables show that estimations at the mean give an incomplete picture, as effects vary across the distribution of GHG efficiency and pressure. More precisely, Table 3 reveals that while the effect of grazing season on GHG emitted per FPCM is always negative, its magnitude linearly increases from -1.04 at the 25th percentile, to -1.47 at the median, to -1.79 at the 75th percentile. Hence, the decrease in GHG emitted per FPCM associated with an additional day spent at grass is larger for low GHG efficiencies than it is for high GHG efficiencies.

Table 3: Results of linear models exploring the relationship between GHG efficiency and independent variables

Variables	FE OLS regression	FE unconditional quantile regressions		
	Average GHG efficiency (Mean)	High GHG efficiency (p25)	Medium GHG efficiency (Median)	Low GHG efficiency (p75)
N surplus	0.21 (0.13)	0.60*** (0.20)	0.60*** (0.19)	-0.031 (0.26)
NUE	-7.60*** (1.42)	-5.23*** (1.80)	-3.36* (1.75)	-8.44*** (2.61)
Milk yield	-0.066*** (0.0090)	-0.043*** (0.011)	-0.042*** (0.012)	-0.056*** (0.019)
Homegrown grass	-0.49 (0.53)	0.47 (0.76)	-0.10 (0.70)	-0.77 (1.06)
Grazing season	-1.20*** (0.19)	-1.04*** (0.32)	-1.47*** (0.33)	-1.79*** (0.38)
BTSCC	0.057 (0.086)	-0.10 (0.085)	0.12 (0.11)	0.069 (0.15)
Herd size	-1.31*** (0.35)	-1.03** (0.45)	-1.66*** (0.45)	-2.02*** (0.66)
Stocking rate	16.70 (13.52)	25.53 (21.02)	18.06 (19.25)	21.58 (28.64)
Specialisation	-5.06*** (0.97)	-3.82*** (1.17)	-4.96*** (1.28)	-5.50*** (1.91)
Discussion group	-0.90 (1.26)	0.30 (2.01)	-1.71 (1.92)	-4.26 (2.78)
Age	1.11* (0.57)	0.34 (0.99)	-0.27 (0.90)	0.36 (1.47)
F statistic	28.49***	10.69***	15.77***	8.60***
R^2	0.78	0.54	0.59	0.58
Adjusted R^2	0.72	0.43	0.50	0.49
Within R^2	0.23	0.085	0.091	0.078

Note: n = 1,905. ***, **, and * significant at the 1, 5, and 10% levels. Coefficients and clustered standard errors in parentheses. Individual and time FE controlled for, and standard errors clustered at the farm level.

Additionally, we find that the effect of NUE is constantly negative across the distribution of GHG efficiency in Table 3. However, the magnitude is heterogeneous across the distribution and at the smallest at the median. NUE has the largest effect for low GHG efficiencies, i.e., at the 75th percentile. More specifically, while an increase of 1 % point in NUE is associated with a GHG decrease of 5.23 g of CO_2e per kg of FPCM at the 25th percentile, it is associated with a GHG reduction of 8.44 g of CO_2e per kg of FPCM at the 75th percentile.

In Table 3, milk yield also has a negative effect on GHG emitted per kg of FPCM across the distribution of GHG efficiency. The magnitude of its effect varies and is at the smallest at the median. The estimation results show that an increase of 1kg of FPCM per cow is associated with a GHG decrease of 0.043 g of CO_2e per kg of FPCM at the 25th percentile, but it is associated with a GHG reduction of 0.056 g of CO_2e per kg of FPCM at the 75th percentile.

Interestingly, while we find that N surplus does not seem to influence GHG efficiency when estimated at the mean, the findings of the quantile regressions reveal a significant effect at the 25th and 50th percentiles. More precisely, for medium to high GHG efficiencies, an increase of 1 kg of N surplus per ha is associated with a GHG increase of 0.60 g of CO_2e per kg of FPCM. This effect is not significant at the 75th percentile, even though farmers with low GHG efficiencies are the ones with the highest N surplus on average (see Table A.1) and would thus be expected to have more scope for improvement in that aspect.

Finally, Table 3 shows that homegrown grass and BTSCC do not have a significant effect on GHG efficiency in any of the regression models.

Table 4: Results of linear models exploring the relationship between GHG pressure and independent variables

Variables	FE OLS regression	FE unconditional quantile regressions		
	Average GHG pressure (Mean)	Low GHG pressure (p25)	Medium GHG pressure (Median)	High GHG pressure (p75)
N surplus	18.20*** (2.47)	7.88** (3.21)	17.49*** (3.53)	28.21*** (5.59)
NUE	50.39** (20.38)	-28.31 (31.83)	68.85** (28.05)	110.30*** (37.65)
Milk yield	1.39*** (0.11)	0.98*** (0.23)	1.43*** (0.24)	1.73*** (0.31)
Homegrown grass	-6.04 (8.10)	-9.23 (12.57)	-4.23 (12.69)	-25.12 (18.24)
Grazing season	-13.41*** (2.49)	-8.09* (4.23)	-19.24*** (5.58)	-15.78*** (5.94)
BTSCC	-0.57 (0.85)	-3.39* (1.92)	0.13 (1.85)	2.76 (2.30)
Herd size	-4.07 (8.13)	1.34 (6.43)	-1.02 (8.69)	-8.87 (13.10)
Stocking rate	2999.09*** (312.94)	1813.76*** (366.34)	2737.27*** (475.36)	3069.94*** (549.97)
Specialisation	-92.22*** (14.11)	-78.03*** (25.37)	-95.79*** (21.21)	-124.23*** (21.39)
Discussion group	-15.70 (19.36)	-19.44 (32.00)	15.77 (36.64)	-24.16 (51.49)
Age	6.99 (7.62)	-12.13 (13.71)	-6.48 (15.80)	-16.87 (26.98)
F statistic	72.63***	7.42***	13.89***	15.17***
R^2	0.90	0.70	0.71	0.68
Adjusted R^2	0.88	0.63	0.64	0.60
Within R^2	0.46	0.087	0.15	0.16

Note: n = 1,905. ***, **, and * significant at the 1, 5, and 10% levels. Coefficients and clustered standard errors in parentheses. Individual and time FE controlled for, and standard errors clustered at the farm level.

As previously mentioned, only reductions in N surplus and improvements in the length of grazing seasons prove to be effective mitigation strategies to decrease GHG emissions on a per-hectare basis, as well as per kg of FPCM. More specifically, Table 4 shows that N surplus has a positive effect on GHG pressure across the distribution. The magnitude of this effect increases linearly from low to high GHG pressures. At the 25th percentile (i.e., for low GHG pressures), an increase of 1 kg of N surplus per ha is associated with an increase of 7.88 kg of CO_2e per ha. At the 75th percentile (i.e., for high GHG pressures), this effect is much larger as it is associated with an increase of 28.21 kg of N surplus per ha. On average, farmers with high GHG pressures have higher N surpluses than farmers with low GHG pressures (see Table A.2; 234.0 versus 115.8 kg of N surplus per ha). Thus, not only would reductions in N surplus in that farmer group be associated with greater GHG mitigation, these farmers are also expected to have more scope for improvement.

As for grazing season, the results in Table 4 show that it has a negative effect on GHG emitted per ha. The magnitude of this effect varies across the distribution. The effect is the largest at the median and the lowest at the 25th percentile. The findings reveal that an additional day of grazing is associated with a GHG mitigation of 8.09 kg of CO_2e per ha for low GHG pressures (i.e., 25th percentile) and of 15.78 kg of CO_2e per ha for high GHG pressures (i.e., 75th percentile).

While enhancements in milk yield and NUE are associated with a GHG reduction per kg of FPCM, these two strategies would deliver the opposite effect on absolute GHG emissions. In fact, Table 4 reveals that milk yield has a positive effect on GHG emitted per ha. The magnitude of this effect increases linearly when moving for low to high GHG pressures. At the 25th percentile (i.e., for low GHG pressures), an increase of 1 kg of FPCM per cow is associated with a GHG increase of 0.98 kg of CO_2e per ha. At the 75th percentile (i.e., for high GHG pressures), it is associated with a GHG increase of 1.73 kg of CO_2e per ha.

Moreover, the findings in Table 4 show that while NUE has a significant effect when estimated at the mean in the FE OLS regression, this does not hold across the whole distribution. More specifically, the effect is not significant at the 25th percentile, i.e., for low GHG pressures. We find that at the median, an increase of 1% point in NUE is associated with an increase of 68.85 of CO_2e per ha. At the 75th percentile (for high GHG pressures), it is associated with an increase of 110.30 kg of CO_2e per ha.

5 Discussion and conclusions

The preliminary results of this analysis reveal that GHG mitigation strategies have a differential effect across the distribution of GHG emissions, with two main implications. First, the findings suggest that relying on estimations of a technology's effect at the mean can be somewhat misleading as this does not reflect the effect of heterogeneity. Second, the study shows that the effect of GHG mitigation strategies is generally larger for high emitting farms than for low emitting farms. While these results are not surprising, they suggest that because more mitigation can be achieved on high emitting farms, extension efforts could be directed predominantly towards this farm profile. Thus, the next steps of this research are to identify to a greater which characteristics are associated with different farm profiles to help extension efforts.

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Appendix

Table A.1: Summary statistics by GHG efficiency profile, 2013-2019 pooled sample (n = 1,905)

Variables	< p25 High (n = 473)	[p25; p50[Medium to high (n = 477)	[p50; p75[Medium to low (n = 476)	>= p75 Low (n = 479)
N surplus	169.90 (67.11)	187.87 (73.77)	178.03 (74.05)	172.34 (64.33)
NUE	25.51 (6.63)	22.99 (6.15)	22.41 (6.71)	19.68 (6.00)
Milk yield	5691.84 (962.26)	5563.58 (940.40)	5202.17 (1012.68)	4648.73 (956.62)
Homegrown grass	78.08 (11.29)	78.48 (10.44)	76.95 (11.11)	74.41 (11.95)
Grazing season	248.53 (25.14)	242.09 (26.33)	235.03 (27.99)	229.96 (28.67)
BTSCC	177.05 (73.94)	168.43 (68.67)	182.71 (77.81)	200.26 (85.24)
Herd size	89.07 (53.50)	86.75 (44.73)	82.05 (46.80)	75.03 (43.15)
Stocking rate	2.04 (0.52)	2.09 (0.49)	2.07 (0.51)	2.04 (0.51)
Specialisation	73.19 (9.68)	67.92 (9.92)	62.86 (10.53)	54.43 (10.58)
Discussion group	6.00 (7.41)	6.42 (8.20)	5.69 (7.80)	3.81 (6.34)
Age	54.57 (10.47)	54.61 (11.19)	55.66 (10.75)	56.82 (9.70)
Gross margin	2654.66 (1085.04)	2565.81 (907.09)	2345.69 (896.71)	2018.76 (859.88)
GHG pressure	10539.62 (3771.85)	12103.97 (3919.35)	12485.82 (4301.37)	13302.82 (4390.57)

Note: means and standard deviations in parentheses.

Table A.2: Summary statistics by GHG pressure profile, 2013-2019 pooled sample (n = 1,905)

Variables	**< p25 Low (n = 473)**	**[p25; p50[Medium to low (n = 477)**	**[p50; p75[Medium to high (n = 476)**	**>= p75 High (n = 479)**
N surplus	115.81 (45.94)	166.51 (51.90)	191.14 (53.25)	234.00 (69.21)
NUE	23.90 (8.58)	22.38 (6.19)	22.15 (5.71)	22.13 (5.81)
Milk yield	4603.95 (967.48)	5130.65 (829.26)	5456.90 (931.43)	5900.98 (1009.62)
Homegrown grass	80.14 (9.50)	79.13 (9.66)	77.68 (10.49)	70.99 (12.95)
Grazing season	235.41 (28.85)	240.89 (27.34)	239.46 (26.44)	239.72 (28.89)
BTSCC	206.63 (92.19)	176.66 (71.82)	173.85 (69.41)	171.66 (70.52)
Herd size	57.31 (33.84)	77.84 (39.66)	88.61 (44.59)	108.74 (54.07)
Stocking rate	1.58 (0.37)	1.97 (0.34)	2.17 (0.33)	2.51 (0.46)
Specialisation	67.25 (14.13)	66.36 (11.43)	63.50 (11.83)	61.20 (10.70)
Discussion group	2.75 (5.20)	4.96 (6.95)	6.42 (8.01)	7.75 (8.58)
Age	56.35 (9.31)	55.66 (10.35)	54.83 (11.39)	54.84 (11.07)
Gross margin	1501.84 (612.91)	2186.79 (643.18)	2643.99 (689.35)	3238.15 (947.93)
GHG efficiency	1079.04 (244.31)	1104.66 (200.16)	1138.68 (201.75)	1184.45 (206.65)

Note: means and standard deviations in parentheses.