EU Milk Quota Abolition, Dairy Expansion and Greenhouse Gas Emissions

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Abstract

This article explores the relationship among farm-level productivity growth, scale and greenhouse gas (GHG) emission intensity during a time period of significant agricultural policy change affecting Ireland's dairy industry. Specifically, we focus on the 2015 EU milk quota abolition, which initiated major dairy expansion in Ireland. We use a representative sample of Irish dairy farms from 2000 to 2017, that includes data on farm specific GHG emissions. Based on this detailed farm level panel data set, we estimate productivity with a control function approach. We then apply fixed effects and dynamic panel data methods to explore the implications of productivity and scale on GHG emission intensity. Our findings indicate that increased productivity is negatively associated with GHG emission intensity, which changes with distinct milk quota abolition phases. Overall, our findings are important for understanding the relationship between policy reforms and GHG emissions in agriculture and how to improve mitigation potential of agriculture.

Key Words

Greenhouse Gas Emissions, EU milk quotas, productivity, dairy farming.

> *"Emissions in Agriculture are projected to continue increasing to 2030 due to growing cattle numbers, increased fertiliser use and ongoing carbon losses from land. If allowed to proceed unchecked, this would seriously undermine our ability to meet our 2030 target for a reduction in national emissions."* Irish Climate Change Advisory Council, Annual Review 2019.

Introduction

It is now well acknowledged that food production is one of the largest drivers of global environmental change by significantly contributing, among other things, to climate change (IPCC, 2019; Willett et al., 2019). Over the 2003-2012 time period, the world's agricultural sector accounted for about 20% of total anthropogenic greenhouse gas (GHG) emissions–more than global emissions from every car, plane, and train (IPCC, 2019; U.S. Environmental Protection Agency). The Intergovernmental Panel on Climate Change (IPCC) estimates that 50% of total agricultural emissions are non-CO_2 GHGs (i.e., methane (CH_4) and nitrous oxide (N_2O)). Moreover, agriculture's high emissions are mostly due to livestock, as GHG emissions from livestock make up about 70% of total emissions from agriculture, forestry and other land use (Tubiello et al., 2013). In line with these figures, global awareness regarding the environmental implications of expanding livestock production is increasing.

This issue is particularly pertinent for the Irish agricultural sector, which is responsible for around one-third of Ireland's total GHG emissions, as Ireland does not have a large industrial base. As the above quote indicates, Ireland has agreed to lower GHG emissions, but it is struggling to move in that direction because a large share of the emissions originate from livestock farms. The expansion of agricultural activity initiated by the EU milk quota abolition in 2015 has led to a significant increase in Ireland's dairy herd, and therefore higher GHG emissions. Any significant lowering of GHG emissions in Ireland will require a contribution from agriculture, unlike in most other developed countries where agriculture

plays a much smaller relative role in economy-wide emissions.

When the quotas were abolished in April 2015[1] in most EU member states the dairy herd began shrinking due to lower milk prices, except in Belgium, Ireland and the Netherlands. Part of the impetus for the quota removal was to allow the most efficient EU dairy farms to expand production and participate in the growing global demand for dairy products. In Ireland, production growth was mainly due to an expanding dairy herd and increased yields per cow on existing farms, with some new dairy farms being created, supported by specific policy measures (Kelly et al., 2020). Conceptually, it has been argued that farms in Ireland became more efficient after quota abolition and GHG emission intensity declined (Kelly et al., 2020). However, this is an empirical question that has not been explored in the literature and is the main focus of this article.

The elimination of EU dairy quotas in 2015 was one of the most significant policy changes affecting Irish agriculture in the recent past (Boysen et al., 2016). Due to WTO disciplines on export subsidies the dairy quota limited Irish access to international markets for dairy products and was therefore an implicit export quota because it prevented the EU producers from responding to the growing international import demand.

Cui et al. (2016) explain how exporting reduces emission intensity in manufacturing. They outline that if firms see an economic benefit to reducing pollution, an inverse relationship between market opportunities and emission intensity is expected. Exporting is associated with the realisation of increased market opportunities. In contrast to manufacturing firms, individual Irish farms do not decide whether or not to export as they sell to local processing plants, but almost all of their output is exported by the processor.[2] Farms can thus respond to improved export opportunities facilitated by quota abolition by increasing output. Two

[1] Even though the removal of the quota was anticipated in advance of 2015, until 2014 the dairy industry was discouraged from expanding production beyond the gradual quota increases or it would be fined by the EU. From 2006 through 2013 the annual number of dairy cows in Ireland expanded by 1.3% per year on average. The annual growth rate of the herd then jumped to 5.8% per year from 2014-2017, largely due to the quota removal.

[2] Over 90% of Irish dairy production is exported with 10% of milk supplies being consumed as fresh milk or as manufactured dairy products on the domestic market (National Milk Agency, 2020).

main pathways in this process are productivity growth, for example through higher milk yields per cow, and increasing the scale of the operation by adding more dairy cows.

The link between agricultural productivity and GHG emissions has been studied on a global and US scale by Jones and Sands (2013) and Baker et al. (2013). Based on partial and general equilibrium models, these studies find that higher productivity is linked to reduced GHG emission intensities. In addition, Bennetzen et al. (2016b) highlight the need to focus on *emission intensities* (i.e. GHG emissions per unit product) in order to understand the mitigation potential in agriculture. Their approach is at the global level and they use a mathematical decomposition method to allocate total emissions to its various components. They found that from 1970 to 2007 there was a global decrease in emission intensity per unit of product for crops (39%) and livestock (44%). This decline is slightly more than one percent per year on average. However, the decline in emission intensity is countered by the doubling of global agricultural production since 1970 (Bennetzen et al., 2016a).

In this article, we take a micro perspective and study the relationship between farm-level productivity, increased farm scale and GHG emission intensity and the role that milk quota abolition played in this process. Specifically, we study GHG emission intensities on Irish dairy farms from 2000 to 2017, a period that includes a significant agricultural policy reform that initiated major structural change in the Irish dairy sector. Our article provides new insights on farm level responses to quota abolition and their relationship to GHG emission intensities based on unique micro farm level panel data that include farm specific GHG emission per kg of milk, based on IPCC and life-cycle analysis (LCA) measurement methods. As such, we explore whether and how improved farm management can contribute to mitigation potential on farms.

Our empirical strategy is based on estimating productivity with a control function approach implementing Wooldridge-Levinsohn-Petrin (WLP) GMM method (Levinsohn and Petrin, 2003; Wooldridge, 2009) and subsequently utilizing fixed-effects and dynamic panel data models to explore the relationship between productivity, scale and GHG emission in-

tensity and how this process is influenced by milk quota abolition. Dynamic panel data methods account for previous' years emission intensity and allow us to instrument endogenous variables.

Our results indicate that Irish farms became more productive over time, with a documented productivity growth of 26% over the observation period. Moreover, increased productivity is negatively associated with GHG emission intensity and most of the effects on GHG emission intensities are of a contemporaneous nature. Specifically, a one percent increase in productivity is associated with a decline in emission intensity of at least 0.26%. We also find that different milk quota abolition phases affected the association between productivity and GHG emission intensities, but our results do not discern a clear relationship between farm scale and GHG emission intensity.

The article is organised as follows: The next section provides background information on the study area. Section 3 explains our data and methods. Results and discussions are in Section 4, while Section 5 concludes.

Background

The EU 2030 Climate and Energy framework set a binding target to cut GHG emissions. EU targets for the emission trading system (ETS) sectors[3] are a 43% reduction compared to 2005, while non-ETS sectors, to which agriculture belongs, are subject to national targets to jointly achieve a 30% cut in emissions. Ireland has committed to reduce non-ETS GHG emissions by 30% by 2030 compared to 2005 emission levels. As the agricultural sector accounts for 44% of non-ETS carbon emissions in Ireland, agriculture is part of the GHG emission reduction targets. Moreover, Ireland has by far the highest proportion of GHG emissions arising from agriculture in the EU.

So far, Ireland's efforts to reduce GHG emissions in line with previous EU targets (i.e., the 2020 Climate and Energy Package) have not been successful. Ireland was expected to

[3]These sectors include transportation, electricity generation, and energy intensive factories.

achieve a one percent reduction at best, and instead agricultural emissions increased by 3.8% in total between 2005 and 2019 (EPA, 2020), which contradicts Ireland's national policy goal to achieve carbon neutrality in the agriculture, land-use and forestry sector by 2050.

Moreover, GHG emissions from agriculture are predicted to increase further, especially if mitigation actions are not widely implemented. The Irish agricultural sector emitted an estimated 21.15 mt CO_2 eq in 2019 (EPA, 2020). Without mitigation actions, it is predicted that GHG emissions from agriculture will increase by approximately 9% by 2030 (compared to 2005), mainly driven by increasing dairy cow numbers and fertilizer use (Lanigan et al., 2018).

To date, no stringent environmental policy, such as a tax or 'cap and trade', has been introduced, but several mitigation pathways for the agricultural sector are in place to achieve the 2030 target. First, in order to reduce methane and nitrous oxide from agriculture, better breeding, grass utilization, and optimization of fertilizer use and slurry spreading are mitigation options. Carbon sequestration and energy efficiency, biofuels and bioenergy are other mitigation measures.

At present, while considerable mitigation potential may exist, it has not been fully implemented in practice in Ireland (Donnellan et al., 2018a). Nevertheless, within the EU, Ireland and Austria are the most carbon-efficient producers of milk in terms of CO_2 eq per kg of milk (Leip et al., 2010). Ireland's dairy production is based on a grass-based system, and GHG emissions measured per tonne of fat and protein corrected milk (FPCM) from grass-based dairy systems have been found to be 15% lower than GHG emissions from confinement systems (O'Brien et al., 2012). Importantly, this is based on LCA measured emissions, which includes on—and off—farm emissions and, unlike IPCC measures, take emissions from the production of concentrates elsewhere into account.

Ireland's grass-based dairy production not only has positive implications for GHG emission intensities, Ireland is also one of the lowest cost dairy producers worldwide (Dillon et al., 2008; Donnellan et al., 2009) and has significantly lower unit costs of production than other

major EU dairy producers (Thorne et al., 2017). Low production costs in Irish dairy farming are based on favorable agronomic and weather conditions that sustain a grass-based, spring calving milk production system where cows are grazed outside from early spring to late autumn. Extending the length of the grazing season can reduce costs of production (Läpple et al., 2012) and is also part of mitigation actions to reduce GHG emissions (Donnellan et al., 2018b).

Ireland's comparative advantage facilitated an increase in dairy cow numbers by over one third between 2010 and 2018, resulting in a 50% increase in milk production over the last decade (Central Statistics Office, 2020), as well as significant export increases, as approximately 90% of dairy products are exported (Kelly et al., 2020). Nevertheless, despite Ireland's favourable GHG emission intensities, the major growth of the dairy sector following the EU milk quota abolition resulted in increased GHG emissions from agriculture, which puts Ireland's dairy sector under pressure. Thus, in order to combine growth with environmental targets, further improvement in emission intensities is required.

Data and Methods

Farm and GHG Data

We have a unique panel data set of a representative sample of Irish dairy farms spanning 2000 to 2017. Our data are based on the Irish National Farm Survey (NFS) conducted by Teagasc, which is part of the EU Farm Accountancy Data Network (FADN). The NFS was established in 1972 and is published annually. Data are collected through a series of face–to–face interviews with farmers by a professional data collection team. Overall, a statistically representative random sample of approximately 900 farms participate in the survey on a voluntary basis each year. This sample is drawn from a farming population of approximately 80,000 farms. Farms are classified into farming systems, based on the dominant farm enterprise measured by gross margin. The NFS collects data on all prominent

farming systems in Ireland (i.e., dairy, cattle, sheep, cereal and mixed livestock) and for purposes of this paper we restrict our sample to dairy farms. While all of the farms in our sample produce milk, it is not unusual for them to have both dairy and beef cow herds on the same farm. For example, about 60% of the gross output on Irish dairy farms typically arises from the dairy side of the enterprise, while the remaining 40% mainly comes from beef production. When restricted to dairy farms, the sample reduces to approximately 300 observations each year. We use an unbalanced panel data set, amounting to a total of 5,639 observations. On average, farms stay in the sample for about 6 years, but patterns vary. Under the assumption that attrition is random, we expect our results not to differ between the unbalanced and balanced sample (Cheng and Trivedi, 2015). We report the results of this comparison in table 5.

The data include detailed information on farm and farmer characteristics, as well as farm-level GHG emissions, measured by total GHG emissions and emission intensity per kg of milk. GHG emissions are estimated using both IPCC and LCA methodology. GHG emissions based on IPCC methodology are available from 2000 to 2017, while GHG emissions based on LCA methodology are available for 2013 to 2017 only, as this method is based on more detailed data requirements.

In relation to the IPCC methodology, GHG emissions are estimated based on accounting conventions using Irish emission factors from the 2017 National Inventory Report for Ireland (Duffy et al., 2017). For this, activity data derived from the NFS data are multiplied by emission factors. Agricultural emissions arise due to enteric fermentation by ruminant livestock resulting in methane, the production and storage of livestock manure resulting in methane and nitrous oxide, as well as nitrous oxide arising from the application of manure and synthetic fertilizers to fields. A complicating factor for the farm based approach is that animals can move between farms. Therefore, an inventory approach is applied. Here, methane emissions and manure production of each livestock category are adjusted to reflect the portion of the year an animal was actually on the farm (Buckley et al., 2019). All non carbon diox-

ide emissions are converted in CO_2 equivalents using appropriate global warming potential factors for methane and nitrous oxide, which are respectively 25 and 298 times greater than the global warming potential of CO_2 (Buckley et al., 2019). IPCC GHG emission intensity is measured per kg of milk.[4]

In relation to the LCA method, agricultural GHG emissions are derived following an approach developed by O'Brien et al. (2014). In contrast to the IPCC method, LCA also includes off-farm GHG emissions. Therefore, all GHG emissions arising from input production (e.g., concentrates and fertilizer) and on-farm production of milk are accounted for. As such, LCA encompasses the overall production process up until milk leaves the farm (i.e. cradle-to-farm gate approach). Using standardised methods and international guidelines, GHG emissions are estimated for Teagasc NFS farms based on IPCC emission factors (IDF, 2015; International Organization for Standardization, 2006). Equivalent to the IPCC methods, all emissions are converted to CO_2 equivalents. LCA GHG emissions are reported per kg of FPCM, which accounts for differences in milk solids between farms.

The sample average for IPCC GHG emissions is 0.80 CO_2 per kg of milk, while LCA GHG emission intensity is considerably higher at 1.21 CO_2 per kg FPCM.

Empirical Framework

We explore whether and how farm-level management change affects the environmental impact of dairy farms and how this relationship varies with policy. As previously mentioned, farms respond to milk quota abolition by increasing output. Two main channels to achieve this are productivity growth and increasing scale by adding more cows.

Increased scale and productivity will lead to changes in GHG emission intensities. Cherniwchan et al. (2017) refer to this adjustment as firm reorganization effect and consequently emission intensity will change depending on whether cleaner or dirtier inputs become more intensively used. This explains why productivity growth does not necessarily result in en-

[4]GHG emission intensity data based on fat and protein corrected milk had several outliers, hence we decided to proceed with the *per kg of milk* measure.

vironmental improvement. For instance, if dairy farms in Ireland expand output through greater use of chemical fertilizer inputs or imported purchased feeds this could lead to productivity gains, but at the same time higher emission intensity. Alternatively, productivity gains could be associated with economies of scale and input savings that lead to more productive farms exhibiting a lower emission intensity. This could be achieved through GHG mitigation pathways such as better breeding, improved grass utilization or optimization of fertilizer use.

While increasing scale by adding more cows increases absolute GHG emissions, we expect the size of the herd to be inversely related to emission intensity, given that the Irish dairy industry is conscious of its environmental impact. This is in line with Cui et al. (2016) and Forslid et al. (2018) who explain that larger scale is associated with better mitigation. In addition, the scale effect can work through increasing or decreasing returns to scale and as such impacts GHG emission intensity through productivity changes. When adding more cows, both increasing or decreasing returns to scale are equally plausible, which depend on the expansion strategy of the farmer. For example, increasing scale through heifers will result in lower average milk yields, while adding higher yielding dairy cows will result in the opposite. We explore these relationships empirically with our data.

Specifically, our empirical strategy follows two steps: First, we estimate total factor productivity (TFP) using a WLP GMM framework (Wooldridge, 2009) and we then apply fixed effects panel data and a dynamic panel data estimation strategy to explore the impact of quota abolition-induced production adjustments on GHG emission intensity.

In relation to TFP estimation, as mentioned, we use a WLP GMM estimator, which was recently applied by Frick and Sauer (2018) in an agricultural context. We first estimate the following production function:

$$Q_{it} = \beta_1 + \beta_2 M_{it} + \beta_3 L_{it} + \beta_4 K_{it} + \beta_5 Land_{it} + \beta_6 LU_{it} + \beta_7 C_{it-1} + \epsilon_{it}. \tag{1}$$

where Q_{it} is farm output of farm i in year t, M_{it} are intermediate inputs, L_{it} is labour,

K_{it} is capital, $Land_{it}$ is land and LU_{it} is livestock units, all expressed in log values. All production inputs, except capital which acts as its own instrument, are instrumented by lagged variables. Labour, land and livestock units are instrumented by their one-year lags, while intermediate inputs were instrumented by a two-year lag. C_{it-1} stands for the variables of the control function which are third degree polynomials of the one period lags of capital and intermediates, as well as their interactions. ϵ_{it} represents random shocks not correlated with inputs and the productivity component which may be correlated with inputs (Wooldridge, 2009).

Productivity is then calculated as follows (Van Beveren, 2012):

$$P_{it} = Q_{it} - (\hat{\beta}_2 M_{it} + \hat{\beta}_3 L_{it} + \hat{\beta}_4 K_{it} + \hat{\beta}_5 Land_{it} + \hat{\beta}_6 LU_{it}). \tag{2}$$

Farm output is measured as the sales value from dairy production (i.e. milk, cull cows and calves), as well as output values from beef, sheep and crop production.[5] Outputs are aggregated into a volume measure by summing their values and deflating the total value by an aggregate farm-specific Törnqvist price index outlined in the Appendix. Intermediates M_{it} are measured as the value of concentrates, fertilizer, electricity, veterinarian and machinery operating expenses, etc. Again, the aggregate value is converted into a volume measure by deflating the value by a farm specific Törnqvist price index. Labour (L_{it}) is measured in total labour units, including both paid and unpaid labour. Capital (K_{it}) is the value of buildings and machinery calculated according to the end of the year valuation based on a replacement cost methodology and deflated by respective price indices. Land ($Land_{it}$) equals total utilized agricultural area measured in hectares. Livestock units (LU_{it}) are the value of livestock calculated as the average of the yearly opening and closing inventories and deflated by the respective price index. All price indices are taken from the Irish Central Statistics Office (CSO).[6] Descriptive statistics of the variables used are reported in Appendix table

[5] Apart from milk, farm outputs are not available in quantities.

[6] Price indices are available at https://www.cso.ie/en/statistics/agriculture/agriculturalpriceindices/.

A2.

As mentioned, our empirical strategy to estimate the relationship between productivity, scale, quota abolition and GHG emission intensity is based on fixed effects and dynamic panel data methods. As a first step, we estimate a panel-data fixed effects model to assess the relationship between farm-level responses to quota abolition and GHG emission intensity, before exploring a dynamic relationship (which is explained below).

Let GI_{it} be GHG emission intensity for farm i at time t, which depends on farm-specific productivity P_{it}, scale effects H_{it}, a set of control variables X_{it}, policy changes over time T_t, a farm-specific effect u_i, and an idiosyncratic error ϵ_{it}, as follows:

$$GI_{it} = \beta_1 + \beta_2 P_{it} + \beta_3 H_{it} + \beta_4 X_{it} + \beta_5 T_t + u_i + \epsilon_{it}, \tag{3}$$

with GI_{it} being the log of GHG emission intensity (CO_2 eq/kg of milk), P_{it} is the log of farm specific productivity, and H_{it} is the scale effect measured as the log of herd size. Stocking rate, kg of nitrogen applied per ha (N/ha), specialisation in dairy (measured as the proportion of dairy cows in the livestock herd) and kg concentrates fed per cow are included as control variables in X_{it}, along with year fixed effects T_t.

In order to test the influence of quota abolition, we estimate a model in which we replace year fixed effects with specific time period dummies accounting for distinct EU quota abolition phases. We identify the following three time periods: the years 2000 to 2007 represent the quota period, 2008 to 2014 characterises the quota abolition preparation period during which gradual production increases were allowed (i.e., the 'soft landing'), while 2015 to 2017 corresponds to the post-quota period with no production restrictions. We interact these time period dummies with productivity and scale to assess potential avenues as to how quota abolition affected GHG emission intensities. For the productivity quota effect, this leads to the following equation:

$$GI_{it} = \beta_1 + \beta_2 P_{it} + \beta_3 H_{it} + \beta_4 P_{it} T_2 + \beta_5 P_{it} T_3 + \beta_6 T_2 + \beta_7 T_3 + \beta_8 X_{it} + u_i + \epsilon_{it}, \tag{4}$$

with T_2 representing the 'soft landing' phase, T_3 being the post-quota period while the quota period serves as the baseline. We estimate an equivalent equation that includes interaction terms between scale and quota periods. In addition, as these equations do not control for annual changes in prices, weather, etc., we also conduct a robustness test by interacting farm level response variables (i.e. P and H) with year dummies.

We also model GHG emission intensity as a dynamic process, where adjustment rates over time depend on previous GHG emission intensities GI_{it-1}, productivity P_{it}, scale effects H_{it}, a set of control variables X_{it}, regional characteristics R_i, policy changes over time T_t, a farm-specific effect u_i, and an idiosyncratic error ϵ_{it}, as follows:

$$GI_{it} = \beta_1 + \beta_2 GI_{it-1} + \beta_3 P_{it} + \beta_4 H_{it} + \beta_5 X_{it} + \beta_6 R_i + \beta_7 T_t + u_i + \epsilon_{it}, \tag{5}$$

with GI_{it} being the log of GHG emission intensity (CO_2 eq/kg of milk), P_{it} is the log of farm specific productivity, and H_{it} is the scale effect measured as log of herd size. Stocking rate, specialisation, kg N applied per ha and kg concentrates fed per cow are included as control variables in X_{it}, along with time periods T_t. We use T_t as time dummies to control for the changing economic and policy environment, surrounding the date of quota abolition. $u_i + \epsilon_{it}$ denotes the error term which includes u_i, the time-invariant unobserved effects, which may be farmer ability, motivation, or differences in geographical locations that affect production. It is easy to see that this can influence GHG emission intensity, productivity, as well as expansion efforts. ϵ_{it} is a disturbance, that is assumed to be identically and independently distributed and serially uncorrelated. The βs are parameters to be estimated.

In general, Arellano-Bond models can be estimated with first differenced or system GMM methods. While the system GMM method is based on stronger assumptions, it is more efficient and has the advantage that time invariant variables, such as regional effects, can be included in the estimation process. The Arellano-Bond estimator begins with first differenc-

ing equation 5, which leads to the following equation:

$$\Delta GI_{it} = \beta_1 \Delta GI_{it-1} + \beta_2 \Delta P_{it} + \beta_3 \Delta H_{it} + \beta_4 \Delta X_{it} + \beta_5 \Delta T_t + \Delta \epsilon_{it}, \tag{6}$$

The differenced error term in equation (6) $\Delta\epsilon_{it} = \epsilon_{it} - \epsilon_{i,t-1}$ is correlated with the differenced lagged dependent variable $\Delta GI_{it-1} = GI_{it-1} - GI_{it-2}$. This implies that an instrumental variable estimation approach is needed.

Lagged levels of the differenced lagged dependent variable are used as instruments in the difference GMM estimator, as $GI_{i,t-2}$ is correlated with $\Delta GI_{i,t-1}$ but not with $\Delta\epsilon_{it}$. An important assumption is that the dependent variable GI_{it} is uncorrelated with subsequent disturbances ϵ_{it+j} for $j = 1, 2, \ldots J$ and that disturbances ϵ_{it} are serially uncorrelated. Testing this assumption is standard in Arrelano-Bond models. However, as the differenced disturbance is expected to show a first order correlation, the test focuses on second order serial correlation. As our panel data set includes 18 years of data, additional instruments are available, which encompass previous observations of GI_{it} prior to $t-2$. In models including all years of data, we limit instruments to 10 time periods.

The system GMM estimator combines the set of moment conditions in the differenced equations and the set of moment conditions in the level equations (Arellano and Bover, 1995; Blundell and Bond, 1998; Bond, 2002). The system GMM estimator provides more efficient estimates of the parameters. These are utilized under the assumption that first differences in dependent variables are uncorrelated with the error terms: $E[(\Delta GI_{i,t-1}(u_i + \epsilon_{it})] = 0$. This assumption is a valid moment condition in the level equations that also applies to any endogenous explanatory variables. The system GMM estimator differences the instruments to make them exogenous to the fixed effects, instead of transforming the variables (Roodman, 2009). We assume that TFP and herd size are potentially endogenous and therefore require instruments. The validity of this assumption is tested by 'C test statistics', which perform estimations with and without the subset of instruments, under the assumption of joint validity of the full instrument set (Roodman, 2009).

Table 1: **GHG emissions and farm characteristics (2000-2017)**

	2000	2003	2006	2009	2012	2015	2017	% change
Total dairy emissions (tonnes CO_2eq)	159.16	182.48	198.14	225.12	242.62	286.33	310.90	95.34
Total farm emissions (tonnes CO_2eq)	271.56	299.33	325.00	359.11	421.72	465.68	501.50	84.67
Emission intensity (kg CO_2eq/kg milk)	0.84	0.83	0.80	0.91	0.77	0.74	0.73	-13.10
Milk Output (liters per farm)	193,313	225,938	256,822	264,001	323,885	396,129	433,022	124.00
Milk yield / cow (liters)	4,673	4,882	5,011	4,658	4,970	5,438	5,388	15.30
Number of dairy cows (per farm)	39.30	44.95	49.29	54.08	63.29	70.77	76.87	95.60
Concentrates fed per cow (kg)	787.85	840.33	966.21	890.35	1,023	937.22	1,035.24	31.40
Specialization (dairy cows/total livestock)	0.62	0.638	0.634	0.64	0.64	0.65	0.66	6.45
Stocking rate (dairy cows/ha)	1.80	1.88	1.85	1.85	1.87	1.98	2.07	15.00
UAA (ha)	37.16	40.38	44.62	47.91	55.40	57.64	58.63	57.78
Dairy forage area (ha)	21.06	23.63	26.53	28.65	33.96	36.16	37.19	76.59

Note: UAA is utilizable agricultural area; Data are weighted to represent the Irish dairy population Source: Own calculations from NFS data

We estimate all models with system GMM based on a two-step method with Windmeijer corrected standard errors (Windmeijer, 2005). In addition, we explore whether the coefficient values of the lagged dependent variable in all presented models are between the coefficient values for the lagged dependent variables obtained from OLS and fixed effects estimates, which is a condition for consistent estimates (Bond, 2002).

Descriptive Statistics

As indicated above, there were considerable changes in Irish dairy production between 2000 and 2017, which are summarized in table 1 for selected years.[7] For example, milk output per farm increased by 124%, milk yield by 15.3% and dairy herd size per farm increased by over 95%. In line with production growth, total farm GHG emissions increased by 85%, while GHG emissions attributed to the dairy industry almost doubled. However, GHG emission intensity, measured in CO_2 eq per kg of milk decreased by 13%.

Next, we graphically explore absolute GHG emissions. This will provide insights about GHG emission reduction potential based on improved emission intensity. Figure 1 shows the trend in GHG emissions from 2000 to 2017, based on weighted NFS data. We follow an approach developed by Levinson (2009) that provides insight into development and reduction potential of GHG emissions. The dashed blue line (farm output) depicts total real value of

[7]Summary statistics for sample data are reported in the Appendix table A2.

milk and beef output[8], scaled so that the year 2000 value equals 100. This line represents how GHG emissions per farm would have changed, if farming technology remained constant and the mixture of beef and dairy was unchanged over this time period. As such, the increase of 119% represents the scale effect. In general, the scale effect captures expanded economic activity with potential negative environmental implications (Grossman and Krueger, 1993). The solid green line (farm emissions) shows average total GHG emissions per farm, again scaled so that 2000 equals 100. In 2017, farm GHG emissions were 85% above their 2000 levels. This represents the combined scale, composition and technique effects (Levinson, 2009). This implies that composition and technique effects reduced emissions per farm by 34% over the 18 year period. The technique effect works through endogenous changes in environmental policy and leads to reduced emission intensity, with environmental benefits, while the composition effect arises from policy-induced changes in factor allocation across sectors (Grossman and Krueger, 1993). While this estimate is based on constant dairy and beef output, it provides a useful insight regarding improvements in emission intensity. In the following empirical analysis, we set out to explore likely contributors to the divergence of the two lines.

Results and Discussion

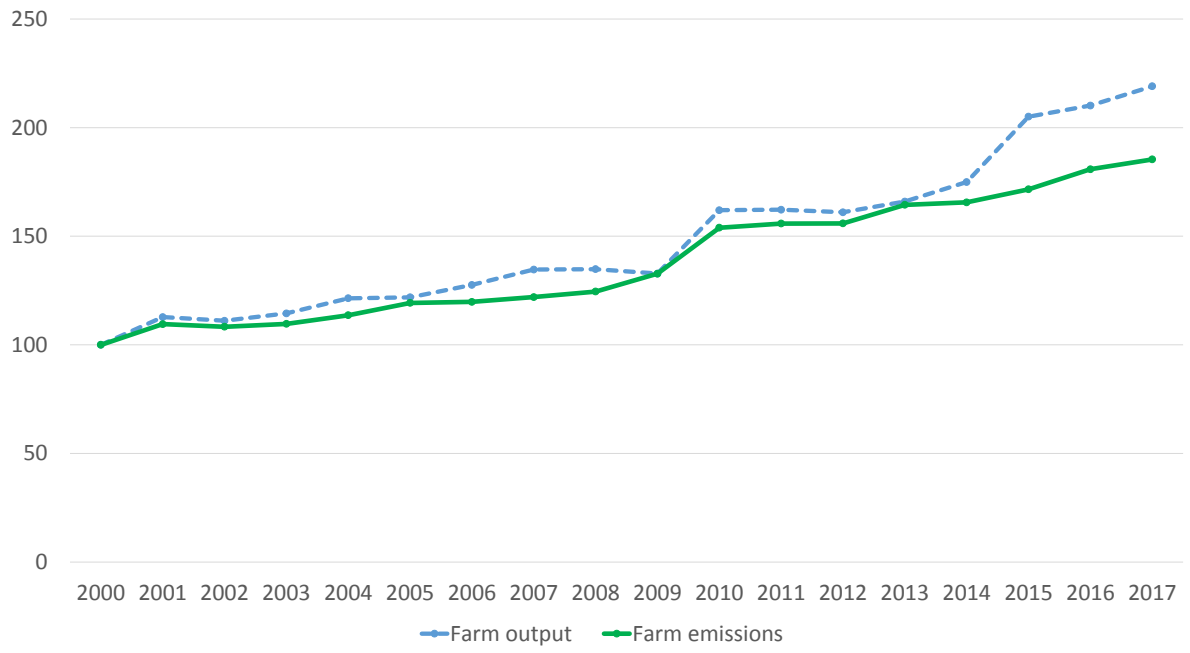
Production Function

We begin by presenting estimation results of the WLP production function model in table 2. In this model, aggregate outputs and intermediates are deflated by a farm-specific Törnqvist index and intermediates are used as proxy variable. In the Appendix, we present models with concentrates as a proxy variable and farm output as an aggregated measure of deflated outputs.

The model in table 2 shows that all elasticities except labour are statistically significant.

[8]Milk and beef output comprises over 95% of output of our sample farms.

Figure 1: **GHG emissions on Irish farms 2000 to 2017**



Source: own calculations based on NFS data

Intermediates and livestock units are the most prominent inputs. Intermediate inputs include concentrates and fertilizer, which are important variable inputs in dairy production, explaining the large effect. Capital and land are less important, but both inputs show a significant and positive effect, which is in contrast to findings by Frick and Sauer (2018). In relation to labour, Newman and Matthews (2007) and Martinez Cillero et al. (2019) also report non-significant and negative labour coefficients (albeit for cattle farms) and explain this with underemployment of labour. A more plausible explanation for the insignificant labour effect for dairy farms may be that labour measurement is capped at 1,800 hours per person per annum, but many dairy farmers may work considerably more.

Figure 2 presents estimated TFP growth over the period from 2000 to 2017, with 2000 being the base year (= 100). Overall, we observe productivity growth of 26% between 2000 and 2017, which is an average growth rate of 1.37%. This compares to an annual average TFP growth rate of 2.16% for Wisconsin dairy farms between 1996 and 2012 (Njuki et al.,

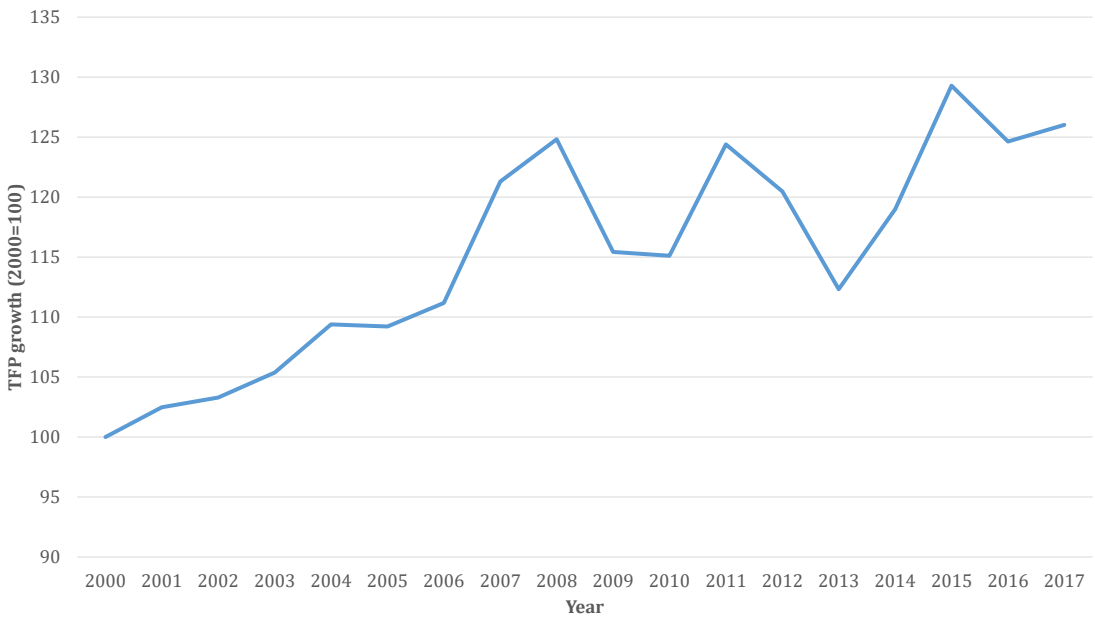
Table 2: **Estimation results of the production function**

Output	
Intermediates (M)	0.603***
	(0.108)
Labour	-0.0128
	(0.0245)
Capital (K)	0.0521***
	(0.0133)
Land	0.0556**
	(0.0241)
Livestock Units	0.298***
	(0.0303)
K_{t-1}	-2.166
	(1.637)
K^2_{t-1}	-0.156
	(0.102)
K^3_{t-1}	-0.0100**
	(0.00488)
M_{t-1}	-0.747
	(2.886)
M^2_{t-1}	-0.237
	(0.432)
M^3_{t-1}	0.0308
	(0.0222)
K_{t-1} x M_{t-1}	0.689
	(0.419)
K^2_{t-1} x M_{t-1}	0.0446**
	(0.0192)
K_{t-1} x M^2_{t-1}	-0.0751**
	(0.0329)
Constant	10.20
	(7.384)
Observations	3,958
R-squared	0.920

All variables in log values.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2020). However, dairy farms in Wisconsin are much more capital and input intensive than typical Irish dairy farms.

Figure 2: **TFP growth on Irish dairy farms 2000 - 2017**



Source: own calculations based on NFS data

Productivity and GHG Emission Intensity

The main focus of this article, however, is on estimating the relationship between productivity, scale and GHG emission intensity per kg of milk. Our main estimates are based on GHG emissions following IPCC measurements, as these data are available from 2000 to 2017.

Table 3 shows the results from a fixed effects (FE) specification and a dynamic panel Arellano-Bond (AB) estimation strategy. The results in table 3 show a negative relationship between productivity and GHG emission intensity. Based on the estimated regression coefficients from the fixed effects estimation strategy (Model 1), a one percent increase in productivity is associated with a decrease in GHG emission intensity by 0.26%. We do not find a significant scale effect, represented by herd size.

The productivity result is supported by the dynamic panel data estimation strategy (Model 2), but coefficient estimates from fixed effects and dynamic panel data methods cannot be directly compared (Piper, 2014). However, before embarking on coefficient interpretation, we assess the validity of the Arellano-Bond model, which depends on no second-order auto-correlation of the disturbances and exogeneity of instrumented variables. Results of diagnostic test statistics that probe these assumptions are reported at the bottom of table 3. The hypothesis of no-second order correlation in the disturbances was not rejected at the 5% significance level as suggested by a p-value of 0.371 (see AR(2)). The Hansen test for over-identification provides information on the general suitability of the model specification and exogeneity of all instrumented variables used in the models. Again, we cannot reject the null hypothesis with a p-value of 0.347 (see Hansen test statistics at the bottom of table 3). In addition, we use C test statistics that specifically test for the orthogonality of a sub-set of instruments, in this case TFP and herd size (Baum et al., 2003). Results from the C test statistics (also at the bottom of table 3) indicate that we fail to reject the null hypotheses of exogeneity of our instrumental variables with a p-value of 0.453.

The Arellano-Bond model allows us to explore short and long-run values of the coefficients. In other words, the explanatory variables reflect contemporaneous information, while the lagged dependent variables reflects the past (Greene, 2003; Piper, 2014). The lagged dependent variable is positive and statistically significant, with an estimated coefficient value of 0.237. This coefficient, representing the entire history of the model, has only a relatively small influence (0.237) on current GHG emission intensity, suggesting that GHG emission intensity is largely contemporaneous. The contemporaneous effect of productivity implies that a one percent increase in productivity leads to a 0.29% decrease in GHG emission intensity. The long-run value of productivity is -0.38[9], and more than half of GHG emission intensity is driven by contemporaneous productivity, while past productivity contributes only about a 40% to GHG emission intensity reduction. Once we control for potential endogeneity of

[9] Calculated as $-0.29/(1-0.237)$.

Table 3: **GHG emission intensity**

ln(GHG/kg milk)	Model 1 FE	Model 2 AB	Model 3 AB
ln(GHG/milk)$_{t-1}$		0.237***	0.227***
		(0.0415)	(0.042)
ln(P)	-0.257***	-0.290***	0.441
	(0.0305)	(0.0424)	(0.371)
ln(herd)	0.0178	-0.0895**	0.075
	(0.0470)	(0.0439)	(0.059)
ln(P) x ln(herd)			-0.189**
			(0.091)
Specialization	0.150**	0.000645	0.004
	(0.0735)	(0.0395)	(0.037)
Stocking rate	0.0373	0.0365**	0.028
	(0.0278)	(0.0157)	(0.0117)
N/ha	0.000150**	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Concentrates/cow/100	-0.00802***	-0.0130***	-0.0137***
	(0.00219)	(0.00205)	(0.0022)
East region		-0.0208	-0.030
		(0.0199)	(0.0161)
South-west region		0.00660	0.007
		(0.0158)	(0.0135)
Farm FE	yes	no	no
Year FE	yes	yes	yes
Constant	-0.306**	0.413***	-0.184
	(0.141)	(0.120)	(0.231)
Observations	5,639	4,699	4,699
R-squared	0.235		
Number of ID	768	638	638
Instruments		436	437
AR(2)		0.371	0.373
Hansen		0.347	0.288
C test		0.453	0.417

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

herd size, we do find a statistically significant negative effect of herd size on GHG emission intensity. A one percent increase in herd size is associated with a 0.09% reduction in emission intensity. A negative association of increased scale and GHG emission intensity is in line with previous findings, see Cui et al. (2016) and is consistent with our initial expectations.

In Model 3, we test whether the effect of productivity varies with size, and results suggest that the productivity effect gets stronger with increasing herd size, as suggested by the negative significant interaction term.

Finally, in relation to the results presented in table 3, it is worth mentioning that all models show a significant negative association of concentrates fed per cow and GHG emission intensity[10]. This indicates that feeding more concentrates may help reduce GHG emission intensity, potentially working through increased milk yields that are often associated with higher concentrates supplementation. However, this effect is very small, as concentrates per cow are measured in 100 kg. Moreover, it is important to recall that GHG emissions measured by the IPCC method do not account for emissions arising from concentrates produced elsewhere.

Milk Quota Abolition Phases

Next, we focus on the implications of quota abolition on GHG emission intensities in more detail. In Model 1, we explore whether GHG emission intensities differ with distinct quota periods. However, we expect that milk quota abolition impacted GHG emission intensity because it influences the scale of farm operations and farm-level productivity. Therefore, we included interaction terms between dummy variables for quota abolition time periods (

$$T_1$$

[10]More detailed investigation not shown here revealed that this effect levels off with increasing concentrates fed.

Table 4: **Quota abolition phases and GHG emission intensity**

ln(GHG/kg milk)	Model 1	Model 2	Model 3	Model 4
ln(P)	-0.258***	-0.256***	-0.211***	-0.227***
	(0.0293)	(0.0294)	(0.0352)	(0.0515)
ln(herd)	-0.0111	0.0194	-0.0149	0.0214
	(0.0426)	(0.0482)	(0.0415)	(0.0417)
Specialization	0.158**	0.152**	0.166**	0.153**
	(0.0711)	(0.0701)	(0.0687)	(0.0667)
Stocking rate	0.0413	0.0407	0.0437*	0.0363
	(0.0261)	(0.0258)	(0.0247)	(0.0221)
N/ha	0.000120**	0.000121**	0.000127**	0.000157***
	-0.00006	-0.00006	-0.00006	-0.00005
Concentrates/cow/100	-0.00801***	-0.00798***	-0.00811***	-0.00803***
	(0.00219)	(0.00218)	(0.00223)	(0.00219)
2008-2014 (T_3)	0.0416***	0.152**	0.121***	
	(0.00701)	(0.0603)	(0.0283)	
2015-2017 (T_3)	-0.0267**	0.103	0.0274	
	(0.0111)	(0.0746)	(0.0512)	
T_2 x ln(herd)		-0.0279*		
		(0.0153)		
T_3 x ln(herd)		-0.0325*		
		(0.0186)		
T_2 x ln(P)			-0.110***	
			(0.0367)	
T_3 x ln(P)			-0.0742	
			(0.0640)	
Farm FE	yes	yes	yes	yes
Year FE x ln(P)				yes
Year FE	no	no	no	yes
Constant	-0.153	-0.269*	-0.179	-0.294**
	(0.115)	(0.150)	(0.113)	(0.128)
Observations	5,639	5,639	5,639	5,639
R-squared	0.180	0.182	0.185	0.245
Number of ID	768	768	768	768

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

= quota period (2000-2007); T_2 = soft landing period (2008-2014) and T_3 = post quota period (2015-2017)) and scale (Model 2) and productivity (Model 3). We also estimate a model that includes year fixed effects and interactions with productivity (Model 4), as the previous models fail to account for annual changes such as prices, weather shocks, etc. Results in table 4 show models based on fixed-effects estimations with GHG emissions calculated with the IPCC methodology.[11]

The results in Model 1 indicate that GHG emission intensity changed significantly over time and GHG emission intensity is significantly lower in the post quota phase when compared to the quota period.

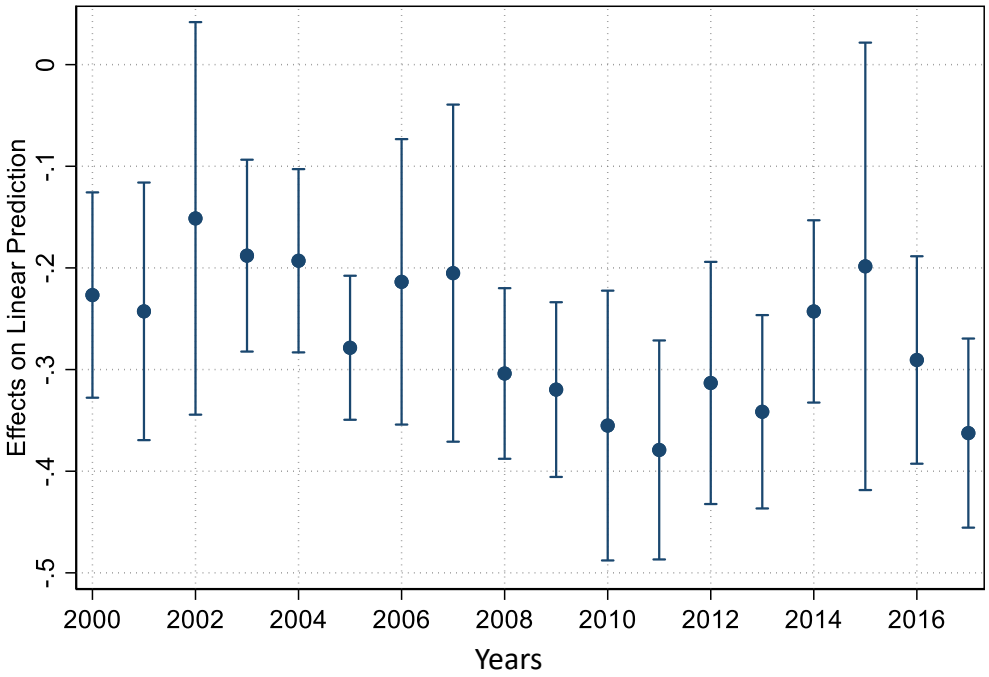
The results of Model 2 explore whether scale effects changed with quota abolition, however results indicate that the interaction terms are jointly not significant.

The results of Model 3 indicate that the impact of productivity on GHG emission intensity changed with different quota abolition periods. More specifically, a one percent increase in productivity is associated with a 0.21% decline in GHG emission intensity during the quota phase, while the role of productivity in reducing GHG emission intensity significantly increased during the soft landing phase when compared to the quota period.

In Model 4 we explore if the changing productivity effect remains when controlling for time fixed effects. Figure 3 shows the average marginal effect of productivity for each year and corresponding 95% confidence intervals. First, all coefficient estimates except for two years are statistically significant, but only two years (2011 and 2017) significantly differ from the base year (i.e. 2000). However, when inspecting the graph, a similar pattern to the results from Model 3 emerges, suggesting a stronger productivity effect during the soft landing phase than during the quota period.

[11] We also estimated dynamic panel data models, but model robustness tests did not provide satisfactory results. In fact, Roodman (2009) stresses the importance of including time dummies in Arellano-Bond models, which further supported our decision to employ fixed-effects methods in this instance. For comparison purposes, we also estimated Model 4 with fixed effects.

Figure 3: **Average marginal effect of productivity**



95% CIs included

Robustness Tests

We test for attrition bias in our sample by comparing results from the unbalanced sample to a balanced sample. However, balancing the data set reduces the sample size from 5,639 to 1,278 observations. This implies that we observe 71 farms over 18 years. In our comparison, we use fixed-effects methods, as an Arellano-Bond estimation strategy did not provide robust results due to the small sample size. Results are reported in Table 5. Model 1 represents the baseline model with year fixed effects, while Model 2 and 3 include interaction terms between the quota abolition phases and productivity and herd, respectively.

Overall, the association between productivity and GHG emission intensity remains statistically significant at similar magnitudes across all models. However, we do observe differences in relation to the scale effect. With balanced data, we do find a positive significant scale effect, which is in contrast to the non significant effect of scale reported in Model 1 in table 3 and table 4.

Considering Model 2 in table 5, the interaction terms between productivity and quota periods are statistically significant and the effect increases over time. In relation to the interaction between the scale effect and quota periods, results from Model 3 in table 5 also confirm the findings from our model with unbalanced data (see Model 2 in table 4) in the sense that the interaction terms are jointly non significant.

We then determine if our findings are also robust when using GHG emissions measured by the LCA methodology. As mentioned, due to data requirements, these measures are only available for a shorter time span, 2013 to 2017, which, however, still covers the major agricultural policy reform in 2015.

Table 6 depicts results from models estimated with fixed effects (FE) model and Arellano-Bond (AB) methods with LCA GHG emissions per kg FPCM. The results largely confirm the findings from the previously reported IPCC data models, see table 3. For example, the fixed-effects model reveals that a one percent increase in productivity is associated with a 0.34% reduction in GHG emissions, while herd size does not have a statistically significant effect. In this model, we find a positive and significant effect of concentrates per cow on GHG emission intensity. This indicates that when off-farm emissions are included in GHG emission calculation, the emission intensity reducing effect of increased concentrates reported in table 3 disappears.

The Arellano-Bond model also shows similar results to the IPCC model. More specifically, the lagged dependent variable is positive and statistically significant, with an estimated coefficient value of 0.16, suggesting that GHG emission intensity is largely contemporaneous. The contemporaneous effect of productivity is 0.38%, while we do not find a statistically significant effect of herd size. The hypothesis of no-second order correlation in the disturbances was not rejected at the 5% significance level as indicated by a p-value of 0.470 (see AR(2) at the bottom of table 6), but we can reject the null hypothesis of exogeneity of overall instruments with a p-value of 0.040 (see Hansen test statistics at the bottom of table 6), while C test statistics that specifically test for the orthogonality of TFP and herd size generate

Table 5: **Productivity and GHG emission intensity - balanced data**

GHG/kg milk	Model 1	Model 2	Model 3
ln P	-0.308***	-0.244***	-0.326***
	(0.0579)	(0.0546)	(0.0518)
ln herd	0.103**	0.0728	0.107**
	(0.0478)	(0.0440)	(0.0458)
Specialization	0.0226	-0.000224	0.0154
	(0.0987)	(0.100)	(0.0989)
Stocking rate	0.00485	0.0188	0.0167
	(0.0202)	(0.0189)	(0.0196)
N/ha	0.000105	0.00	0.000103
	(0.00)	(0.00)	(0.00)
Concentrates/Cow/100	-0.0132***	-0.0145***	-0.0136***
	(0.00198)	(0.00166)	(0.00158)
2008-2014 (T_2)		0.150***	0.154**
		(0.0440)	(0.0748)
2015-2017 (T_3)		0.106	0.160
		(0.0664)	(0.104)
ln(P) x T_2		-0.163***	
		(0.0606)	
ln(P) x T_3		-0.186**	
		(0.0778)	
ln(herd) x T_2			-0.0310*
			(0.0177)
ln(herd) x T_3			-0.0480**
			(0.0237)
Year FE	yes	no	no
Farm FE	yes	yes	yes
Constant	-0.433**	-0.301**	-0.397***
	(0.164)	(0.128)	(0.135)
Observations	1,278	1,278	1,278
R-squared	0.391	0.326	0.316
Number of ID	71	71	71

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

a p-value of 0.235. However, this suggests that the Arellano-Bond model does not provide a satisfactory fit for this shorter panel data set and the results should be interpreted with caution. Overall, the models based on LCA data confirm the same trends observed over a longer time span based on IPCC data. Importantly, it confirms the robustness of the inverse relationship between productivity and GHG emission intensities, especially as LCA data encompass more detailed measures of GHG emissions.

Table 6: **GHG emission intensity regression results 2013 - 2017 (LCA data)**

ln(GHG/FPCM)	Model 1 FE	Model 2 AB
ln(GHG/FPCM)		0.159**
		(0.0628)
ln(P)	-0.337***	-0.378***
	(0.0390)	(0.0593)
ln(herd)	0.00974	-0.0168
	(0.0539)	(0.0312)
Specialization	-0.452***	-0.613***
	(0.116)	(0.0812)
Stocking rate	-0.0391**	-0.0228
	(0.0164)	(0.0152)
N/ha	0.00062***	0.00042***
	(0.00)	(0.00)
Concentrates/Cow/100	0.00301**	-0.00082
	(0.00148)	(0.00137)
East region		0.0181
		(0.0168)
South-west region		-0.0118
		(0.0145)
Year FE	yes	no
Farm FE	yes	yes
Constant	0.597***	0.873***
	(0.191)	(0.133)
Observations	1,527	1,124
R-squared	0.553	
Number of ID	373	338
Instruments		45
AR(2)		0.47
Hansen		0.04
C test		0.235

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

Little is known about the specifics of how agricultural policy reforms, and resulting farm level adjustments, affect agricultural GHG emission intensities. The effects of policy induced changes may be smaller than in the manufacturing sector, because unlike in manufacturing, it is more difficult for farms to alter their emission intensities. Furthermore, the number of farms far exceeds the number of factories in any manufacturing sector, which makes it more difficult to implement emission policies for agriculture. To date, global efforts to reduce agricultural GHG emissions have been weak, and given decarbonisation progress in other sectors, agriculture may become the largest contributor to GHG emissions by 2050 (OECD, 2019).

This suggests the need for further empirical evidence, which this article provides by exploring the relationship between productivity, scale and GHG emission intensities and the role of EU milk quota abolition in this process. The Irish agricultural industry has responded to milk quota abolition by substantially expanding dairy production and exports, which led to increased GHG emissions as a by-product. Strong national growth targets for the dairy sector and simultaneous (conflicting) commitments to reduce GHG emissions raise concerns regarding policy coherence. This highlights the importance of exploring mitigation potential on farms.

We utilized farm-level panel data from Irish dairy farms, spanning 18 years from 2000 to 2017. This data includes detailed measures on farm-level GHG emissions based on the IPCC methodology. We complement this analysis with GHG emissions measured by the LCA methodology, which accounts for on- and off-farm emissions. In fact, this method also accounts for emissions arising from the production of major inputs, such as concentrates and fertilizer.

We assessed how quota abolition induced production changes relate to emission intensity per kg of milk. After estimating farm-level productivity with a Wooldridge-Levinsohn-Petrin GMM framework (Wooldridge, 2009), we employed fixed-effects and dynamic panel data

methods to explore the relationship between productivity, scale and GHG emission intensity and how this relationship varied over milk quota abolition phases.

Consistent with previous literature (e.g., Cui et al. (2016)), we find a negative relationship between productivity and GHG emission intensity. Specifically, our findings reveal that a one percent increase in productivity is associated with a decline in GHG emission intensity of at least 0.26%. While we do not find a clear relationship between farm scale and GHG emission intensity directly, our findings reveal that the association between productivity and GHG emission intensity increases with scale. Our results also suggest that distinct milk quota abolition phases altered the association between productivity and GHG emission intensity. In addition, our findings of the inverse relationship between productivity and GHG emission intensity are robust to different GHG measurement techniques (i.e. IPCC versus LCA method).

Despite limited mitigation potential of the agricultural sector, our graphical analysis of sector level GHG emissions (see figure 1) indicates that a combined composition and technique effect reduced emissions per farm by over 30% over an 18 year period. However, farmers still often fail to realise the full mitigation potential of their farm. Therefore, more could be done to reduce GHG emissions from agriculture. Our findings suggest that further reduction in GHG emission intensity can be achieved by increasing productivity. This is in line with Baker et al. (2013) and Jones and Sands (2013) who claim that increasing productivity is an important source of mitigation. However, this may need to be complemented with further measures to directly reduce GHG emissions (Guerrero and Nakagawa, 2019).

The implications of this article are also relevant for understanding, and possibly reducing, environmental effects that Brexit and impending trade deals (e.g., with Mercosur) may have on the Irish agricultural sector, as it is likely that impending changes in international trade will further support dairy production, mainly due to substitution between dairy and beef cattle. The average Irish dairy farm emitted 3.6 times more GHG emissions than the average cattle or sheep farm in 2017, due to differences in production intensity (Buckley et al., 2019).

Thus, further reducing GHG emission intensities on dairy farms will remain an important consideration.

Finally, this article is one of the first studies focusing on the relationship between productivity, agricultural policy reform and GHG emission intensity in the agricultural sector using micro-level data. We show that reductions in GHG emission intensity are possible by adjusting production methods. However, whether or not this will lead to lower absolute GHG emissions from the agricultural sector requires a macro perspective, which is worth further investigation.

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Appendix

Output and Input Aggregation

As output measure, we used sales values of dairy production (i.e. milk, calves and cull cows), beef, sheep and crop production. Aggregated total sales value is converted in an implicit quantity measure by deflating it by a farm-specific Törnqvist price index, following the method outlined in Newman and Matthews (2007).

As individual prices are not reported, we use price indices from the Irish Central Statistics Office. The Törnqvist price index is calculated as follows:

$$lnr_{it} = \sum_{m=1}^{M} 0.5(s_{mit} + \bar{s}_{mb})(lnr_{mt} - lnr_{mb}). \tag{7}$$

s_{mit} is the share in output m of the overall farm output on farm i in year t, $\bar{s}_{mb}$ is the average share of output m in the base year b (2015), r_{mt} is the price of output m in year t and r_{mb} is the price of output m in the base year b (Newman and Matthews, 2007). We applied the same method to deflate intermediate inputs.

Production Function Estimates

We compare four different production functions, presented in table A1. All models are based on a WLP GMM estimation method. Model 1 and Model 3 follow the 'normal' Levinsohn Petrin (Levinsohn and Petrin, 2003) specification and use intermediates as proxy variable. Model 2 and 4 test a different specification and use concentrate feeds as proxy variable, following Frick and Sauer (2018).

Farm output in Model 1 and 2 is based on the sum of sales values deflated by the respective price index. Farm output in Model 3 and 4 is based on the Törnqvist index method described previously[12]. Estimated elasticities across all models are similar, except that land is not significant in Model 4.

[12]Model 3 is presented in table 2.

Table A1: **Production function estimates**

Output	Model 1	Model 2	Model 3	Model 4
Intermediates (M)	0.539***		0.603***	
	(0.110)		(0.108)	
Concentrates (F)		0.255***		0.139***
		(0.0499)		(0.0497)
Variable inputs (M-F)		0.417***		0.609***
		(0.0280)		(0.0350)
Labour	-0.0141	-0.0323	-0.0128	-0.0340
	(0.0246)	(0.0242)	(0.0245)	(0.0241)
Capital (K)	0.0490***	0.0542***	0.0521***	0.0367***
	(0.0133)	(0.0131)	(0.0133)	(0.0128)
Land	0.0642***	0.0660***	0.0556**	0.0299
	(0.0242)	(0.0238)	(0.0241)	(0.0235)
Livestock Units	0.327***	0.323***	0.298***	0.320***
	(0.0301)	(0.0294)	(0.0303)	(0.0268)
K_{t-1}	-3.446**	-1.739**	-2.166	-1.469*
	(1.639)	(0.770)	(1.637)	(0.757)
K^2_{t-1}	-0.242**	0.0577	-0.156	0.0412
	(0.101)	(0.0604)	(0.102)	(0.0564)
K^3_{t-1}	-0.0114**	-0.00322	-0.0100**	-0.00326
	(0.00488)	(0.00361)	(0.00488)	(0.00350)
$M_{t-1}(F_{t-1})$	0.410	-0.720	-0.747	-0.491
	(2.909)	(0.760)	(2.886)	(0.783)
$M^2_{t-1}(F^2_{t-1})$	-0.541	-0.0535	-0.237	-0.0628
	(0.437)	(0.120)	(0.432)	(0.123)
$M^3_{t-1}(F^3_{t-1})$	0.0497**	0.00850	0.0308	0.00823
	(0.0222)	(0.00885)	(0.0222)	(0.00856)
$K_{t-1}xM_{t-1}(F_{t-1})$	1.089***	0.230	0.689	0.210
	(0.418)	(0.159)	(0.419)	(0.153)
$K^2_{t-1}xM_{t-1}(F_{t-1})$	0.0562***	0.00533	0.0446**	0.00664
	(0.0190)	(0.0123)	(0.0192)	(0.0120)
$K_{t-1}xM^2_{t-1}(F^2_{t-1})$	-0.105***	-0.0183	-0.0751**	-0.0181
	(0.0326)	(0.0169)	(0.0329)	(0.0161)
Constant	10.91	9.045***	10.20	6.580*
	(7.293)	(3.433)	(7.384)	(3.389)
Observations	3,958	3,958	3,958	3,958
R-squared	0.918	0.911	0.920	0.915

All variables are in log values
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: **Summary statistics of sample (pooled over 2000-2017)**

Variable	Obs	Mean	Std. Dev.	Min	Max
Output (€)[1]	5,643	151,006.50	99,910.44	5,203.99	747,259.90
Intermediate inputs (€)[1]	5,643	93,273.12	69,415.61	3,469.14	649,516.2
Concentrates (€)[1]	5,643	22,149.73	20,663.92	88.88	181,322
Miscellaneous inputs (€)[1]	5,643	70,174.8	52,718.81	2,925.33	462,760.60
Labour units	5,643	1.660	0.69	0.01	6.93
Capital(€)[1]	5,643	143,021.7	122,552.9	476.84	932,486.3
Livestock Units (LU) (€)[1]	5,643	121,707.30	81,863.22	3,367.02	1,086,178
Land (ha)	5,643	57.08	30.90	3.70	281.40
GHG IPCC (kg GHG/kg milk)	5,639	0.80	0.17	0.18	4.19
GHG LCA (kg GHG/kg FPCM)	1,527	1.21	0.23	0.61	2.58
Dairy herd size (# of dairy cows)	5,643	64.39	37.79	3.50	308.75
Specialization (dairy cows/LU)	5,643	0.62	0.12	0.33	1.00
Stocking rate (LU/ha)	5,643	1.88	0.51	0.40	7.45
N/ha (kg)	5,643	176.39	77.22	0.00	642.16
Concentrates fed/ cow (kg)	5,643	931.49	471.10	0.00	5,626.13
East region	5,643	0.17		0.00	1.00
South west region	5,643	0.66		0.00	1.00
North west region	5,643	0.16		0.00	1.00

Notes: 1 indicates deflated values.