The role of extension services and technology adoption in farm sustainability

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Declaration of work

I, Lorraine Balaine, certify that this thesis has not been submitted as an exercise for a degree at this or any other university. All research contained herewith is entirely my own and the use of materials from other sources has been properly and fully acknowledged.

Signature

12 / 02 / 2021

Date

Abstract

The objective of this PhD thesis is to assess the role of extension services and technology adoption in enhancing farm sustainability with the goal of informing the debate on how to achieve sustainable intensification. Based on Irish farm-level data, the thesis presents three separate analyses embodied in the technology adoption and extension literature.

The first analysis explores the potential of a farm technology, i.e., milk recording, in simultaneously enhancing the economic, environmental, and social dimensions of farm sustainability. Using propensity score matching and robustness checks, the findings reveal that milk recording can lead to economic and social benefits. Conversely, milk recording does not impact farm environmental sustainability.

The second analysis examines pathways between extension participation, farm management, and economic and environmental sustainability. Farm management is represented by grassland management and reproductive efficiency. Seemingly unrelated regressions models and treatment-effects bounds are estimated to achieve partial identification. The results show that extension has a positive impact on reproductive efficiency but does not affect grassland management. Improving extension effectiveness on these components of dairy management could result in economic gains, while the effect on environmental sustainability is mixed.

The third analysis compares farmer cohorts engaging or not with mixed public-private and private extension services. Differences in farm and farmers' characteristics are analysed with a mixed logit model, while farm economic and environmental sustainability is compared based on linear regression models. The findings show that farm size, dairy specialisation, and farm management vary across cohorts. Extension is associated with higher economic performance but does not affect environmental sustainability. No significant differences are found between mixed public-private and private extension participants for both sustainability dimensions.

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List of abbreviations and acronyms

ATT	Average Treatment Effect on the Treated
BTSCC	Bulk Tank Somatic Cell Count
CO_2e	Carbon Dioxide Equivalent
DEP	Dairy Efficiency Programme
EU	European Union
FE	Fixed Effects
FGLS	Feasible Generalised Least Squares
FPCM	Fat-Protein-Corrected-Milk
GHG	Greenhouse Gas
GMM	Generalised Method of Moments
ha	Hectares
IIA	Independence of Irrelevant Alternatives
IPW	Inverse-Probability Weighting
IPWRA	Inverse-Probability-Weighted Regression Adjustment
kg	Kilograms
KTP	Knowledge Transfer Programme
LCA	Life Cycle Assessment
NN	Nearest-Neighbour
NNM	Nearest-Neighbour Matching
OLS	Ordinary Least Squares
POM	Potential Outcome Mean
PSM	Propensity Score Matching
RA	Regression Adjustment
SCC	Somatic Cell Count
SUR	Seemingly Unrelated Regressions
Teagasc NFS	Teagasc National Farm Survey
VIF	Variance Inflation Factor
3SLS	Three-Stage Least Squares

Chapter 1 - Introduction

1.1. Context of the thesis

In 1987, the Brundtland report defined sustainable development as an "economically viable, environmentally sound and socially acceptable development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (United Nations, 1987). Even though sustainability was not a new concept, this definition marked a significant milestone and led to a general consensus over the three-dimensionality of sustainability, i.e., economic, environmental, and social (Dillon et al., 2016a; Firbank et al., 2018; Franks, 2014; Pretty et al., 2010). However, even over thirty years after the Brundtland report, the interpretation and resulting operational content of sustainability still remain a subject of debate (Firbank et al., 2018; Franks, 2014; Hediger, 1999; Pretty, 2018). In fact, different conceptions can be found throughout the literature and are best described as lying on a spectrum from "weak" to "strong" sustainability (Ang and Passel, 2012; Dietz and Neumayer, 2007; Hediger, 2006, 1999). The former is routed within economic principles of neoclassical capital theory, which assume substitutability of different capital forms, notably human-made and natural capitals. Consequently, weak sustainability implies that changes in environmental quality can be traded off against changes in economic richness as long as the total stock of aggregated capital is maintained constant over time. The latter is founded upon principles of environmental conservation and considers that natural capital cannot be substituted. As the loss of some natural resources is irreversible, strong sustainability suggests that a certain level of environmental assets should remain untouched or be restored over time.

While the viewpoints of weak and strong sustainability are theoretically separated, some argue that they are equally crucial for guiding management rules (Hediger, 2006, 1999). That is because trade-offs across sustainability dimensions are inevitable, but the overall integrity of ecosystems must be protected to satisfy basic human needs both at present and in the future. A field in which such considerations are very pertinent is agricultural production. Indeed, as the world population continues to grow, strategies must be found to increase food supply (Firbank et al., 2018; Garnett et al., 2013; Godfray et al., 2010; United Nations, 2017). Nonetheless, there is limited scope to expand agricultural land without cultivating currently natural regions (Godfray et al., 2010; Licker et al., 2010). Additionally, pressure on agricultural land is increasing due to rapid urbanisation at a global scale (García-Nieto et al., 2018; Godfray et al., 2010; Wang, 2019). A potential solution is to improve yields on existing production areas (Franks, 2014; Garnett et al., 2013; Licker et al., 2010). Productivity growth must however be achieved without causing further damage to natural resources and in a socially acceptable manner (Franks, 2014; Garnett et al., 2013). This is particularly challenging as agricultural intensification has so far been accompanied by considerable harm to the environment and conflicts regarding animal welfare and food supply governance (Bernard and Lux, 2016; Dawkins, 2017; Pretty, 2018).

The concept of “sustainable intensification” emerged in the late 1990s to reconcile the need for agricultural productivity growth and greater sustainability (Petersen and Snapp, 2015). Ever since, it has drawn significant policy and research attention, notably in the past decade (Council of the European Union, 2014; Department of Agriculture Food and the Marine, 2015; Food and Agricultural Organization of the United Nations, 2020a; Pretty, 2018; Struik and Kuijper, 2017). Sustainable intensification is centred around the idea that more food can be produced given a fixed, or declining, input base by making better use of natural and human resources (e.g., land, water, knowledge) and new technologies (Barnes et al., 2016; Franks, 2014; Godfray, 2015; Pretty, 2018). In this way, agricultural production could be increased by enhancing system efficiency and without cultivating more land, thus incurring no additional environmental cost or even restoring damaged ecosystem services (Pretty, 2018). At farm level, achieving sustainable intensification requires innovation and specifically the adoption of new, efficiency-focused management strategies and technologies (Petersen and Snapp, 2015; Pretty, 2018; Salois, 2015).

Sustainable intensification can “be distinguished from earlier manifestations of intensification because of the explicit emphasis on a wider set of environmental as well as socially progressive outcomes” (Pretty, 2018, p. 1). In other words, it involves a shift from the predominant intensification paradigm, which mainly supported weak sustainability conceptions. By standing as an explicit call for treating the three sustainability dimensions, i.e., economic, environmental, and social, with equal attention, the sustainable intensification strategy encourages greater incorporation of the strong sustainability viewpoint in agricultural production.

Despite being a promising approach, concerns have been raised about the use of sustainable intensification as a policy goal and as a guide for improved agricultural sustainability (Garnett et al., 2013; Godfray, 2015; Petersen and Snapp, 2015; Struik and Kuijper, 2017). The main issue lies in the vague nature of the term, which, for some, represents a contradiction in itself (Garnett et al., 2013; Godfray, 2015; Petersen and Snapp, 2015). Its interpretation tends to be too narrowly focused on production, thereby failing to engage with biological processes that can support environmental friendly production systems (Garnett et al., 2013; Petersen and Snapp, 2015; Struik and Kuijper, 2017). In some cases, sustainable intensification has been “appropriated to support particular worldviews including doing nothing – business-as-usual” (Godfray, 2015, p. 200), with no significant departure from current agricultural practices (Petersen and Snapp, 2015). Hence, there exists some concern that sustainable intensification is used to justify intensification strategies, which accelerate the move towards high-input high-tech agriculture (Godfray, 2015). While agricultural intensification can lead to a decrease in environmental costs per input base or output unit, its effect on absolute measures of environmental performance is less evident (Crosson et al., 2011; O’Brien et al., 2012; Salou et al., 2017). That is because environmental improvements can only be achieved if high levels of input application are avoided and the absolute environmental cost associated with the intensification process is offset by greater efficiency (Crosson et al., 2011). Moreover, it is important to recognise that enhanced efficiency can provide incentives to further increase production scale, thereby outweighing potential environmental benefits or even resulting in unintended deterioration as a ‘rebound’ effect (Alcott, 2005; Barnes et al., 2019).

Therefore, the pursuit of sustainable intensification is a twofold challenge of encouraging a shift towards more efficient farming practices and ensuring that adopted changes are indeed sustainability enhancing.

The first point relates to a ‘classical’ technology adoption problem, which has been widely explored in the literature (Foster and Rosenzweig, 2010; Macours, 2019; Pannell et al., 2006; Pannell and Zilberman, 2020; Rogers, 1995; Takahashi et al., 2020). At policy level, technological change has been traditionally fostered through the provision of extension services (Anderson and Feder, 2004; Birkhaeuser et al., 1991; Feder et al., 2011; Norton and Alwang, 2020; Takahashi et al., 2020). A large body of research has focused on the determinants of technology uptake and the diffusion process (Kuehne et al., 2017; Montes de Oca Munguia and Llewellyn, 2020; Pannell et al., 2006; Weersink and Fulton, 2020), as well as the impact of extension participation on productive and economic outcomes at the farm level (Davis et al., 2012; Läpple et al., 2020; Nakano et al., 2018a; Pan et al., 2018). Stemming from the recognition that seemingly profitable technologies are not always adopted and that extension services sometimes have a limited effect, research priorities have evolved over the years (Feder et al., 2011; Klerkx, 2020; Pannell and Zilberman, 2020; Takahashi et al., 2020). Issues that deserve further attention include, among others, more detailed evaluations of technology impacts and the search for more effective extension systems, notably through improved public and private sector coordination (Feder et al., 2011; Norton and Alwang, 2020; Takahashi et al., 2020).

Regarding the second point about sustainability-enhancing changes, the empirical literature has so far provided insufficient information as to which technologies can help farmers to achieve productivity growth in a sustainable manner (Petersen and Snapp, 2015). While potential sustainability benefits of new technologies or extension programmes are extensively discussed in the literature, sustainability claims are seldom verified (Balafoutis et al., 2017; Lovarelli et al., 2020; Norton and Alwang, 2020; Tullo et al., 2019). Lack of supporting empirical evidence tends to make the sustainable intensification strategy less credible as new technologies can be fostered based on the false pretence that they will enhance farm sustainability (Godfray, 2015; Pretty, 2018). As not all farming practices are equally suited to achieve greater sustainability, rigorous empirical assessments are needed across several aspects of farm sustainability (Fumagalli et al., 2012; Latruffe et al., 2016). In this way, technologies that resolve trade-offs across sustainability dimensions while increasing production levels could be identified before encouraging their widespread uptake. This would inform the development of extension programmes which focus on farming practices with proven sustainability benefits, thereby contributing to both productivity growth and enhanced farm sustainability.

Within this context, this PhD thesis aims at assessing the role of extension services and technology adoption in enhancing farm sustainability and at informing the debate on how to achieve sustainable intensification. Specifically, it examines the suitability of farm technologies and management strategies in enhancing several aspects of farm sustainability. It further explores the mechanism through which extension participation affects farm sustainability by gaining insights into the link between extension, farm management, and sustainability performance. Finally, it investigates how public and private sectors can coordinate to effectively deliver extension services that enhance farm sustainability outcomes.

The thesis uses original evidence from dairy farms in the Republic of Ireland (hereafter referred to as Ireland). The Irish dairy sector is currently undergoing major changes following the removal of European Union (EU) milk quotas in 2015 (Donnellan et al., 2018; European Commission, 2015). With governmental support, Irish milk production increased by about 53% between 2008 and 2018 and further growth is expected (Department of Agriculture Food and the Marine, 2015, 2010a; Eurostat, 2020a; Kelly et al., 2020). Despite positive economic outcomes, increased reliance on external inputs and significant expansion of the national dairy herd raise sustainability concerns (Buckley and Donnellan, 2020; Donnellan et al., 2018; Duffy et al., 2019; Hoekstra et al., 2020). They also challenge the achievement of environmental commitments that Ireland has undertaken under EU and international agreements (Environmental Protection Agency, 2019a; European Commission, 2019a, 2014, 2010). Thus, addressing sustainability issues and reaching sustainable intensification is key to the successful development of the Irish dairy industry (Department of Agriculture Food and the Marine, 2015; Kelly et al., 2020). Accordingly, the Irish government has aligned agri-development goals with a dynamic extension environment, whereby services are commonly delivered in a participatory manner under the form of farmers' discussion groups (Department of Agriculture Food and the Marine, 2020, 2010b; Läpple et al., 2020; Teagasc, 2015). Farm-level efforts to increase milk production while reducing adverse environmental effects are encouraged (Department of Agriculture Food and the Marine, 2020; Lanigan et al., 2018; Teagasc, 2015).

1.2. Main research objectives

The overall goal of this PhD thesis is to evaluate the role of extension services and technology adoption in enhancing farm sustainability and to inform the debate on how to achieve sustainable intensification. More precisely, the thesis is divided into three empirical chapters, which address the following research objectives:

1. **Explore the potential of technology adoption to simultaneously enhance the economic, environmental, and social dimensions of farm sustainability (Chapter 4);**
2. **Examine pathways between extension participation, farm management, and farm economic and environmental sustainability (Chapter 5); and**

3. **Compare farmers participating in mixed public-private and private extension across farm economic and environmental sustainability performances (Chapter 6).**

1.3. Description of the dataset

Incorporating farm sustainability outcomes into an examination of extension and technology impacts is not an easy task. In contrast to economic sustainability, defining and measuring environmental and social sustainability is complex (Latruffe et al., 2016; Lebacq et al., 2013; Lynch et al., 2019). The literature tends to be skewed towards the economic dimension of farm sustainability, in part due to the lack of data across the environmental and social dimensions (Lebacq et al., 2013). The breadth and detail of data required for thorough farm sustainability assessments present a critical challenge for survey design and implementation (Lynch et al., 2019). This issue is reinforced by the need for comprehensive information about farmers' adoption and extension behaviours, preferably over time, which is scarce in itself (Anderson and Feder, 2004; Mullally and Maffioli, 2015; Pannell and Claassen, 2020).

In this PhD thesis, data challenges are addressed by using the Teagasc National Farm Survey (NFS) dataset. The Teagasc NFS is a rich and original enhancement of the farm-level data recorded for EU Farm Accountancy Data Network purposes (Dillon et al., 2016a) and has five main objectives (Teagasc, 2017). First, in the frame of the Farm Accountancy Data Network, the Teagasc NFS fulfils Ireland's statutory obligation as an EU Member State to provide the European Commission with financial and technical data related to agriculture[1]. Second, the Teagasc NFS data is exploited to determine the financial situation of Irish farms, notably by measuring the level of gross output, input costs, family farm income, investments, and

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[1] The Farm Accountancy Data Network is a European system of sample surveys, which aims at monitoring the income and business activities of agricultural holdings and evaluating the impact of EU agricultural policies across Member States (Council of the European Union, 2009; European Commission, 2018).

liabilities (e.g., Buckley et al., 2020; Donnellan et al., 2020). Third, the survey allows for the assessment of current levels and trends in the performance of Irish farms across the three sustainability dimensions (i.e., economic, environmental, and social) (e.g., Buckley and Donnellan, 2020). Fourth, the Teagasc NFS is used to develop figures about returns, costs, and performance occurring in farming, which are used by farm advisors and farmers in planning business activities. Finally, the survey collates a detailed farm-level dataset for research and policy analysis that includes farming practices and extension participation behaviours.

The Teagasc NFS is carried out annually on a nationally representative sample of approximately 900 Irish farms, which participate on a voluntary basis. The selection plan for the data collection is developed in conjunction with the Irish Central Statistics Office. More specifically, it is based on the most recent national farm-level data from the EU Agricultural Census (carried out every 10 years) or the Farm Structure Survey (carried out between censuses), for which the Central Statistics Office is responsible (Central Statistics Office, 2018; European Commission, 2018). These national surveys dictate the number of farms to be selected by region, type of farming system, and economic-size class for the Teagasc NFS. Farm economic size is measured by their standard output, defined as the average monetary value of the agricultural output at farm-gate prices[2] (Central Statistics Office, 2020a). The collected data is then weighted by the Central Statistics Office to ensure national representativeness[3].

The method of farm classification into farming systems is based on the EU farm typology, which was set out in Commission Decision 78/463 and its

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[2] Standard output is not a measure of farm income, as it does not take into account costs, direct payments (such as the Single Farm Payment), value added tax, or taxes on products (Central Statistics Office, 2020a). It can be estimated by farming enterprise within the same farm.

[3] It should be noted that only farms with a standard output of €8,000 or more are included in the sample (i.e., equivalent to 6 dairy cows, 6 hectares of wheat, or 14 suckler cows). A separate survey is conducted on small farms, which are only cattle and sheep farms (Dillon et al., 2017). Moreover, pig and poultry farms are not included in the Teagasc NFS because of the small number of Irish farms in these systems (Teagasc, 2017).

subsequent amendments (Donnellan et al., 2020; European Commission, 1978). Irish farms are classified into six farming systems (i.e., dairy, cattle rearing, cattle other, sheep, arable, or mixed livestock) according to their main source of gross output. The title thus refers to the dominant enterprise in terms of economic size. For the purpose of this PhD thesis, only the dairy subsample is used, which encompasses specialist dairy farms, and arable and mixed livestock farms with a dairy enterprise.

1.4. Structure of the thesis

The main body of the thesis consists of the three empirical chapters (Chapter 4, Chapter 5, and Chapter 6). These are preceded by two other chapters, in addition to the present introduction.

Chapter 2 contains a literature review to identify the gaps addressed in the thesis. First, the chapter gives an overview of the determinants of technology adoption. Second, more detail is provided on the role of extension services in improving technology adoption and farm performance. Third, the place of sustainability in the technology adoption and extension literature is explored. The chapter ends with a summary highlighting the contributions of this PhD thesis to the literature.

Chapter 3 introduces the Irish context in greater detail. First, changes in the Irish dairy sector are contrasted with other EU counterparts preceding and following EU milk quota removal. Second, this is followed by a thorough description of dairy farming within Irish agriculture. Third, a selected number of sustainability challenges associated with dairy farming is reported, with a specific focus on Greenhouse Gas (GHG) emissions and water quality concerns. Fourth, an overview of Irish extension services is provided. The chapter finishes with a summary, which emphasises the contributions of this PhD thesis to the debate of how to achieve sustainable intensification on Irish dairy farms.

Chapter 4 explores the ‘win-win-win’ potential of a farm technology, i.e., milk recording, to simultaneously enhance the economic, environmental, and social dimensions of farm sustainability. To do so, it estimates the impact of milk recording adoption on a selected set of farm sustainability indicators. Relevant literature on the impact of new technologies on sustainability outcomes is reviewed. A background section presenting the Irish context and the technology is then provided. The methodology is outlined by detailing how the impact evaluation problem is resolved in this chapter (i.e., Propensity Score Matching (PSM)). A presentation of outcome variables and the data is provided, along with some descriptive statistics. Estimation results and the discussion are then reported, followed by the conclusions and policy implications.

Chapter 5 examines pathways between extension participation, farm management, and economic and environmental sustainability. More specifically, the impact of extension on specific farm management indicators is examined, followed by an estimation of their impact on farm sustainability. A contextual background section detailing hypothesised management pathways between extension and farm sustainability performance is reported. The regression framework and econometric strategy are explained in a section that includes a description of the Fixed Effects (FE) Seemingly Unrelated Regressions (SUR) models and the partial identification strategy estimated in this chapter. The data and some descriptive statistics are then presented. Finally, estimation results and the discussion are reported, followed by concluding remarks.

Chapter 6 compares three farmer cohorts, i.e., farmers engaged with mixed public-private extension, farmers involved in private extension, and non-participants, in two ways. Differences in their farm and farmers' characteristics are explored, as well as disparities across farm economic and environmental sustainability performances. This chapter initially provides a background section on the different types of extension service provision. The methodology is then outlined, including a data description and a focus on non-linear and linear regression models implemented in the chapter. The results and discussion are provided next, while the chapter ends with conclusions and policy implications.

The final chapter (Chapter 7) contains the conclusion, which incorporates the main findings of this PhD thesis, the recommendations for policy making and future research, as well as some limitations of the thesis.

1.5. Thesis outputs

There has been a number of outputs to date from the research undertaken for this PhD thesis. The analysis presented in Chapter 4 was published in *Land Use Policy*. The studies presented in Chapter 5 and Chapter 6 are due to be submitted to agricultural economics journals in the coming months. The PhD research was also presented at various conferences and seminars (both internationally and domestically).

More detail on the outputs is listed below.

1.5.1. Journal article

Balaine, L., Dillon, E.J., Läpple, D., Lynch, J., 2020. Can technology help achieve sustainable intensification? Evidence from milk recording on Irish dairy farms. *Land Use Policy* 92, 104437. https://doi.org/10.1016/j.landusepol.2019.104437

1.5.2. Working papers

Balaine, L., Läpple, D., Dillon, E.J., Buckley, C., 2020. Extension and management pathways for enhanced farm sustainability: Evidence from Irish dairy farms.

Balaine, L., Buckley, C., Dillon, E.J., 2020. Mixed public-private and private extension systems: A comparative analysis using farm-level data from Ireland.

1.5.3. Conference and seminar presentations

Balaine, L., Dillon, E.J., Läpple, D., Lynch, J., 2020. Can technology help achieve sustainable intensification? Evidence from milk recording on Irish dairy farms – Presented at:

- Agricultural Economics Society annual conference, April 2018 in Warwick, United Kingdom; and
- 166th European Association of Agricultural Economists seminar on sustainability in the agri-food sector, August 2018 in Galway, Ireland.

Balaine, L., Läpple, D., Dillon, E.J., Buckley, C., 2020. Extension and management pathways for enhanced farm sustainability: Evidence from Irish dairy farms. – Presented at:

- Brownbag seminar of the Department of Agricultural Economics at Mississippi State University, December 2018 in Starkville, MS, United States of America;
- Agricultural Economics Society annual conference, April 2019 in Warwick, United Kingdom;
- Irish Postgraduate and Early Career Economics workshop, June 2019 in Galway, Ireland;
- Brownbag seminar of the Teagasc Rural Economy and Development Programme, October 2019 in Athenry, Co. Galway, Ireland; and
- Brownbag seminar of the Department of Economics at the National University of Ireland Galway, November 2019 in Galway, Ireland.
- This working paper is accepted for the XVI European Association of Agricultural Economists congress in Prague, Czech Republic, which is postponed to July 2021. It was also accepted for the Agricultural & Applied Economics Association annual meeting in Kansas City, MO, United States of America in August 2020, which was not attended due to COVID-19.

Balaine, L., Läpple, D., Buckley, C., Dillon, E.J., 2020. Identifying and understanding heterogeneity in the effectiveness of peer-to-peer extension: Evidence from Irish farmers' discussion groups – Accepted for the Agricultural Economics Society annual conference in Leuven, Belgium in April 2020, which was cancelled.

1.5.4. Outreach article

Balaine, L., Dillon, E.J., Läpple, D., 2019. Milk recording – a winning formula for dairy farmers. *TResearch* 14(1), 32-33. URL https://www.teagasc.ie/media/website/publications/2019/TResearch_Spring2019_MilkRecording_p32-33_proof.pdf

Chapter 2 - Literature review

2.1. Introduction

Technology adoption has been a longstanding theme in the economics literature. Theories of macroeconomic development explain disparities in per-capita income and growth across countries through differences in technological progress (Comin and Hobijn, 2004; Mowery and Rosenberg, 1991; Romer, 1990; Solow, 1956). Therefore, technological diffusion can be an important means of spurring economic development. However, new technologies can only contribute to macroeconomic development if they are adopted by individual firms (Hall and Khan, 2003; Parente, 1994). In other words, technological progress and subsequent economic growth relies on the decisions of individual agents to adopt new technologies.

Consistent with the promises of aggregate economic growth, a large body of literature focuses on adoption processes of individual firms, with agriculture being a prominent field of analysis (Feder et al., 1985; Foster and Rosenzweig, 2010; Takahashi et al., 2020). While initially the reasons for understanding farm-level technology adoption were to address issues of low economic returns and productivity, the literature increasingly recognises the potential role of new technologies in achieving greater sustainability in agricultural production (Pannell and Claassen, 2020; Weersink and Fulton, 2020).

Within this context, a good understanding of farmers' adoption behaviours is essential to design and implement policies that can accelerate the diffusion of new technologies, and hence increase farm productivity and/or achieve greater sustainability (Pannell and Claassen, 2020). Identifying potential constraints to adoption can help develop effective extension models.

Even though it has been stated in the literature that technology adoption and extension participation can contribute towards sustainable agricultural development, empirical evidence is missing regarding their impact on the three sustainability dimensions (i.e., economic, environmental, and social). Thorough sustainability impact assessments can have important public policy implications, as financial support can be justified if technology and extension provide immediate economic benefits to farmers, as well as wider sustainability enhancements (Barnes et al., 2019). The main goal of the current PhD thesis is thus to address this literature gap by incorporating a wide range of farm sustainability outcomes into the analysis of technology and extension impacts.

This chapter is divided into four main sections. The first section (2.2) gives an overview of the determinants of technology adoption. The second section (2.3) describes literature on the role of extension services in fostering technology adoption and improving farm performance. The third section (2.4) focuses on efforts to incorporate the three dimensions of farm sustainability into the technology adoption and extension literature. Finally, the fourth section (2.5) provides a summary and highlights the research direction for this PhD thesis.

2.2. Determinants of technology adoption

The technology adoption literature has been concerned with the understanding of farmers' adoption behaviours for decades, with the purpose of informing public policies to foster productivity growth and/or greater sustainability in agricultural production (Feder et al., 1985; Foster and Rosenzweig, 2010; Pannell and Claassen, 2020; Pannell and Zilberman, 2020). Designing and implementing effective policies to encourage farm-level technology uptake raises the fundamental question of why farmers choose to adopt certain technologies in the first place (Pannell and Zilberman, 2020).

"Innovations are adopted because they generate some perceived benefits" (Chavas and Nauges, 2020, p. 42). However, what is perceived as a benefit may vary across farmers, situations, and time (Chavas and Nauges, 2020; Pannell et al., 2006; Weersink and Fulton, 2020). Therefore, "landholder adoption […] depends on their expectation that it will allow them to better achieve their goals. If the landholder does not perceive that goals are likely to be met, adoption will certainly not follow" (Pannell et al., 2006, p. 1408).

While some point out the "widely observed puzzling phenomenon […] [of] the low adoption rate of seemingly profitable technology" (Takahashi et al., 2020, p. 31), others highlight the heterogeneity in farmers' objectives and the importance of assessing new technologies against them (Pannell et al., 2006; Weersink and Fulton, 2020). Objectives can vary due to circumstances, culture, and personal preferences and may include economic, social, and environmental outcomes (Pannell et al., 2006; Vanclay, 2004; Weersink and Fulton, 2020). More specifically, considerations of "(i) material wealth and financial security; (ii) environmental protection and enhancement (beyond that related to personal financial gain); (iii) social approval and acceptance; and (v) balance of work and lifestyle" (Pannell et al., 2006, p. 1410) may play an important role in adoption decisions, thereby partially explaining the "nonadoption of profitable innovations and the adoption of unprofitable ones" (Weersink and Fulton, 2020, p. 74).

Since adoption is led by farmers' personal goals and the technology's anticipated outcomes, it "is based on subjective perceptions or expectations rather than an objective truth" (Pannell et al., 2006, p. 1408). That is because "by definition, a new technology is not fully known or understood ahead of time. Thus, the perceived benefits of an innovation depend on the information available to each decision maker" (Chavas and Nauges, 2020, p. 42). Chavas & Nauges (2020) highlight that farmers face uncertainty about the suitability and relevance of the technology for the specific conditions under which they operate, as well as how best to use it. The authors also explain that there may be uncertainty about the technology's future returns and its variability in returns. Consequently, learning about the new technology can reduce uncertainty (Chavas and Nauges, 2020) and "alter [its] net returns and thus the timing and extent of adoption (and whether it should occur at all)" (Weersink and Fulton, 2020, p. 69).

Within this context, exploring factors that can influence the timing of, extent of, or returns to adoption is an important task to better understand farmers' adoption behaviours. In the literature, several authors have emphasised the lack of convergence on the determinants of adoption (Montes de Oca Munguia and Llewellyn, 2020; Weersink and Fulton, 2020). This is likely due to the heterogeneity in farmers' profiles and farming conditions (Foster and Rosenzweig, 2010; Pannell and Zilberman, 2020), which means that "understanding adoption requires understanding the local situation" (Weersink and Fulton, 2020, p. 71). Nevertheless, the literature has identified a range of factors, whose effect may vary depending on the situation, but that are likely to play a role. These can be divided into three categories, i.e., farm and farmers' traits, the characteristics of the technology itself, and the institutional context (Montes de Oca Munguia and Llewellyn, 2020; Pannell et al., 2006; Weersink and Fulton, 2020). These will be further described hereafter in this section.

2.2.1. Farm and farmers' characteristics

In terms of farm characteristics[4], farm size, adoption, and returns tend to be positively correlated. Barham et al. (2004) found that farms with larger dairy herds were more likely to have adopted recombinant bovine somatotropin (a growth hormone) in Wisconsin, United States of America. Tate et al. (2012) showed that in the United Kingdom, adopters and non-adopters of enterprises associated with renewable energy significantly differed by farm area, with adopters having significantly larger farms. In their review article, Foster and Rosenzweig (2010) highlight that "a large farmer faces the same cost of learning, but in the event that he receives good news about the new technology, he can adopt that new technology on a larger scale and receive higher expected profits. Thus large farmers are more likely to adopt a new technology initially independent of any relationship between landholding and costs of inputs" (p. 407).

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[4] Please note that the set of characteristics discussed in this section is not exclusive.

Similarly, factors describing the level of production specialisation and intensity can positively influence technology adoption and returns. Based on measures of crop diversity at farm level, Michler et al. (2019) showed that adopters of improved chickpea varieties were more specialised than their counterparts in Ethiopia. Barnes et al. (2019) revealed that specialisation as measured by the ratio of arable land to total land had a positive effect on the probability of adopting precision agricultural technologies for arable crop growers in five European countries. In the Irish context, Läpple et al. (2017) found that livestock density had a positive effect on the likelihood of adopting milk recording on dairy farms. These results may be related to economies of scale and a reduction in cost on a per-unit basis, thereby suggesting higher expected returns to technology adoption (Barnes et al., 2019).

Labour availability can have mixed effects on adoption depending on the nature of the new technology (Feder and Umali, 1993). For labour-intensive technologies, it can be an inhibiting factor. Fontes (2020) argues that the slow uptake of soil and water conservation technologies (despite their economic profitability) can be explained by the induced 35% increase in plot-level adult labour in Ethiopia. For labour-saving technologies, labour availability does not limit adoption. In Denmark, the adoption of automatic milking systems decreased the need for hired labour and enabled farmers to dedicate more of their time to the generation of off-farm income (Sauer and Zilberman, 2012). Issues arise in empirical applications as labour availability and inputs are often unobserved or incompletely reported (Barham et al., 2004; Duflo et al., 2008). If the relationship between new technologies and their labour requirements is not accounted for, returns to adoption may be overestimated, which can explain why seemingly profitable technologies are not adopted (Foster and Rosenzweig, 2010; Takahashi et al., 2020). As family labour is the predominant labour source on family farms (such as the ones in Ireland) (Eurostat, 2016), household size can be used as proxy for labour availability (Kebebe et al., 2017; Lee, 2005).

In terms of farmers' characteristics, the presence of an off-farm income can have conflicting effects on technology uptake. On the one hand, off-farm income can increase the farmer's investment capacity, thus having a positive effect on the adoption of capital-intensive technologies. Marenya and Barrett (2007) found that the ability of farmers to buy fertiliser relies on off-farm income in Kenya. The authors emphasised that new practices could not be adopted without initial financial capital obtained through off-farm employment. However, this may not be true "if reasonably good credit markets exist, [as] then we would not expect off-farm income to change a farm's degree of liquidity access" (Sauer and Zilberman, 2012, p. 246). On the other hand, off-farm employment may suggest that "the household is not focused on the farming operation and is, therefore, not investing even if it has less of a budget constraint" (Sauer and Zilberman, 2012, p. 246). Moreover, farmers with off-farm employment face higher opportunity costs of labour, which can justify why adoption and its expected returns are not worthwhile to them (Läpple, 2010; Moser and Barrett, 2003). As a result, off-farm income can have a negative effect on the probability of adopting new technologies, as found for instance in Sauer and Zilberman (2012).

The effect of age on technology uptake can be ambiguous since it is highly correlated with farming experience (Feder et al., 1985; Genius et al., 2014). In the context of modern irrigation technologies in Crete (Greece), Genius et al. (2014) asserted that on the one hand, experience "provides increased knowledge about the environment in which decisions are made" (pp. 334–335) and is thus expected to positively affect adoption. The authors highlighted that on the other hand, "younger farmers with longer planning horizons may be more likely to invest in new irrigation technologies as they foresee longer future profits arising from efficient water use" (p. 335). Both arguments were verified in empirical settings. For example, Sauer and Zilberman (2012) found years of farming experience to have a positive effect on the likelihood of adopting automated milking systems in Denmark. Findings by Läpple and Van Rensburg (2011) showed that age is negatively correlated to the adoption of organic farming on Irish farms.

A common finding in the technology adoption literature is that more educated farmers are more likely to adopt new technologies (Foster and Rosenzweig, 2010). For example, both Koundouri et al. (2006) and Genius et al. (2014) found that education levels of Crete farmers are positively associated with higher adoption rates of modern irrigation technologies. Foster and Rosenzweig (2010) emphasise that there are three main mechanisms that can explain the link between education level and technology adoption. First, "more educated agents are wealthier, and thus the education-adoption relationship represents an income effect" (Foster and Rosenzweig, 2010, pp. 413–414). Second, "more educated agents have better access to information" (Foster and Rosenzweig, 2010, p. 414). Third, "more educated agents are better able to learn – to decode new information faster and efficiently" (Foster and Rosenzweig, 2010, p. 414). Greater learning abilities and access to information can help farmers reduce the uncertainty surrounding new technologies (Chavas and Nauges, 2020; Huffman, 2020). Consequently, the adoption of new technologies can in turn be associated with higher payoffs for more educated farmers (Foster and Rosenzweig, 2010; Genius et al., 2014).

Finally, farmers' personality traits can influence their willingness to adopt new technologies (Pannell et al., 2006). Amongst them, risk aversion is a commonly examined characteristic in adoption studies (e.g., Barham et al., 2015, 2014; Di Falco and Chavas, 2009; Emerick et al., 2016; Kassie et al., 2015). "Risk aversion describes an individual's tendency to take or avoid risks in their decision making. […] The more risk-averse a landholder is, the greater will be his or her tendency to adopt an innovation that is perceived to reduce risk […] or to not adopt an innovation that is perceived to increase risk" (Pannell et al., 2006, p. 1412). Barham et al. (2014) found that risk aversion has an impact on the timing of adoption of genetically modified soy (which offers improved weed control) in experiments conducted on Midwestern grain farmers (United States of America). Most farmers exhibit aversion to downside risk (e.g., risk of crop failure or reduced yields), which implies that are more likely to adopt new technologies that reduce that type of risk (Chavas and Nauges, 2020). Kassie et al. (2015) showed that crop diversification and minimum tillage reduced exposure to downside risk in maize production. They concluded that development agencies should encourage the adoption of these risk-reducing strategies to enhance productivity and production risk mitigation.

2.2.2. Characteristics of the new technology

Rogers' theory on the diffusion of innovations identified five main attributes of new technologies that can influence their adoption (Rogers, 1995). These are the technology's relative advantage, compatibility, complexity, trialability, and observability.

Rogers (1995) explains that "[*r*]*elative advantage* is the degree to which an innovation is perceived as better than the idea it supersedes. […] It does not matter whether an innovation has a great deal of "objective" advantage. What does matter is whether an individual perceives the innovation as advantageous. The greater the perceived relative advantage of an innovation, the more rapid its rate of adoption is going to be" (p. 15). Adesina and Zinnah (1993) examined the effect of this characteristic in the use of new rice varieties in Sierra Leone. Four binary variables indicated the perceived superiority of the new varieties relative to the existing ones in terms of yields, cooking time, tillering capacity, and ease of threshing. The authors found positive effects of the four dummy variables on the probability of adopting and the intensity of use.

According to Rogers (1995), "[*c*]*ompatibility* is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters. An idea that is not compatible with the prevalent values and norms of a social system will not be adopted as rapidly as an innovation that is compatible" (p. 15). Läpple (2010) explored the role of farmers' attitudes in the decisions to adopt and abandon organic beef farming in Ireland. She found that farmers who expressed a higher level of environmental concern faced a higher probability of adopting organic farming, as well as a lower probability of abandoning it.

The concept of compatibility also extends to the farmer's existing set of technologies, practices, and resources, as it will determine the cost and difficulty of making the transition to the new technology and whether it is relevant (Pannell et al., 2006). For this reason, in their empirical analysis of the adoption of automatic milking systems, Sauer and Zilberman (2012) accounted for two joint sequential decisions, i.e., first the decision to increase the scale of milk production by expanding the herd and second the decision to invest in the new milking technology. They argued indeed that "[i]f the farmer decides not to increase the herd size […] then the automatic milking system adoption decision […] is not relevant" (p. 237). Khaledi et al. (2010) examined the effect of transaction costs on the decision to convert to organic farming in Canada. They found that transaction costs, as measured by access to infrastructure and services, satisfaction with marketer performance, and issues of marketing and internet use, could constrain the adoption of the new farming system.

Rogers (1995) defines "[*c*]*omplexity* [as] the degree to which an innovation is perceived as difficult to understand and use. Some innovations are readily understood by most members of a social system; others are more complicated and will be adopted more slowly. […] In general, new ideas that are simpler to understand will be adopted more rapidly than innovations that require the adopter to develop new skills and understandings" (p. 15). In the empirical literature, the complexity of insurance products has been identified as a potential reason for their low uptake (Carter et al., 2017; Cole et al., 2013; Macours, 2019). For instance, Giné and Yang (2009) implemented a randomised control trial to examine whether the provision of insurance against a major source of production risk induced farmers to take out loans to adopt a new crop technology in Malawi. They found that the take-up rate was 33% for farmers who were offered the uninsured loan, whereas it was 13 percentage points lower for farmers who were offered insurance with the loan.

Rogers (1995) describes "[*t*]*rialability* [as] the degree to which an innovation may be experimented with on a limited basis. New ideas that can be tried on the instalment plan will generally be adopted more quickly than innovations that are not divisible. […] An innovation that is trialable represents less uncertainty to the individual who is considering it for adoption, as it is possible to learn by doing" (pp. 15–16). In an empirical setting, Alcon et al.

(2011) explored whether trialability, as defined by whether the farmer had tested the technology in part of his/her farm prior to uptake, had an effect on the adoption of drip irrigation technology in south-eastern Spain. They found that this characteristic is associated with an increase in the speed of adoption.

Finally, Rogers (1995) points out that "[*o*]*bservability* is the degree to which the results of an innovation are visible to others. The easier it is for individuals to see the results of an innovation, the more likely they are to adopt. Such visibility stimulates peer discussion of a new idea, as friends and neighbo[u]rs of an adopter ask him or her for innovation-evaluation information about it" (p. 16). Pannell et al. (2006) adds that observability can positively affect adoption notably "due to its influence on trialability. Trialling a practice becomes less costly, and thus more likely to be seen as worthwhile, the greater the observability of trial outcomes. Higher observability means that fewer trials may be necessary to sufficiently reduce uncertainty to make the choice between adoption and non-adoption" (p. 1417). In their widely cited article, Foster and Rosenzweig (1995) showed that farmers learn by doing and learn from other farmers in order to decipher the optimal management of a new technology. In their model, farmers observe each year the results of their own experimentation and other farmers' experimentations with the new technology, thereby drawing conclusions for the next production year.

The attributes identified by Rogers (1995) are not the only characteristics of new technologies that can affect adoption. For example, the level of investment costs and the possibility to reverse back to the initial system at low or no cost are important considerations for farmers (Läpple et al., 2017; Pannell et al., 2006; Weersink and Fulton, 2020). It is also worth mentioning that finding empirical evidence of the impact of technology characteristics in the literature is a difficult task. Montes de Oca Munguia and Llewellyn (2020) conducted an empirical analysis of adoption studies to investigate which variables are included to predict and explain technology adoption.

They focused on a sample of 100 studies from 1957[5] to 2016 and found that the characteristics of new technologies have been consistently underrepresented. In their sample, only 10% of variables relate to the technology's attributes, against 46% for variables representing farmers' characteristics.

Montes de Oca Munguia and Llewellyn (2020) argue that "[t]he underrepresentation of innovation-related variables in [their] sample suggests that the innovation under study itself is poorly defined or poorly understood, or that its advantage over alternatives is taken for granted" (p. 88). The authors highlight that "relatively few studies pair[…] adopters' preferences, attitudes, intentions and beliefs with corresponding aspects of relative advantage of the innovation (profit advantage, environmental advantage, risk reduction)" (p. 89). According to them, adoption studies could be improved by "interact[ing] preferences of the adopter with corresponding innovation factors" (p. 89). In that regard, Macours (2019) emphasises in her review article the importance of distinguishing between types of innovations, such as yield-enhancing, variance-reducing, and water- and labour-saving technologies. She points out the need to better understand farmers' preferences prior to developing and diffusing new technologies.

2.2.3. Institutional context

The policy context can affect technology adoption as it may alter the relative advantage of certain practices over others (Pannell et al., 2006). European Union (EU) milk quota removal resulted in an increase in dairy production in the EU, but responses varied across Member States in line with their production advantages (Läpple and Sirr, 2019). Notably, farmers in Ireland and in the Netherlands adopted intensification and expansion strategies to benefit from the growth in global demand for dairy products (Kelly et al., 2020; Läpple and Sirr, 2019; Samson et al., 2016). According to Bertoni et al. (2018), the Common Agricultural Policy Greening, which was officially implemented in 2014 for the 2014-2020 period, has led to readjustments in

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[5] Date at which the seminal work by Griliches (1957) established the practice of using regression models to explore technology adoption in agriculture.

farmland use in regions of Italy with high-intensity agriculture. In their preliminary analysis, the authors found that the policy change encouraged a decrease in maize monoculture in favour of other cereals and legume crops like soybean and alfalfa. Ferguson and Olfert (2016) estimated the impact of removing a railway transportation subsidy in 1995 on technology adoption for Western Canadian farms. They showed that higher freight rates, and hence lower farm-gate prices, induced farmers to adopt efficiency-enhancing technologies, to increase their fertiliser usage, and to make significant farmland use changes over the 1991-2001 time period.

The adoption of new technologies can be restricted by budget constraints. Hence, easy access to credit can play a role in enabling farmers to invest (Feder et al., 1985; Foster and Rosenzweig, 2010). In the Irish context, Läpple et al. (2015) found that access to credit, as measured by whether the farmer had taken out a loan or not, positively affects innovation at the farm level. Zeller et al. (1998) showed that in Malawi, participation in agricultural credit programmes substantially raised the cropping share of hybrid maize and tobacco, and increased crop incomes. Nevertheless, Foster and Rosenzweig (2010) also warn that "[i]f all agents can borrow, then the adoption of a new technology depends only on net returns […], and therefore not on the characteristics of the agent […]. If the ability to borrow, however, depends on the agent having assets that can be used as collateral, or if borrowing is not an option so that the agent must supply his own funds, then such agent characteristics as wealth or the history of prior income reali[s]ations will affect current input and technology choices that have an investment element" (p. 419).

As previously mentioned, farmers face uncertainty about new technologies, and notably about how to use them, whether they are suitable for the farm's specific conditions, and what their expected benefits are (Chavas and Nauges, 2020; Foster and Rosenzweig, 2010). This uncertainty can be reduced through learning. Therefore, improving access to information can speed up the learning process and hence technology adoption (Asfaw et al., 2012; Shiferaw et al., 2015; Takahashi et al., 2020). Previous literature has identified lack of information as one of the main limitations to technology adoption (Genius et al., 2014; Sauer and Zilberman, 2012; Shiferaw et al., 2015). That is because "[o]nce a new technology is created, its adoption [inevitably] depends on the diffusion of associated knowledge" (Chavas and Nauges, 2020, p. 47). Farmers can seek information from a combination of sources including, among others, research institutions, advisory services, non-governmental organisations, peers, and the media (Baird et al., 2016; Isaac et al., 2007; Oreszczyn et al., 2010; Šūmane et al., 2018). Formal advisors and peers tend to be the predominant and most trusted advice sources (Šūmane et al., 2018; Sutherland et al., 2013). Hence, extension services and peer-to-peer interactions play a key role in diffusing knowledge within farming communities and fostering technological change (Genius et al., 2014; Krishnan and Patnam, 2014; Takahashi et al., 2019). As there is an extensive literature on extension and peer-to-peer learning, these will be discussed in detail in the following section.

2.3. The role of extension services in improving technology adoption and farm performance

New technologies may be in line with farmers' personal objectives, but this is not sufficient to ensure their uptake. Ineffective information dissemination systems can limit their diffusion and may require policy interventions to improve access to knowledge (Takahashi et al., 2020). A popular approach has been to focus on facilitating the provision of extension services for farmers (Anderson and Feder, 2004; Birkhaeuser et al., 1991; Norton and Alwang, 2020; Takahashi et al., 2020). Agricultural extension encompasses a wide range of education and advisory services for farmers. Its objective is to encourage knowledge transfer and technology adoption to "bridge the gap between discoveries in the laboratory and changes in the individual farmer's fields" (Birkhaeuser et al., 1991, p. 608). It aims at helping farmers develop analytical competencies and critical thinking to "improve […] decision making and skills needed to apply agricultural innovations" (Norton and Alwang, 2020, p. 9). Therefore, promoting access to extension services has been traditionally seen as a means to raise farm productivity and incomes, with the overarching goal of contributing to wider rural and agricultural development (Anderson and Feder, 2004; Birkhaeuser et al., 1991; Davis et al., 2012).

Agricultural extension is prevalent all around the world (Swanson and Davis, 2014) and has attracted significant funding from governments and international organisations (Anderson and Feder, 2004; Birkhaeuser et al., 1991; Norton and Alwang, 2020). For example, from 1965 to 1986, the World Bank supported 460 extension projects in 79 countries, accounting for an investment of USD 1.8 billion (Birkhaeuser et al., 1991). In 2010, federal funding for extension activities of the United States of America National Institute of Food and Agriculture amounted to about USD 350 million (Wang, 2014). Pillar I of the EU Common Agricultural Policy enabled to fund an €18 million scheme to encourage Irish dairy farmers to participate in discussion groups from 2010 until 2012 (Läpple and Hennessy, 2014).

Given significant investments and potential to reach desired agricultural outcomes, the impact of extension services has been widely explored in the literature through a variety of approaches. Some articles examined the relationship between extension and total factor productivity growth, with positive findings. Rahman and Salim (2013) showed that extension expenditure positively influenced total factor productivity growth in Bangladesh agriculture over the 1948-2008 period. Similar results were found in the Chinese context from 1980 to 1995 by Jin et al. (2002) and in Ethiopia from 2004 to 2014 in the Bachewe et al. (2018) study.

A branch of research investigated the question of extension's impact from the perspective of overall programme cost-effectiveness and found a mixed record of success. Jin and Huffman (2016) estimated that the real social rate of return to public investments in agricultural extension was above 100% in the United States of America. In other words, their findings suggest that the benefits of agricultural extension exceeded its total cost. Marsh et al. (2004) also evaluated that the net benefits of expenditure on agricultural extension were positive in Western Australia. Conversely, when Benin et al. (2011) assessed the impact of the national agricultural extension programme in

Uganda, they estimated that the rate of return of programme expenditure was substantially smaller, i.e., between 8 and 49%. In their review article, Birkhaeuser et al. (1991) found that rates of return varied drastically across studies and countries, and could be as low as 13%.

When focusing on farm-level outcomes of extension participation, empirical evidence is also nuanced. On the one hand, some articles found that extension has positive effects. Pan et al. (2018) showed that participation fostered the adoption of improved cultivation methods and led to enhanced food security for smallholder female farmers in Uganda. In the Uruguayan context, Mullally and Maffioli (2015) found that participation in the livestock extension programme allowed cattle producers to improve their farm management by increasing net sales and the production of calves. Maffioli et al. (2011) demonstrated that extension services had a positive impact on the adoption of higher-quality grape varieties for Argentinian grape producers.

On the other hand, there is also farm-level evidence that extension participation may not always be effective. Ragasa and Mazunda (2018) explored the impact of extension on farm productivity and food security in Malawi. They found that extension had an insignificant effect, except for a small share of farmers who reported the extension advice as “very useful”. Similarly, Läpple and Hennessy (2015) found that extension participation had differential effects depending on farmers’ profile. More precisely, farmers who started participating after the introduction of subsidised extension membership did not significantly benefit from the programme, while farmers who had joined before improved their farm economic performance. Another example of extension’s lack of effectiveness can be found in Ragasa et al. (2013), where the authors proved that frequency of extension visits did not affect farm productivity in Ethiopia.

Therefore, the literature suggests that extension services can have limited effects at the farm level and may lack cost-effectiveness, depending on the context. Under circumstances where governmental budgets allocated to agriculture are under pressure and contributions of the agricultural sector in gross domestic products and employment are becoming smaller, consistent funding for extension can be difficult to secure (Anderson and Feder, 2004; Faure et al., 2012; Feder et al., 2011; Norton and Alwang, 2020). Agriculture is undergoing major structural changes and "becomes more dualistic in nature with small but growing commercial farms coexisting with smaller semisubsistence farms in developing countries and large commercial farms coexisting with smaller, mostly part-time, commercial farms in developed countries" (Norton and Alwang, 2020, p. 10). Moreover, there is greater recognition that agriculture is multifunctional (Dillon et al., 2016a; Franks, 2014; Pretty et al., 2010). In this context, farmers' role may not be solely confined to food production and can incorporate wider environmental and societal goals. As a result, farmers' information needs and hence models of extension delivery have been evolving over the past decades (Anderson and Feder, 2004; Faure et al., 2012; Feder et al., 2011; Norton and Alwang, 2020; Takahashi et al., 2020).

In search of more successful extension systems, two main avenues have been explored. First, a body of literature aims at improving learning methods by combining extension efforts with peer-to-peer learning. While seminal studies had highlighted the important role of peers in the diffusion of knowledge and new technologies (Conley and Udry, 2001; Foster and Rosenzweig, 1995; Munshi, 2004), there has been a recent boost in the number of articles that investigate peer-to-peer interactions within and outside the frame of extension services (Davis et al., 2012; Maertens, 2017; Nakano et al., 2018b; Sampson and Perry, 2019; Shikuku et al., 2019; Songsermsawas et al., 2016; Takahashi et al., 2020). Second, a strand of the extension literature is interested in changes in service provision, and, more precisely, a move away from purely public systems on to a wider range of public and private modes (Feder et al., 2011; Norton and Alwang, 2020; Umali-Deininger, 1997). Therefore, these two aspects of the literature are further described in this section.

2.3.1. Combining peer-to-peer learning and extension efforts to enhance knowledge transfer

Peer-to-peer learning has the potential to effectively disseminate new technologies and can notably play a role at early stages of the diffusion process when expected returns of the new technology are uncertain and risk is high (Chavas and Nauges, 2020; Weersink and Fulton, 2020). Farmers can observe peers who have already adopted the new technology, update their beliefs, and make more informed decisions (Conley and Udry, 2001; Foster and Rosenzweig, 1995; Munshi, 2004; Takahashi et al., 2020). Additionally, farmers can exchange experience-based knowledge, often seen as more trustworthy and intrinsic to resilient and sustainable agriculture (Isaac et al., 2007; Šūmane et al., 2018). That is because it is practical, personal, and of local relevance (Šūmane et al., 2018).

Empirical studies have provided evidence of positive peer effects on technology adoption and agricultural revenue (Larsen, 2019; Sampson and Perry, 2019; Songsermsawas et al., 2016). Nevertheless, some articles have also demonstrated that social networks can inhibit technology adoption through peer pressure (Maertens, 2017; Weersink and Fulton, 2020). They can have little to no impact as “some technologies may be either too idiosyncratic or too complex for peer effects to play a role” (Songsermsawas et al., 2016, p. 174). According to Chavas and Nauges (2020), peer effects can be “weaker when the profitability of the technology depends on characteristics that vary across the population of potential adopters (e.g., soil quality). Learning from others is made even more difficult if those important characteristics that condition the outcome of a new technology are not easily observable” (p. 45). This suggests that “peers may only serve as effective channels of information diffusion among farmers under certain circumstances and for particular kinds of technologies” (Songsermsawas et al., 2016, p. 174).

Within this context, a growing body of literature recommends combining both peer-to-peer learning and extension services to maximise farmers’ learning opportunities. More specifically, the idea is to develop extension models that exploit the relationships between farmers, while providing additional formal expertise and structure through extension. Three main combinations have been considered in the literature.

First, some studies examined whether traditional, one-to-one extension programmes and peer learning networks can complement each other. Krishnan and Patnam (2014) evaluated the role of learning from both extension agents and neighbours in the adoption of improved seeds and fertiliser in Ethiopia. Their findings revealed that the initial impact of extension agents was high, but the effect wore off over time. Inversely, neighbours had a positive and persistent effect on the adoption of the new technologies. In the Greek setting, Genius et al. (2014) found that both extension and peers played an important role in technology adoption over time, while the effectiveness of each channel was enhanced by the presence of the other. Similar results were found by Ainembabazi et al. (2017) in Africa, where the combination of both extension participation and peer-to-peer learning was the most effective way of fostering technology adoption.

Second, another research focus has been to analyse whether extension programmes can be effective in transferring knowledge to the whole farming community by targeting a selected set of key farmers in charge of subsequently training their peers. Nakano et al. (2018b) explored the adoption process of new technologies that aim at improving rice production in Tanzania. They specifically focused on the technology dissemination pathway between key farmers who receive training through extension services, intermediate farmers who are trained by key farmers, and ordinary farmers. The authors found that key farmers adopted the new technologies immediately after training. They also showed that in the course of time, the technologies diffused from key farmers, to intermediate farmers, and ordinary farmers (in that particular order). As a result, paddy yields increased, with a time lag between key, intermediate, and ordinary farmers. Nakano et al. (2018b) concluded that “given that extension officers or aid agencies can train only a limited number of farmers at a time, farmer-to-farmer extension offers a reasonable option for technology dissemination program[me]s […] [as] intensive training to selected farmers can enhance the performance of other farmers" (p. 348). In the frame of a randomised control trial, Shikuku et al. (2019) assessed the effect of incentives for the diffusion of agricultural knowledge by farmers in Uganda. Their article provides evidence that incentivising farmers in contact with extension to further disseminate acquired knowledge can be effective.

Third, some articles focus on the within-effectiveness of participatory extension programmes, i.e., whether participatory extension is effective in encouraging knowledge exchange among participating farmers. Participatory extension takes place in a group setting and is based on the principles of social learning, where participants are encouraged to share information and learn from their peers (Davis et al., 2012; Läpple et al., 2020). Advisors act as discussion facilitators rather than instructors (Röling and van de Fliert, 1994). In the frame of this extension approach, Davis et al. (2012) evaluated the impact of a farmer field school project in East Africa. They found that extension participation increased agricultural income and crop productivity for women, low-literacy, and medium land size farmers. Raghunathan et al. (2019) assessed the effect of women's self-help groups in India on access to information on agricultural practices, their role in agricultural decision-making, the use of better agricultural practices, and production diversification. The authors found that membership increased women's access to information and participation in some agricultural decisions. However, they found that self-help groups had a limited impact on the adoption of improved agricultural practices and diversification strategies, likely due to financial constraints, social norms, or domestic workload.

In summary, previous literature has shown that both peers and extension can play a role in the diffusion of knowledge within the farming community. Combining their efforts, under different formats, can be a way to enhance their effectiveness. However, the extent to which results are obtained at the farm level seems to be context specific.

2.3.2. Diversifying the provision of extension services: public, private, and mixed public-private systems

According to Birkhaeuser et al. (1991), "the public good nature of many elements in agricultural knowledge justifies public-sector involvement in information provision" (p. 608). The authors explain that "information on improved agricultural technology is often a public good because the provider of the information cannot exclude other potential users from free access to information provided to one user, and the value of the information is not directly affected by the number of users" (p. 607). In other words, agricultural knowledge has the characteristics of non-excludability and non-rivalry and can thus be disseminated through a public extension system to correct market failure.

Nevertheless, several reasons can explain why public extension might be suboptimal. Firstly, Birkhaeuser et al. (1991) assert that heavy investments in extension may be useful only at early stages of the technology diffusion process when the gap between farmers' current productivity and the potential productivity offered by the new technology is high. Over time, the gap closes, thereby diminishing marginal returns to public extension. "Once agriculture has stabili[s]ed, knowledge has been diffused, and private entrepreneurs (e.g., input suppliers) have taken up significant information-diffusion tasks, the role of extension is reduced, and the corresponding public investment should decline" (Birkhaeuser et al., 1991, p. 608).

Secondly, not all agricultural knowledge is a public good, which can justify providing extension through a different means than a public system (Umali-Deininger, 1997). For example, Anderson and Feder (2004) explain that only general agricultural knowledge (e.g., market information, cropping patterns) is a public good. More specialised knowledge (e.g., fertiliser recommendations for specific farm conditions) can exhibit the characteristics of high excludability and low rivalry, i.e., "some farmers can be excluded from access, even though the value to other users is not diminished by one farmer's use" (Anderson and Feder, 2004, p. 43). The authors recommend providing information associated with toll goods through combined efforts between public and private sectors.

Thirdly, Feder et al. (2011) argue that there are inherent limitations to public extension, which could be overcome by using the market mechanism and following a more demand-driven private model. Notably, incentive structures for public extension agents are inefficient as agents are accountable to their superiors as opposed to their farmer-clients. The authors also emphasise that public extension programmes are not always relevant to farmers' needs and priorities because of the lack of information and feedback returning to the extension agent. Additionally, demand for farm-specific information on agricultural practices has increased, with more farmers being willing to pay fees for service (Norton and Alwang, 2020). That is because "[f]armers and farming conditions vary widely even within relatively small regions, requiring heterogeneous technologies […] and the option to pick and choose among alternatives" (Norton and Alwang, 2020, p. 9).

As a result, a global privatisation process of extension services has been triggered (Feder et al., 2011; Ferroni and Zhou, 2012; Klerkx et al., 2006; Knierim et al., 2017; Prager et al., 2017). One caveat of providing extension exclusively through a private system is that resource-poor farmers may not be able to afford the service. In that regard, Feder et al. (2011) highlight that there is scope for the private sector to play a role "as providers of extension services in institutional arrangements where the funding still comes from the [S]tate" (p. 47). The authors reviewed different types of such mixed public-private (also known as "hybrid") arrangements, including the distribution of vouchers to farmers (who can then express their advisory demand through the voucher's "purchasing power"), and the contracting out of service provision to the private sector. In this way, the public sector remains the main source of funding while "enabling beneficiaries to articulate their needs and get them attended to by extension providers, and to be aware of and reactive to the effectiveness of delivery" (Feder et al., 2011, p. 47).

Public and private sectors could play complementary roles in extension service provision by focusing on different profiles of farmers (Feder et al., 2011; Ferroni and Zhou, 2012; Knierim et al., 2017). By relying on market competition, the private sector could satisfy the information needs of more commercial, larger-scale farmers (Feder et al., 2011). In this way, reliance on public funding could be reduced for some segments of the farming population. The public sector could then predominantly target resource-poorer farmers. However, Norton and Alwang (2020) assert that while "[t]his pluralism facilitates flexibility, encourages demand-driven services, and relieves part of the financial burden on the public sector[,] […] it also complicates coordination to ensure that the needs of all farmers are met" (p. 16). The authors further argue that "[i]t creates challenges for ensuring that extension providers are accountable, economies of scale are achieved, and that the public sector extension service is not starved for resources or eliminated" (p. 16).

To date, very few empirical studies are concerned with the disparities between the different extension models, in spite of the ongoing debate over their roles (Feder et al., 2011; Zhou and Babu, 2015). First, an examination of differences in profiles between farmers involved in public, private, and mixed extension systems is required. Knierim et al. (2017) and Prager et al. (2017) explored this question, but only from the perspective of service providers. Thus, an evaluation from a farmer perspective is needed (Feder et al., 2011). Second, the variation in the effectiveness of public, private, and mixed extension has been rarely studied, with Sutherland et al. (2013)'s qualitative study as a notable exception. Overall, Feder et al. (2011) emphasise that despite being promising approaches, there is a lack of evidence that private and mixed public-private systems can be successful in fully overcoming the limitations of public extension.

Finally, in the context of promoting sustainable agricultural development, caution must be exercised over the type of extension available to farmers. The demand-driven model of private extension signifies that farmers will pay for the information that they specifically seek. Because farmers who are able to pay fees for services are more likely to have large, commercial farms (Feder et al., 2011), the private sector may favour advice related to production or lifestyle objectives rather than sustainability concerns such as the environment (Sutherland et al., 2013). Inversely, the public sector has to strike a balance between meeting the immediate economic interests of individual farmers and addressing wider public concerns with respect to sustainability (Klerkx et al., 2006; Sutherland et al., 2013). This suggests that publicly funded extension may be more suited to enhance all dimensions of farm sustainability than a fully private system.

2.4. Sustainability in the technology adoption and extension literature

While it has been stated in the literature that technology adoption and extension services can contribute to sustainable agricultural development (Norton and Alwang, 2020; Pannell and Claassen, 2020; Weersink and Fulton, 2020), empirical evidence beyond economic outcomes still remains scarce. In early studies, the motivation for examining technology uptake and extension participation was to address issues of low economic returns and farm productivity (Anderson and Feder, 2004; Birkhaeuser et al., 1991; Weersink and Fulton, 2020), which may explain why the literature is skewed towards the economic dimension of sustainability.

Another reason why economic outcomes are overrepresented relative to other sustainability dimensions may be that researchers and extension agents tend to expect profits to be farmers' main driving force (Vanclay, 2004). In fact, it is commonly assumed that farmers behave as profit maximisers in adoption studies (Weersink and Fulton, 2020). However, a large body of literature demonstrates that farmers do not only have economic goals (Pannell et al., 2006; Vanclay, 2004; Weersink and Fulton, 2020). This justifies the need to incorporate non-economic outcomes into empirical studies.

The question of non-economic returns to technology adoption and extension participation can also have important implications for policy makers in determining whether continued public support should be granted to encourage widespread technology diffusion. In the context of promoting precision agricultural technologies, Barnes et al. (2019) highlighted that "the main argument for government intervention relies on the[ir] ability […] to improve resource use efficiency at such a level that public goods will be protected and preserved whilst increasing the supply of food needed for a growing population" (p. 171).

Consequently, more thorough assessments of technology and extension impacts are needed to inform farmers' adoption decisions and potential policy interventions. However, evaluating alternative practices or extension programmes in the frame of wider sustainability concerns relies on the ability to define and reliably estimate farm sustainability outcomes (Fumagalli et al., 2012; Latruffe et al., 2016). "In the case of technologies used by profit-maximising entities, it is clear that technology profitability is the key measure" (Foster and Rosenzweig, 2010, p. 398). Yet, measurement of outcomes is not evident when expected returns are non-monetary (Foster and Rosenzweig, 2010). Defining and measuring farm sustainability can be particularly challenging (Dillon et al., 2016a; Latruffe et al., 2016) and scarcity of data availability in the environmental and social dimensions can limit the possibility to explore impacts beyond the economic dimension (Lebacq et al., 2013).

Nonetheless, exploring a wider range of sustainability outcomes is increasingly important as not all farm practices or extension programmes may be equally suited to help farmers achieve greater sustainability in agricultural production. Previous literature has underlined that even though there can be synergies between sustainability goals, indisputable trade-offs also arise and are difficult to resolve (Defries et al., 2016; Fader et al., 2018; Heck et al., 2018).

Therefore, two main issues are further described in this section. First, the debate over the defining and measuring of farm sustainability is discussed. Second, the difficulty in reconciling different dimensions of farm sustainability is explored.

2.4.1. Defining and measuring sustainability outcomes

As previously highlighted, the 1987 Brundtland report played a significant role in recognising the tri-dimensional nature of sustainability (United Nations, 1987). Ever since, a growing body of literature has focused on interpreting and measuring economic, environmental, and social sustainability across many disciplines (Dillon et al., 2016a; Latruffe et al., 2016; Lebacq et al., 2013; Lynch et al., 2019).

In the context of livestock farming, the three sustainability dimensions can be described as follows (Lebacq et al., 2013). First, economic sustainability is defined as the economic viability and profitability of farming systems and commonly includes concepts of farm income, efficiency, and productivity. Second, environmental sustainability generally refers to input management and the quality of natural resources. It covers environmental themes associated with nutrients, pesticides, non-renewable resources (i.e., energy and water), land management, Greenhouse Gas (GHG) emissions, biodiversity, and soil quality. Third, social sustainability can be divided into two levels. At farm community level, internal social sustainability relates to the well-being of the farmer and his/her family and encompasses themes associated with education, working conditions, and quality of life. At societal level, external social sustainability is defined by society's expectations of agricultural production, including its multifunctionality, the extent of practice acceptability (including animal health and welfare standards), and product quality.

The measuring of sustainability, nonetheless, generates more debate. While it has been argued that "precise measurement is impossible, as it is site-specific and dynamic" (Dillon et al., 2016a, p. 32), the use of sustainability indicators is increasingly popular (Bélanger et al., 2012; Dillon et al., 2016a; Fumagalli et al., 2012; Latruffe et al., 2016; Lebacq et al., 2013). "Sustainability indicators are quantifiable and measurable attributes of a system that are judged to be related to its sustainability. They are statistical constructs which support decision-making by revealing trends in data that can then be used to develop policy measures or to analyse the effects of policies already implemented" (Dillon et al., 2016a, p. 32). In the Irish context, previous studies have used the Teagasc National Farm Survey (NFS) dataset to develop sustainability indicators and assess levels and trends in farm sustainability performance (e.g., Buckley et al., 2016a, 2016b, 2015; Buckley and Donnellan, 2020; Dillon et al., 2016a; Ryan et al., 2016; Thomas et al., 2020). Some examples are provided in Table 2.1.

Sustainability indicators have not yet been widely used in the technology adoption and extension literature. However, their application could allow for the comparison of adopters and non-adopters or participants and non-participants in terms of sustainability performance, as well as the estimation of sustainability impacts of the technology or programme under consideration. In so doing, particular attention should be given to the choosing of suitable sustainability indicators as outcomes of interest. According to Lebacq et al. (2013), "the main challenge is using a transparent selection process to avoid assessment subjectivity" (p. 311). A central dilemma arises as indicators need to be sensitive to variations caused by the new on-farm practice or programme (Bélanger et al., 2012), but guiding their choice with this goal may influence the outcome of the analysis (Latruffe et al., 2016). Thus, thought must be given to the conceptual framework surrounding the sustainability assessment (Lyytimäki and Rosenström, 2008; Musango and Brent, 2011) and potential indicators must be considered in the light of pre-established criteria (Bélanger et al., 2012; Latruffe et al., 2016; Lebacq et al., 2013).

Table 2.1: Examples of sustainability indicators previously used with the Teagasc NFS dataset

Dimensions	Indicators	Description	References
Economic	Gross output per animal or hectare (ha)	Measure of total production value. It is equal to the total value of crops and crop products, livestock and livestock products, and earnings from other gainful farming activities.	Buckley and Donnellan (2020); Dillon et al. (2016a); Läpple and Thorne (2018); and Ryan et al. (2016).
	Gross margin per animal or ha	Measure of farm profitability. It is calculated as gross output less direct production costs, divided by farm or herd size.	Buckley and Donnellan (2020); Dillon et al. (2016a); Läpple and Thorne (2018); and Ryan et al. (2016).
	Family farm income per unpaid labour unit	Measure of the economic return on unpaid family labour. Family farm income is calculated as farm gross output minus all farm costs (i.e., direct production costs, overhead costs and external costs), minus depreciation and farm taxes, plus all subsidies. A labour unit is defined as a person over 18 years of age, working at least 1,800 hours per year.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).

Dimensions *(Continued from previous)*	Indicators	Description	References
Economic	Economic viability	Dummy variable taking the value of 1 if family labour can be remunerated at greater than or equal to the minimum wage in Ireland and there is sufficient income to provide an additional 5% return on non-land-based assets, 0 otherwise.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	Market orientation	Proportion of total output derived from the market rather than subsidies.	Buckley and Donnellan (2020); Dillon et al. (2016a); Läpple and Thorne (2018); and Ryan et al. (2016).
Environmental	Nutrient surpluses per ha (for phosphorus or nitrogen)	Magnitude of nutrient surpluses, which may result in nutrient losses to water bodies. It is calculated on the basis of nutrient inputs less nutrient outputs divided by farm size.	Buckley et al. (2016a, 2016b, 2015); Buckley and Donnellan (2020); Dillon et al. (2016a); Ryan et al. (2016); and Thomas et al. (2020).

Dimensions *(Continued from previous)*	Indicators	Description	References
Environmental	Nutrient use efficiencies (for phosphorus or nitrogen)	Proportion of nutrients retained in the farm system. It is calculated as the ratio of nutrient outputs to nutrient inputs.	Buckley et al. (2016a, 2016b, 2015); Buckley and Donnellan (2020); Dillon et al. (2016a); Ryan et al. (2016); and Thomas et al. (2020).
	GHG emissions per ha	Agricultural GHG emissions, divided by farm size.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	GHG emissions per output unit	Agricultural GHG emissions, divided by the output produced on the farm.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	Ammonia emissions per animal or ha	Ammonia emissions, divided by farm size.	Buckley and Donnellan (2020).
	Ammonia emissions per output unit	Ammonia emissions, divided by the output produced on the farm.	Buckley and Donnellan (2020).

Dimensions *(Continued from previous)*	Indicators	Description	References
Social	Household vulnerability	Dummy variable taking the value of 1 if the farm business is not economically viable and the farmer does not have an off-farm employment as an income source, 0 otherwise.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	Agricultural education	Dummy variable taking the value of 1 if the farmer has received formal agricultural education, 0 otherwise.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	Isolation risk	Dummy variable taking the value of 1 if the farmer lives alone, 0 otherwise.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	High age profile	Dummy variable taking the value of 1 if the farmer is over 60 years old and no other household member is under 45 years of age, 0 otherwise.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).
	Workload	Total amount of hours worked on the farm.	Buckley and Donnellan (2020); Dillon et al. (2016a); and Ryan et al. (2016).

Bélanger et al. (2012) suggest six main selection criteria, described in Table 2.2. Calculations must be easy to implement, notably in accordance with data availability, and reproducible. If the goal is to use research findings to inform stakeholders' decisions, it is important that selected indicators do not require a high level of technical expertise and are of interest to them. In addition to these criteria, Lebacq et al. (2013) also recommend submitting indicators to a validation process to ensure their robustness (e.g., expert appraisal, third party accreditation, peer-review process).

Table 2.2: Criteria for selecting farm sustainability indicators

Category	Criterion	Questions
Practicality	1. Easy to implement	The data required to estimate this indicator has already been collected for other purposes and is thus readily available. If the data is not readily available, it can easily be collected.
	2. Immediately understandable	The indicator does not require a high level of technical expertise to be understandable.
	3. Reproducible	The calculations can be replicated in other settings.
Usefulness	4. Sensitive to variations	The indicator can pick up on-farm changes caused by the new technology adopted by the farmer, or the extension programme.
	5. Adapted to the objectives	The indicator is linked to the overall sustainability objectives.
	6. Relevant for users	The indicator is useful for farmers and other stakeholders (e.g., advisors, policy makers, industry) and can help inform adoption decisions or policy interventions.

Note: Adapted from Bélanger et al. (2012, p. 425).

From a practical standpoint, indicators can be implemented as sets of indicators (Latruffe et al., 2016). A set of indicators allows for the consideration, interpretation, and communication of findings about the three sustainability dimensions separately, while comprehensively and reliably representing the complexity of the system (Lebacq et al., 2013). This could be particularly useful in adoption and extension studies as different stakeholders may have a variety of goals and thus be interested in distinct sustainability dimensions and aspects (e.g., economic versus environmental, nutrient pressure versus GHG emissions).

2.4.2. Reconciling sustainability dimensions

The ability to increase agricultural efficiency and productivity while enhancing the social and environmental dimensions of sustainability has been questioned in the literature as trade-offs may arise (Dawkins, 2017; Foote et al., 2015; Franks, 2014; Garnett et al., 2013). A few examples can be mentioned. In New Zealand, the intensification of milk production has resulted in an increase in the use of external inputs (e.g., feed, fertiliser, and water) and has had significant environmental costs arising from nitrate contamination of drinking water, nutrient pollution to lakes, soil compaction, and GHG emissions (Foote et al., 2015). According to Lean and Playford (2008), the rise in milk production in intensive grass-based dairy systems in Australia and New Zealand increased lameness prevalence, and enhanced risk of mastitis and culling for udder health, thereby having negative effects on animal health and welfare. In Ireland, dairy expansion has led to an increase in labour requirements (Deming et al., 2018). Dairy farming involves long working hours, which can affect farmers' work-life balance, mental health, and stress level (Deming et al., 2018; Hostiou et al., 2020; Lunnor Kolstrup et al., 2013). These factors may be a cause for the disengagement of the younger generation from farming and difficulty to secure farm successors (Beecher et al., 2019; Hostiou et al., 2020).

Nevertheless, some argue that synergies between sustainability dimensions can also be achieved (Dawkins, 2017; Hocquette et al., 2014; Llonch et al., 2017). Livestock-based agriculture can play an important role in landscape management and biodiversity conservation (Bernués et al., 2011; Herzon et al., 2018). Improving animal health and welfare may seem costly and labour-intensive for farmers in the short run but can decrease avoidable economic losses associated with yield and product quality reductions in the medium to long run (Huijps et al., 2010a, 2010b). Moreover, it may improve the societal acceptability of livestock-based systems by increasing product quality and limiting culling decisions (Dawkins, 2017). Enhancing herd health can also reduce environmental costs associated with dairy or meat production by decreasing resource wastage (Llonch et al., 2017; Özkan Gülzari et al., 2018; Özkan et al., 2015).

Consequently, in order for new technologies and extension programmes to contribute to sustainable agricultural development, they should be designed to help resolve trade-offs across sustainability dimensions, and create or reinforce synergies.

In the context of the environmental sustainability dimension, Montes de Oca Munguia and Llewellyn (2020) explain that research has a tendency to explore “the adoption of generic categories (e.g., sustainable practices, best management practices) rather than specific practices”, thus making it “very difficult to ascertain the advantage or opportunity of adopting the innovation in relation to alternative or existing practice” (p. 89). Indeed, empirical evidence in that regard is lacking. Most analytical frameworks focus on the adoption of presupposed sustainability-enhancing practices rather than providing proof of their actual sustainability impacts. The study by Knook et al. (2020) is a relevant example of this issue. The authors’ aim was to assess the impact of a participatory extension programme that focused on climate-friendly farming in the United Kingdom. While they examined the voluntary uptake of potential on-farm emission mitigation practices, they did not verify empirically that their adoption significantly reduces GHG emissions.

This lack of empirical proof has been previously underlined in the literature. For instance, Lovarelli et al. (2020) highlighted that “the quantification of the environmental, economic and social sustainability of […] livestock production equipped with precision livestock farming techniques has not yet been carried out” (p. 10) and that further research is needed to fill this literature gap and provide information for stakeholders. Llonch et al. (2017) emphasised that “there is still a great lack of knowledge on the repercussions for animal welfare of the known (and emerging) strategies to reduce GHG emissions. The consequences that such strategies could have on animal welfare must not only be identified, but also quantified and contrasted. This will allow a realistic and informed debate on what strategies should or should not be adopted to improve the environmental sustainability of livestock production without compromising animal welfare" (p. 282). In a review article about synergies and trade-offs between animal welfare and efficient farming, Dawkins (2017) also explained that "the true commercial value of good welfare needs to be documented at both producer level and societal level so that animal welfare is no longer seen as just an 'ethical extra' but as having commercial clout in its own right" (p. 205).

Despite the above, there are a few examples of empirical studies in the literature that aim at reconciling sustainability dimensions. For example, in the technology adoption literature, Huijps et al. (2010b, 2010a) approached the issue of herd health management from the perspective of cost-effectiveness. They showed that the implementation of different measures for improved dairy cow teat hygiene, such as wearing milkers' gloves and performing post-milking teat disinfection, were cost-efficient. Thus, these measures can enhance animal health while avoiding the adverse economic effects of bacterial contamination. Therefore, their studies reveal that synergies can be created between the economic and social dimensions of farm sustainability.

Again from the perspective of technology cost-effectiveness, an expanding strand of the literature employs marginal abatement cost curve approaches to assess the worthwhileness of potential GHG mitigation strategies (De Cara and Jayet, 2011; Eory et al., 2018; Lanigan et al., 2018; Moran et al., 2011). Based on this method, Lanigan et al. (2018) showed in the Irish context that improving the genetic merit of beef and dairy herds can simultaneously result in private economic gains and agricultural GHG mitigation. Adoption can thus help farmers meet their immediate economic needs while individually contributing to the country's GHG reduction effort. This highlights how technological change can reconcile the economic and environmental dimensions of sustainability. Inversely, the Lanigan et al. (2018) study also demonstrated that altering slurry spreading techniques or draining impeded mineral soils could reduce GHG emissions but would be costly for farmers. This highlights a trade-off across sustainability dimensions and questions voluntary uptake.

When looking at the evidence in the extension literature, Maffioli et al. (2011) examined the effect of a publicly subsidised extension programme aimed at improving yields (i.e., economic dimension) and product quality (i.e., social dimension) for grape producers in Argentina. More specifically, the article investigated the role of extension services in achieving synergies between aspects of economic and social sustainability. Their findings showed that the programme was successful in encouraging the adoption of higher-quality grape varieties, which led to a sharp decrease in yields right after uptake. The authors also proved that the negative effect on yields faded after an adjustment period.

To the best of my knowledge, the article by Nordin and Höjgård (2017) is the only study that explores the simultaneous impact of scheme participation on economic and environmental outcomes. Participation in the extension programme was free of charge as it was partly funded by the public sector and delivered through a mixed public-private arrangement. Its focus was to increase the efficiency of nutrient utilisation, reduce nutrient leakage, and improve general farm efficiency. The analysis showed that visits by an extension agent significantly decreased farm nitrogen surpluses, thus reducing the risk for nutrient leakage and eutrophication. Extension visits also increased farm value added but did not have any significant effect on farm costs. In their conclusion, Nordin and Höjgård (2017) explained that the increase in farm value added resulting from extension participation would cover programme costs. Hence, they argued that “accordingly, one might consider not making the program[me] completely free of charge to participating farms” (p. 59).

Overall, these two studies are interesting examples of how several sustainability dimensions can be incorporated into the examination of an extension programme to inform whether public support is worthwhile. It provides evidence that extension participation can enhance synergies between sustainability dimensions.

2.5. Summary and research direction

Technology adoption can help farmers increase farm productivity and achieve greater sustainability in agricultural production. Therefore, it has been a central topic in agricultural economics research. The literature has been particularly concerned with the fundamental questions of why farmers adopt new innovations and how technological diffusion can be accelerated.

New technologies are adopted by farmers if they generate some perceived benefits, which can be of economic, social, or environmental nature. Farmers' goals and farming conditions vary drastically, thus explaining why not all technologies are suited or relevant for each individual farm. Moreover, farmers face a great deal of uncertainty before adoption regarding technology returns and variability in returns. This also holds true for the environment under which they will operate in the future. Uncertainty about the technology itself can be reduced through learning, notably by trialling the technology, observing other farmers' experimentations, or participating in extension services.

Extension services encourage knowledge transfer and skill acquisition within the farming community. They facilitate access to information and thus foster technology adoption. Promises of achieving desired agricultural outcomes have justified significant public funding. However, empirical evidence shows that extension participation has a mixed record of success in terms of both farm-level outcomes and cost-effectiveness.

In search of improved extension programmes, two avenues are explored in the literature. First, extension could build on existing peer-to-peer relationships and networks to combine and enhance the effect of peer-to-peer learning and extension participation. Second, as there are limitations inherent to public extension, greater involvement of the private sector in service provision could reduce the financial burden on the public sector, while addressing the information needs of a wider range of farmers.

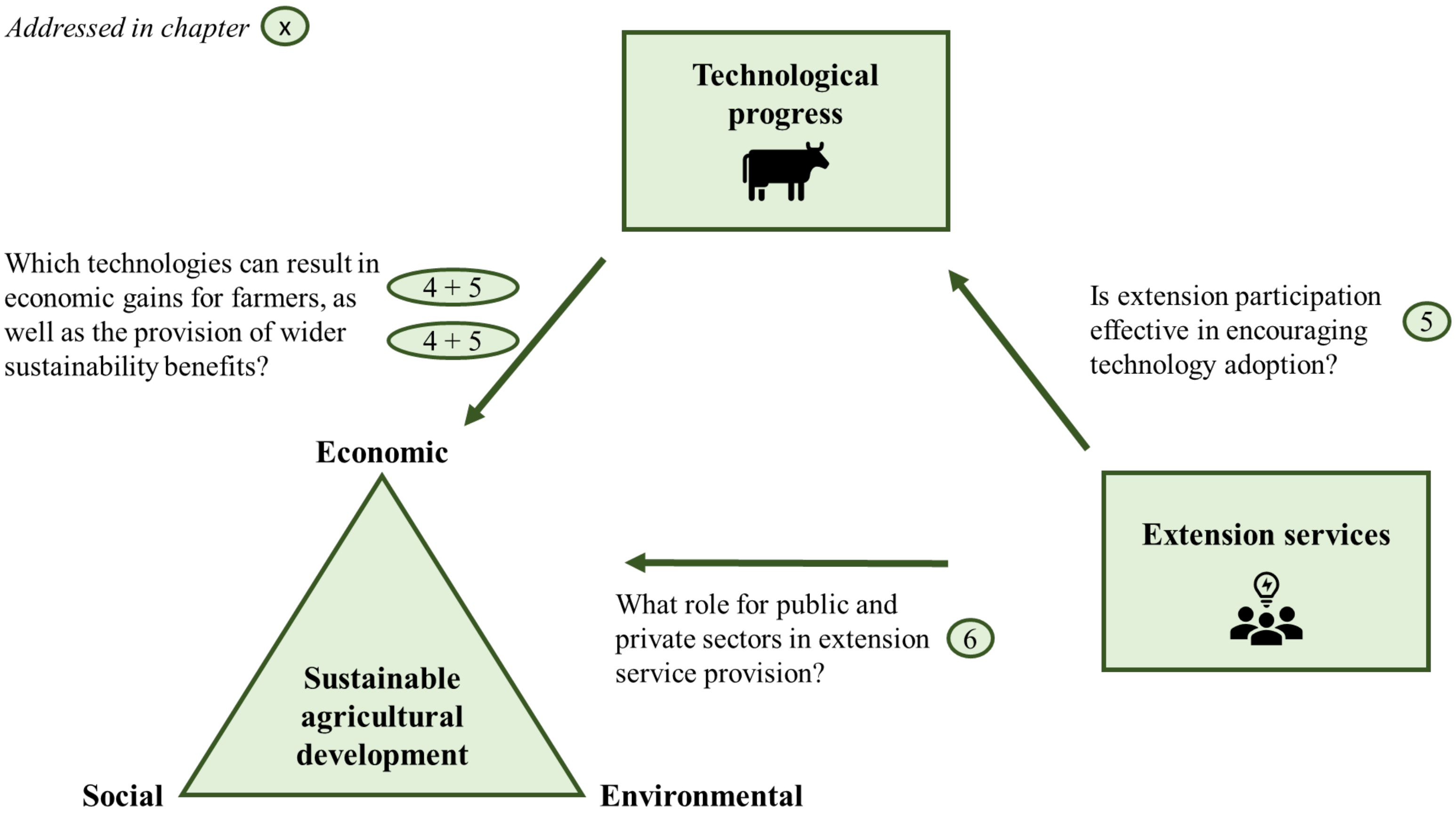
Even though it has been stated in the literature that technology adoption and extension services can contribute towards sustainable agricultural development, empirical evidence beyond farm economic performance remains scarce. In order to inform farmers' uptake decisions and potential policy interventions, empirical evidence is needed by further incorporating the three sustainability dimensions (i.e., economic, social, and environmental) into the assessment of technology and extension impacts. This relies on the ability to define and measure sustainability outcomes at the farm level, to which an indicator approach can contribute. Particular attention should be paid to the choosing of such indicators by establishing selection criteria and validation processes before empirical analysis.

Technology adoption and extension participation can help farmers create or reinforce synergies between sustainability dimensions and resolve trade-offs. As not all technologies may be equally suited for this purpose, more research is needed to expand the scope of current adoption and extension studies on to a more holistic view of farm sustainability.

This PhD thesis contributes to the literature in three main ways. First, in all empirical chapters (Chapter 4, Chapter 5, and Chapter 6), the thesis adopts a multidimensional approach to measure farm sustainability and incorporates a wide set of farm sustainability outcomes into the analyses of technology and extension effects. In this way, the thesis can help to identify farming practices and develop extension systems that improve farm sustainability outcomes. Second, greater insights into the effectiveness of extension systems are gained by examining the effect of participation on farming practices and sustainability in Chapter 5. Third, the role of public and private sectors in delivering extension services is explored in Chapter 6. Specific emphasis is given to the profiles of farmers that they can target, as well as their sustainability outcomes. Figure 2.1 summarises the main questions addressed in this PhD thesis.

Overall, the thesis brings empirical evidence into the debate on how to achieve sustainable intensification. It examines in detail extension effectiveness for greater farm sustainability to address the twofold challenge of meeting farmers’ private needs while simultaneously providing wider public benefits in relation to agricultural production.

Figure 2.1: Research direction for the PhD thesis



Chapter 3 - Contextual background

3.1. Introduction

In April 2015, European Union (EU) milk quotas were abolished, thereby setting in motion a process of dairy expansion and intensification in Ireland (Eurostat, 2020a, 2020b). Five years after quota removal, the Irish dairy sector has achieved the largest growth across EU Member States and further expansion is expected (Eurostat, 2020a; Lanigan et al., 2018). As ongoing, rapid changes raise significant environmental and social challenges, the need to continue growing in a sustainable manner is particularly salient (Donnellan et al., 2018; Hoekstra et al., 2020; Kelly et al., 2020, 2017; Lanigan et al., 2018). Changes in farming practices and knowledge transfer can help farmers achieve this goal and have thus a critical role to play in the process of sustainable dairy expansion and intensification (Donnellan et al., 2015; Kelly et al., 2020; Teagasc, 2015).

The main objective of this chapter is to present the contextual background of the PhD thesis. First, EU and Irish milk production developments preceding and following quota removal are reviewed (section 3.2). Second, the Irish dairy sector is described in greater detail (section 3.3). Third, a selected number of sustainability challenges associated with dairy farming are reported, with a specific focus on Greenhouse Gas (GHG) and water quality concerns (section 3.4). The importance of farm-level technology adoption and improved farm management is also highlighted for increasing productivity and overcoming sustainability concerns on Irish dairy farms. Fourth, an overview of Irish extension services is provided (section 3.5), while the chapter ends with a summary (section 3.6).

3.2. Implications of European Union milk quota removal with a specific focus on Ireland

In the late 1970s and early 1980s, the oversupply of milk on EU markets led to the well-known problem of ‘milk lakes’ and ‘butter mountains’, with adverse effects on world market prices (European Commission, 2015)[6]. In response, the EU introduced milk quotas in 1984 to cap dairy production, which allowed each Member State to only produce a fixed quantity per year. For over 30 years, EU milk production was limited in this way.

Since the early 2000s, global dairy consumption has risen significantly, driven mainly by emerging economies (e.g., in Asia). This made the quota regime restrictive as EU dairy farmers did not have the flexibility to respond to and benefit from the growing demand for dairy products. Therefore, in the 2003 Common Agricultural Policy reform, the decision was made to abolish milk quotas in 2015. In 2008, the EU reconfirmed this choice and announced detailed measures for the 2009-2015 time period to achieve a “soft-landing”. EU Member States and dairy farmers thus started preparing for quota removal, and milk quotas were increased by 1% every year between 2009 and 2013.

3.2.1. Heterogeneous responses to quota removal across the European Union

Milk quota removal has allowed the EU to reinforce its position in the international dairy market by increasing production by 15% overall between 2008 and 2018 (Eurostat, 2020a). The EU is the largest milk producer in the world, accounting for approximately 23% of global production in 2018 and 156 million tonnes of milk (Food and Agricultural Organization of the United Nations, 2020b).

Nonetheless, responses to quota removal varied across Member States, reflecting differences in relative competitiveness and national efforts to

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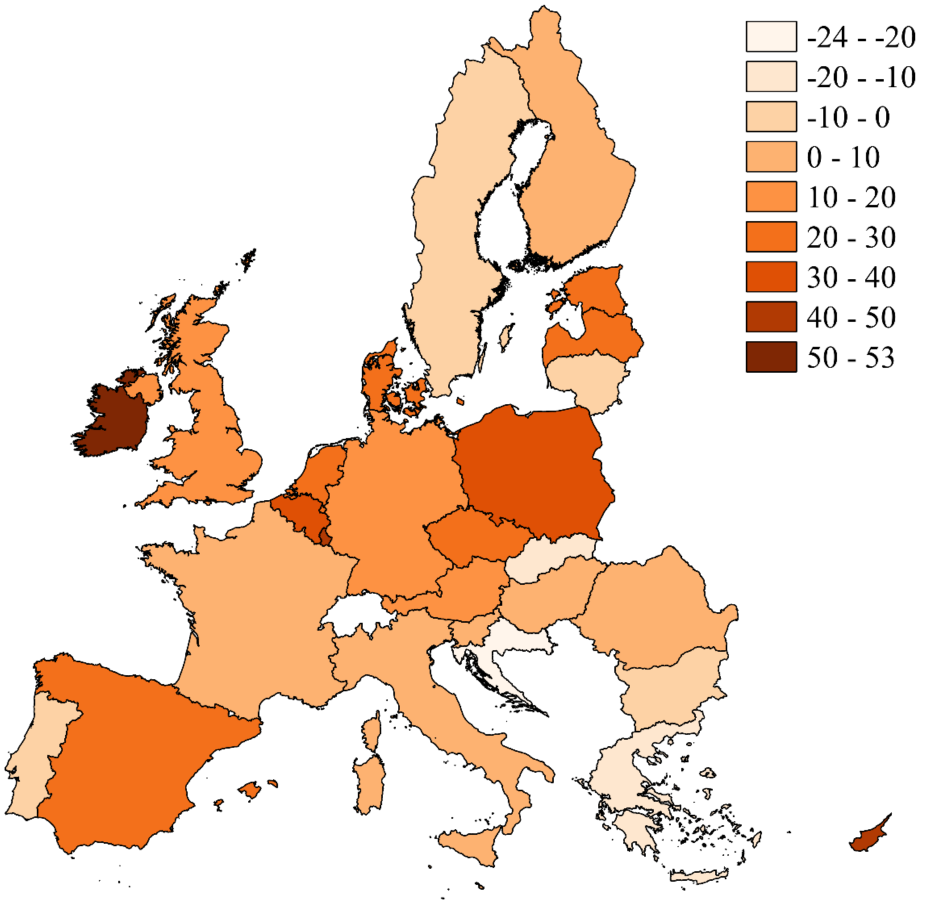
[6] Please note that these first two paragraphs are based on information contained in European Commission (2015).

reshape dairy sectors (Bórawski et al., 2020; Läpple et al., 2020; Philippidis and Waschik, 2019). The policy change implied less protection for EU farmers, with a greater exposure to milk price volatility and market competition (Bojnec and Fertő, 2014; Giles, 2015). As a result, it triggered a process of concentration of milk production in the most favourable geographical areas with a comparative advantage (Donnellan et al., 2015; Läpple and Sirr, 2019). Figure 3.1 shows that between 2008 and 2018, milk production contracted in seven countries (i.e., Portugal, Greece, Bulgaria, Slovakia, Sweden, Croatia, and Lithuania), while it increased to varying degrees in remaining EU countries.

Figure 3.1: Changes in milk production 2008-2018 across EU Member States (in % change)

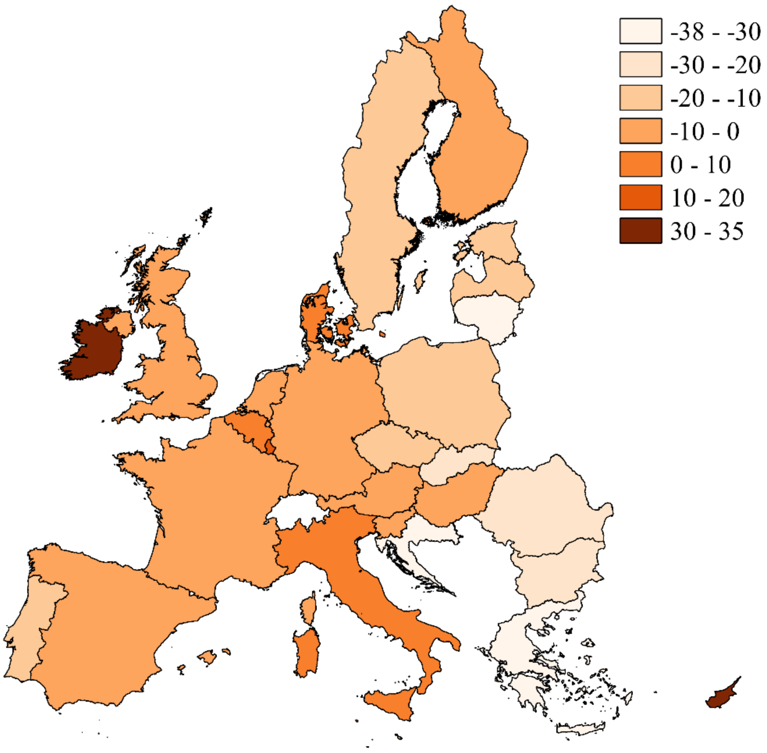


Source: Eurostat (2020a).

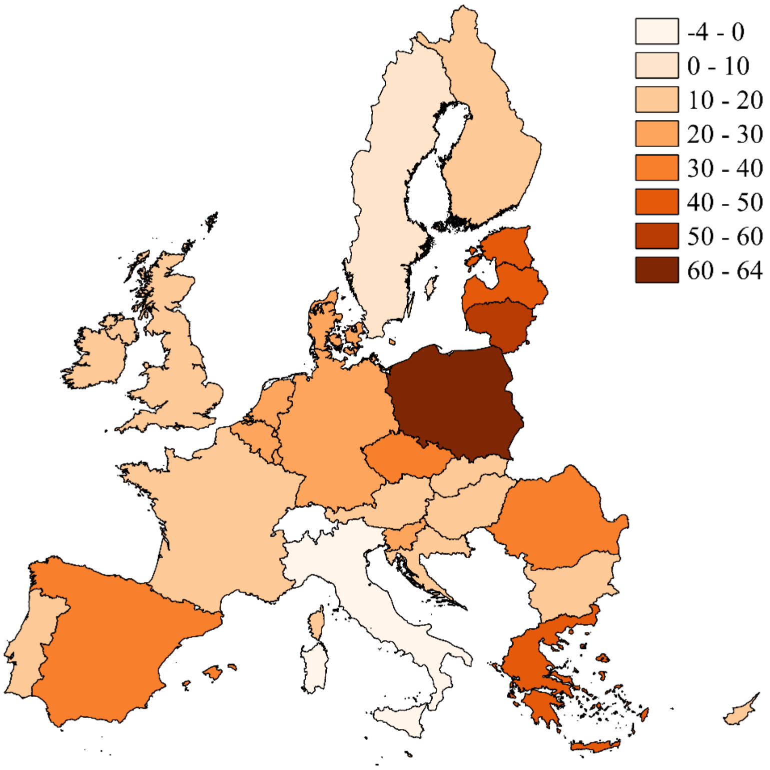
Structural changes in European dairy sectors started in 2008, with the confirmation of milk quota abolition, and resulted from two main mechanisms: adjustments in the size of dairy herds and changes in milk yield per cow, represented in Figure 3.2 (a and b, respectively). Along with Italy, Luxemburg, Belgium, Denmark, and Cyprus, Ireland is one of the few countries where growth was partially achieved through an increase in dairy cow numbers. Other growing dairy sectors (notably the largest producers such as Germany, France, the United Kingdom, the Netherlands, or Poland), contracted the size of their national herds. In line with general productivity growth in agriculture, cow milk yields increased across the EU (except Italy), even in countries where production decreased.

Figure 3.2: Structural changes 2008-2018 across EU Member States

a) Dairy cow numbers (in % change)



b) Milk yield per dairy cow (in % change)



Source: Eurostat (2020a, 2020b).

3.2.2. Irish dairy sector growth

The Irish dairy sector achieved the largest growth of all EU Member States, with milk production increasing by 53% between 2008 and 2018 (Eurostat, 2020a). The national dairy herd expanded by 34% and cow milk yields improved by 16% (Eurostat, 2020a, 2020b). As a result, Irish dairy output represented 5.2% of EU dairy production in 2018, an increase by 39% since 2008 (Eurostat, 2020a).

Conditions conducive to growth fostered such an expansion. In 2010, the Irish government announced ambitious growth targets for the agricultural sector as part of the ‘Food Harvest 2020’ agri-food strategy (Department of Agriculture Food and the Marine, 2010a). Overall, the aim was to increase the value of primary agricultural output by 33% by 2020 relative to the 2007-2009 average, with detailed objectives and supporting actions by subsector. For the dairy sector, the target was to increase milk production by 50%. To this end, the government paved the way for transformation of the dairy industry by implementing specific schemes and policies (Department of Agriculture Food and the Marine, 2010b; Kelly et al., 2020), with a few examples described hereafter:

- Tax relief for long-term land leasing: With land mobility being generally low in Ireland due to cultural factors (Hennessy, 2006; Leonard et al., 2017), the government implemented in 2014 tax relief for long-term leasing (Kelly et al., 2020; Revenue, 2019). In this way, land leasing was made more attractive to farm owners to facilitate access to land for expanding dairy farmers (Kelly et al., 2020).

- 'New Entrant Scheme': During the soft-landing period, the government allocated one quarter of the 1% increase in milk quotas to new entrants into dairy farming (Department of Agriculture, Food and the Marine, 2010b; Kelly et al., 2020). The purpose was to attract new dairy farmers into the industry and hence establish new enterprises for the first time in 30 years (McDonald et al., 2014). In total, 410 new entrants benefited from the scheme (Kelly et al., 2020).

- 'Dairy Efficiency Programme' (DEP): Expanding and improving knowledge transfer to dairy farmers was also seen as an important means to support farmers in the growth process (Department of Agriculture, Food and the Marine, 2010a). Thus, the government subsidised farmers' participation in extension from 2010 until 2012, with the goal of increasing the number of participants and encouraging efficiency gains in the dairy sector (Department of Agriculture Food and the Marine, 2010b; Läpple and Hennessy, 2014). This scheme will be further described in section 3.5.3.

Moreover, there was scope to increase cow numbers on existing dairy farms (Donnellan et al., 2015; Läpple et al., 2020; Läpple and Sirr, 2019). Under the milk quota regime, dairy farmers had implemented diversification strategies to produce within quota constraints (Läpple et al., 2020). Greater specialisation in dairy production at farm level was thus possible after quota abolition, notably by farming more intensively and substituting other livestock or tillage areas with dairy cows (Läpple et al., 2020; Läpple and Sirr, 2019). Consequently, considerable farm-level investments were made to support growth (Donnellan et al., 2015; Kelly et al., 2017; Läpple et al., 2020).

While the ‘Food Harvest 2020’ growth targets may have seemed ambitious when first introduced (Kelly et al., 2020; Läpple and Hennessy, 2012), they were achieved two years ahead of schedule (Eurostat, 2020a). Further dairy growth is expected in the frame of the governmental ‘Food Wise 2025’ agri-food strategy[7] (Department of Agriculture Food and the Marine, 2015).

3.3. Dairy farming within Irish agriculture

In 2016, there were a total of 137,500 farms in Ireland according to the Farm Structure Survey[8] from the Irish Central Statistics Office (2018). Only 16,100 were specialist dairy farms, thereby representing 11.7% of all farms, as shown in Figure 3.3. Irish agriculture is mainly livestock based and is dominated by beef production (57% in 2016), followed by dairy and sheep (11%) farming. Specialist tillage farms accounted for only 3.4% of all farms in 2016.

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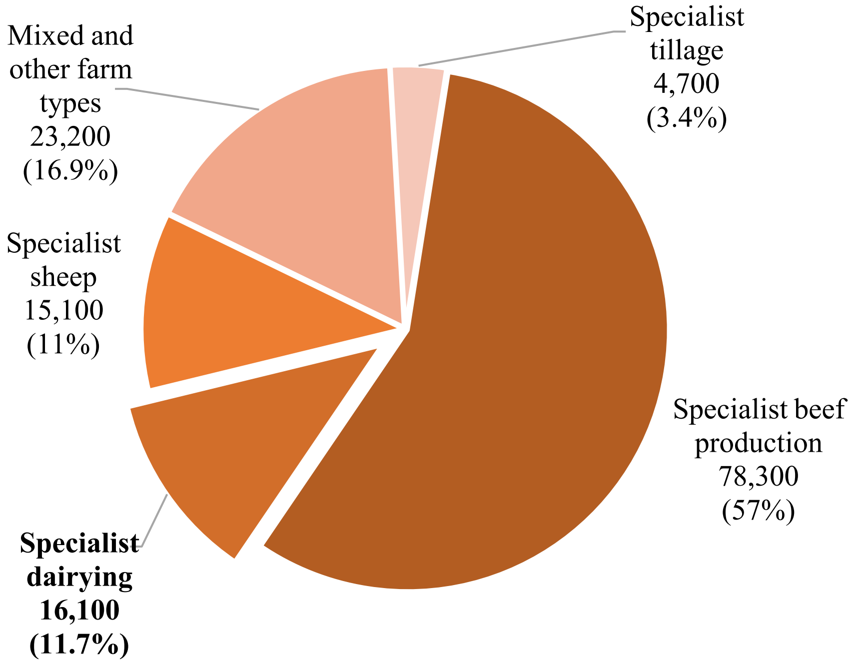
[7] ‘Food Wise 2025’ goals are not sector specific and include a 85% increase in the value of agri-food exports, a 70% increase in the value added in the agri-food, fisheries, and wood products sector, and a 65% increase in the value of primary production between 2015 and 2025.

[8] 2016 was the date of the last Farm Structure Survey. This is the reason why I use 2016 figures to describe the structure of Irish agriculture.

Figure 3.3: Number and proportion of farms by subsector 2016

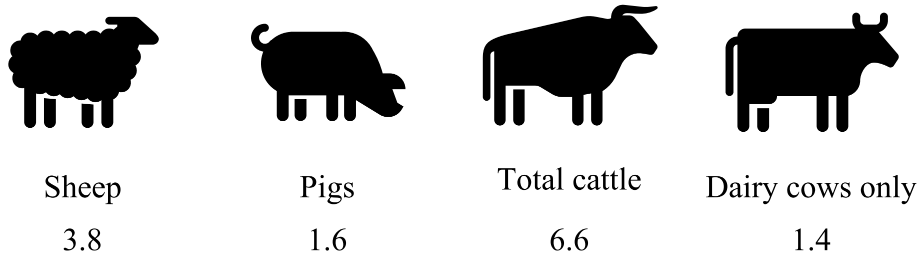


Note: Farms are classified into farm types, which represent the primary area of specialisation. The classification is based on the relative standard output of the different farming subsectors.
Source: Farm Structure Survey from the Irish Central Statistics Office (2018).

3.3.1. Numbers and regional distribution of dairy cows within Ireland

In terms of livestock numbers, figures from the Livestock Survey from the Central Statistics Office (2020a) are presented in Figure 3.4. They indicate that in 2018, there were 6.6 million cattle, including 1.4 million dairy cows, 3.8 million sheep, and 1.6 million pigs. This again highlights the small size of the dairy sector in terms of numbers relative to other farming sectors. While dairy cows represented 20.8% of total cattle numbers in 2018, this ratio increased by almost 12% between 2008 and 2018 (and 17% between 2008 and 2019) due dairy expansion (Central Statistics Office, 2020b, 2009).

Figure 3.4: Livestock numbers in Ireland 2018 (in million)



Source: Livestock Survey from the Central Statistics Office (2020a).

Figure 3.5 (a and b, respectively) shows the number of dairy cows and degree of specialisation in dairy production by Irish county (Central Statistics Office, 2020b). Dairy specialisation is measured by the proportion of dairy cows to total cattle numbers. The southern region[9] is the traditional dairy region, with favourable weather and agronomic conditions for dairying (Dillon et al., 2018b; Läpple et al., 2012). In 2018, the South contained 72.5% of Irish dairy cows and had a ratio of dairy cows to total cattle of 26.9%. These figures compare with lower percentages for the North-West region (i.e., 11.3% of Irish dairy cows and 9.6% of cows to total cattle) and the East-Midland region (i.e., 16.2% of Irish dairy cows and 14.9% of cows to total cattle). Almost 26% of Irish dairy cows were based in County Cork alone, which also displayed the largest degree of dairy specialisation (33.6%).

Interestingly, although production and cow numbers remain concentrated in the South, dairy growth was achieved in both traditional and non-traditional dairy areas (Dillon et al., 2018b). Presently, future growth is expected predominantly in these non-traditional regions, where there may be more scope for further dairy expansion.

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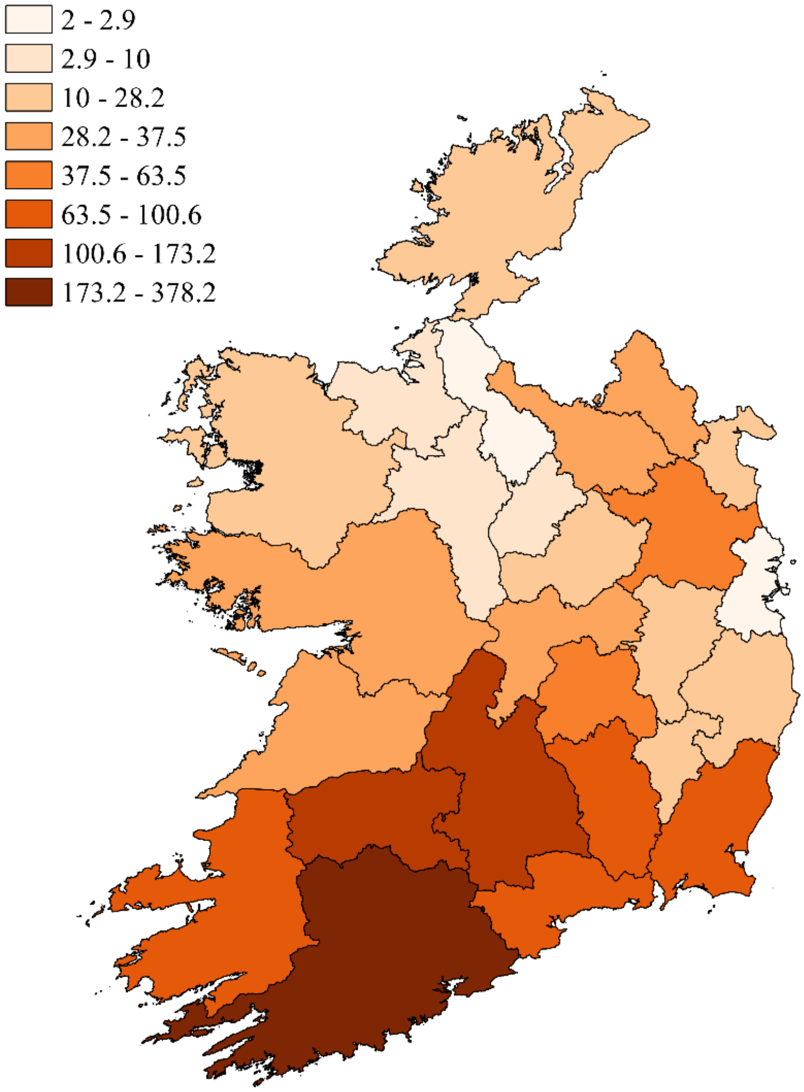
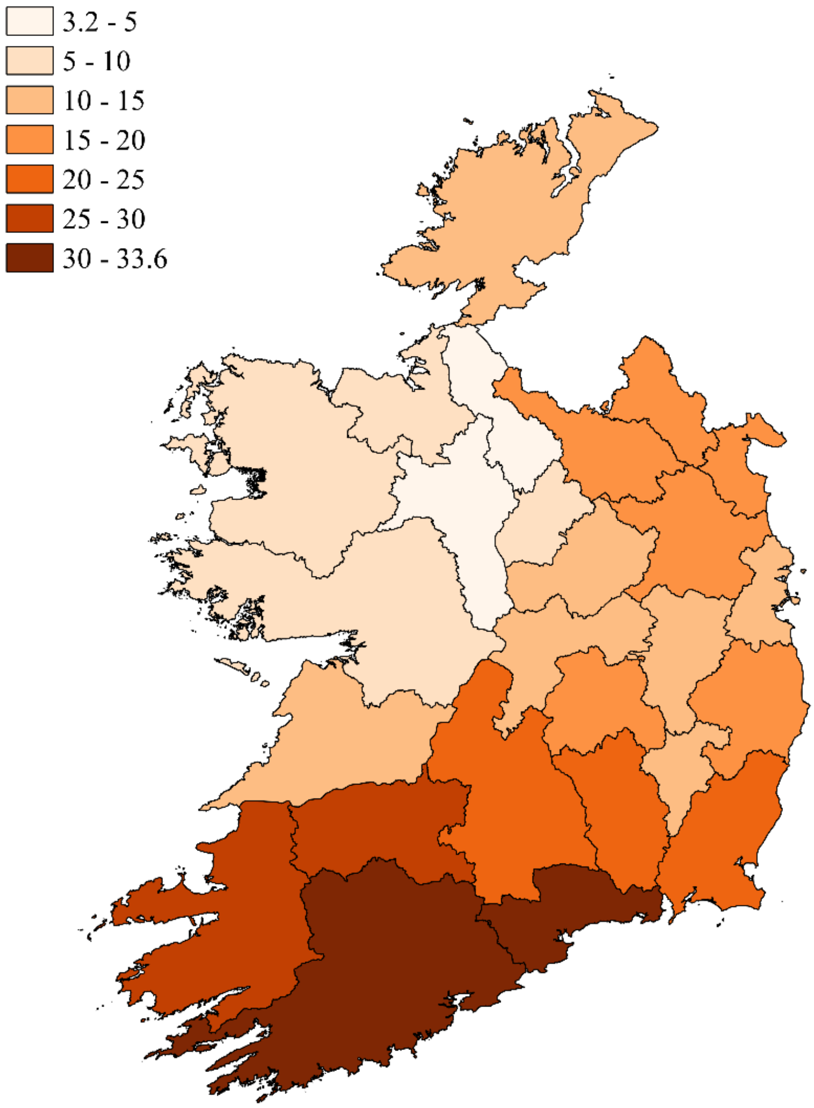
[9] The southern region includes the following counties: Limerick, Tipperary, Clare, Wexford, Kilkenny, Carlow, Waterford, Cork, and Kerry.
The northern and western region includes the following counties: Leitrim, Sligo, Cavan, Donegal, Monaghan, Galway, Mayo, and Roscommon.
The eastern and midland region includes the following counties: Dublin, Kildare, Meath, Wicklow, Louth, Laois, Longford, Offaly, and Westmeath.

Figure 3.5: Dairy cows across Irish counties

a) **Number of animals 2018 (in '000 heads)**



b) Proportion of dairy cows to total cattle 2018 (in %)



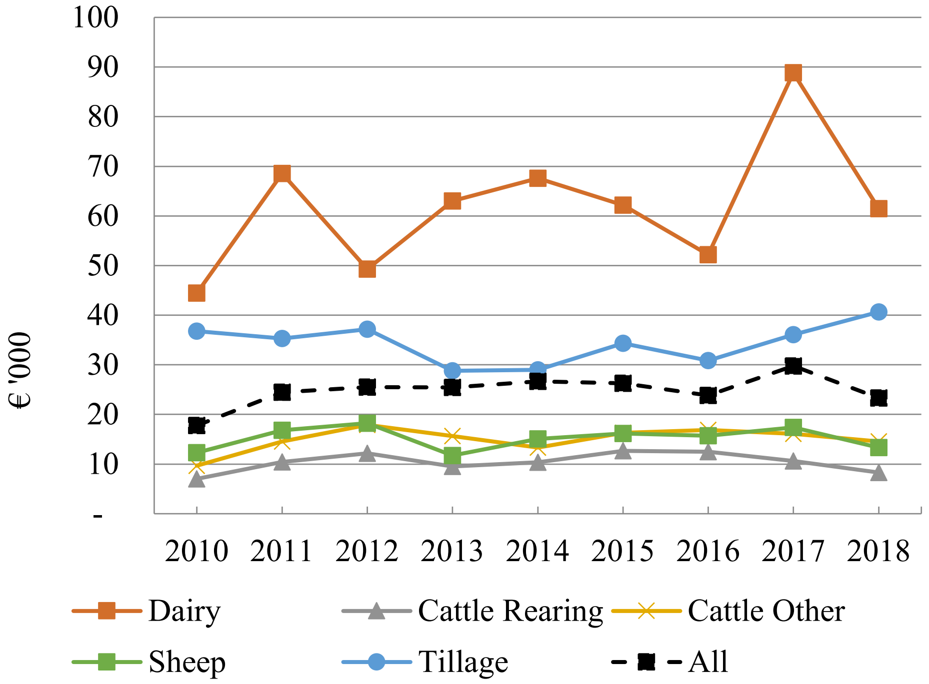
Source: Livestock Survey from the Central Statistics Office (2020a).

3.3.2. Economic contributions of the Irish dairy sector

Dairy production is by far the most profitable farming system in Ireland. When looking at trends in family farm incomes over the 2010-2018 time period in Figure 3.6, data from the Teagasc National Farm Survey (NFS) illustrates that specialised dairy farming achieved much higher incomes than all other farming systems (Dillon et al., 2018b). It is also worth mentioning that a significantly smaller share of dairy farmers work off-farm in comparison with other farming systems (12% for specialist dairy versus 39%

and 32% for cattle rearing and sheep in 2018, respectively) (Dillon et al., 2018b).

Figure 3.6: Average family farm incomes by agricultural system 2010-2018 (in €)



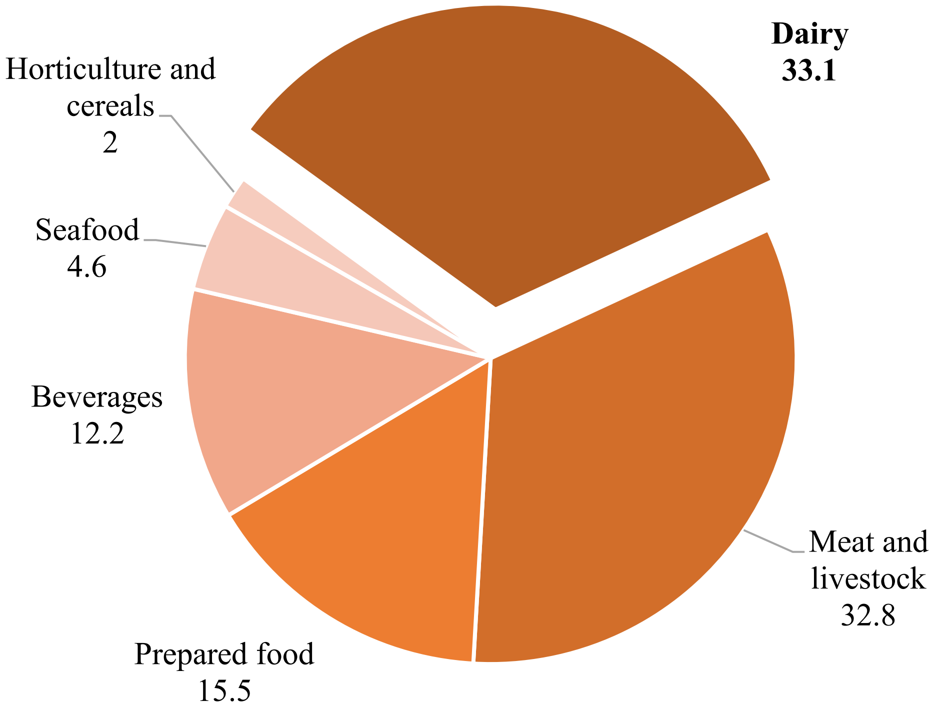
Note: Family farm incomes reported in terms of nominal values.
Source: Results from the Teagasc NFS, presented in Dillon et al. (2018b).

Additionally, the Irish dairy sector is export oriented, with 90% of milk supplies destined for the export market and only 10% consumed domestically (National Milk Agency, 2020). It was the strongest performer of all Irish agri-food sectors in terms of both export volumes and value in 2018, accounting for about €4 billion and 33% of agri-food exports (Bord Bia, 2018). Figure 3.7 displays the value of agri-food exports by subsector in 2018 and highlights the strong position of the dairy industry relative to other subsectors. In 2018, Ireland ranked eighth largest dairy exporting nation in the world in terms of value (Food and Agricultural Organization of the United Nations, 2020c).

Irish dairy export values increased by 78% between 2008 and 2018 (Bord Bia, 2018). At the farm level, dairy gross output per hectare (ha) increased by 12% during the 2015-2017 period relative to the 2010-2012 average

(Buckley et al., 2019). Therefore, the position of dairy farming within Irish agriculture has been further strengthened over the last decade.

Figure 3.7: Value of agri-food exports by subsector 2018 (in %)

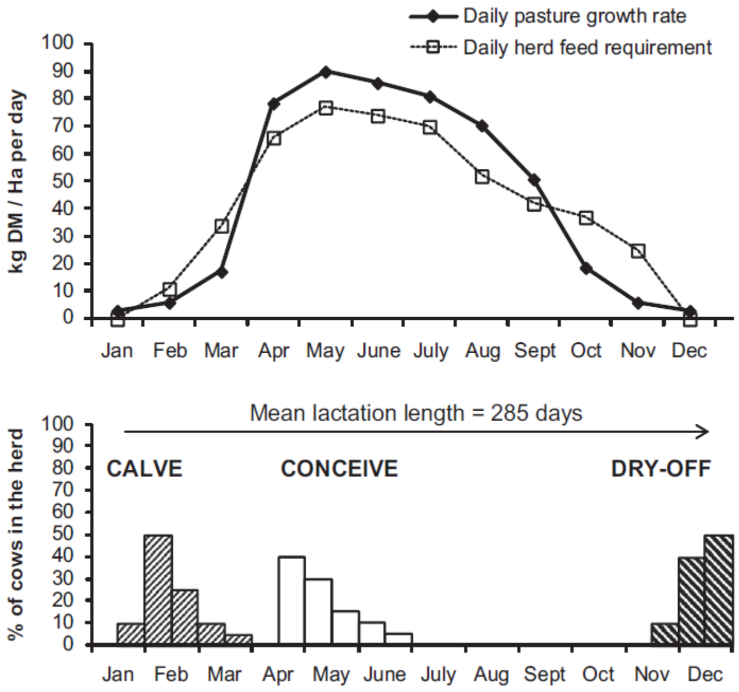


Note: Meat and livestock includes beef, pig meat, sheep, poultry, and live animals.
Source: Bord Bia (2018) estimates.

3.3.3. The Irish grass-based production system

The Irish dairy sector gains from a competitive advantage on international markets by relying on a low-cost grass-based production system, where cows graze outdoors from early spring until late autumn (Dillon et al., 2008). The temperate climate allows for the growth of a large amount of grass, which represents the main and cheapest feed source of dairy cows (Hanrahan et al., 2018; Läpple et al., 2012; O'Brien et al., 2018). Indeed, it was estimated in O'Brien et al. (2018) that 80% of the diet of Irish dairy cows is composed grass. Best practice for Irish dairy farmers is thus to maximise homegrown grass in the diet of dairy cows with appropriate supplementation from concentrates when grass supply and grazing conditions are not suitable (O'Brien et al., 2018). Hence, farmers mainly operate spring-calving systems[10], as represented in Figure 3.8. In 2018, approximately 83.8% of calves with a dairy dam were born between January and April (Department of Agriculture Food and the Marine, 2019). Conversely, only about 6.6% were born between September and December (Department of Agriculture Food and the Marine, 2019). Farmers aim at achieving 365-day compact calving patterns to capitalise on long grass-growing seasons (Butler, 2014; Hanrahan et al., 2019; Lane et al., 2013). In this way, seasonal grass growth, herd feeding requirements, and reproductive cycles can be synchronised (Butler, 2014). As a result, Irish milk production is highly seasonal.

Figure 3.8: Schematic representation of grass growth, herd feeding requirements, and reproductive cycle for spring-calving dairy herds



Source: Butler (2014).

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[10] Autumn-calving herds represent a small share of Irish dairy herds. While production costs are larger due to reduced pasture grazing in the winter months, milk prices at the farm gate are also much higher (Central Statistics Office, 2020c; Lawrence et al., 2014).

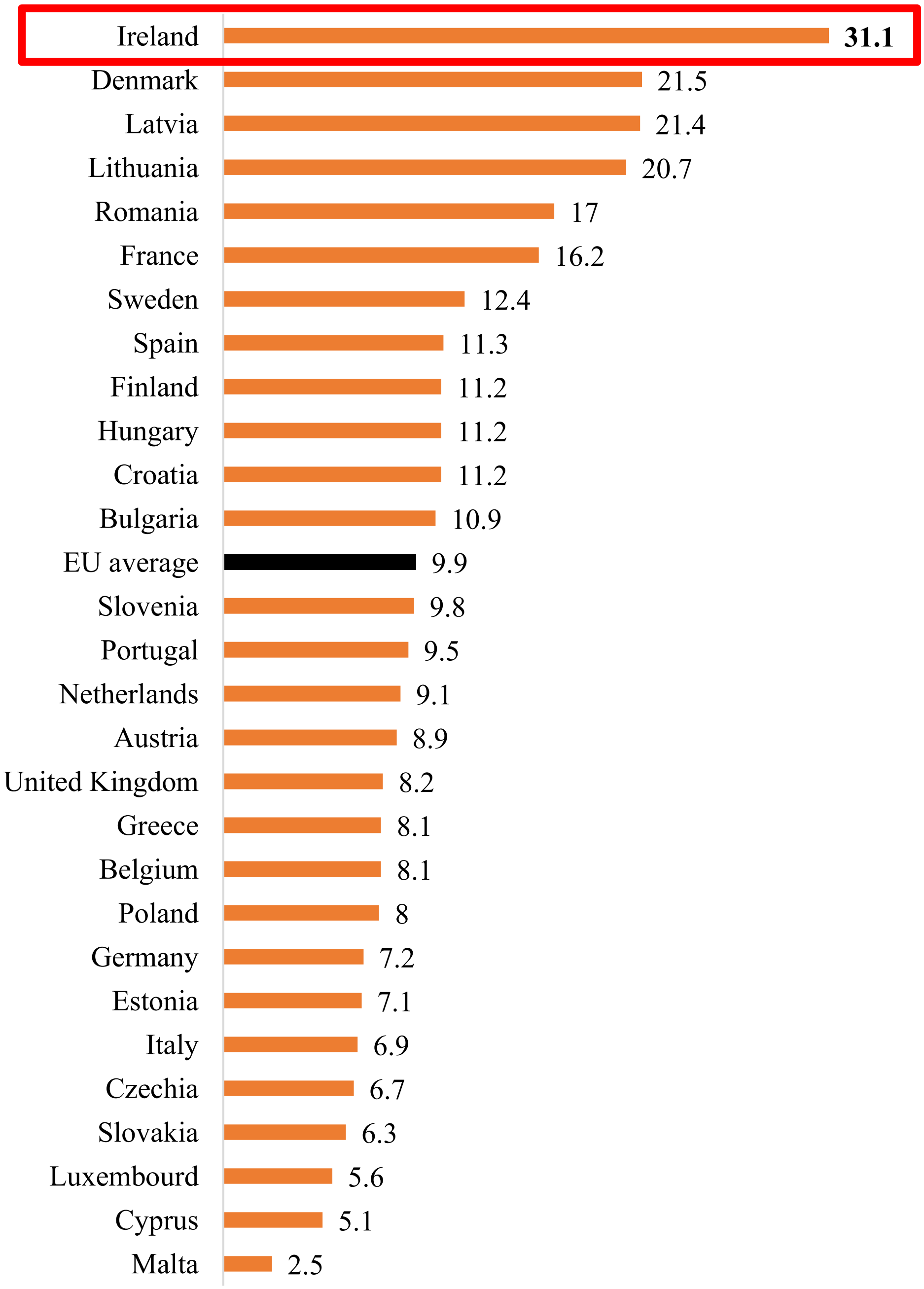
3.4. Sustainability challenges associated with dairy farming

Achieving sustainable intensification of Irish milk production is not an easy task. While farm economic performance and the value of dairy exports have increased since quota removal (Bord Bia, 2018; Buckley et al., 2019), other sustainability concerns are growing in tandem. These include GHG emissions (Donnellan et al., 2018; Lanigan et al., 2018), ammonia emissions (Buckley et al., 2020b), nitrogen losses to water bodies (Hoekstra et al., 2020), increased workload and limited availability of skilled labour (Kelly et al., 2017), surplus production of unwanted male calves (Holden and Butler, 2018), increased antimicrobial use (Martin et al., 2020; More et al., 2017), biodiversity loss (Chen and Holden, 2018), and pressure on freshwater resources (Murphy et al., 2017). Addressing these sustainability concerns is key to the successful development of the Irish dairy industry (Kelly et al., 2020). As GHG and water quality concerns are focused upon in this PhD thesis, they are described in greater detail in this section.

3.4.1. GHG emissions

Agriculture is the largest contributor to GHG emissions by sector in Ireland, accounting for 31.1% of total national emissions in 2018 (Eurostat, 2020c). The ratio of agricultural GHG emissions to total emissions is the highest in Ireland across EU Member States, as shown in Figure 3.9. This is due to the livestock-based nature of Irish agriculture and the small contribution of industrial processes to the national GHG inventory (Central Statistics Office, 2018; Eurostat, 2020d).

Figure 3.9: Contributions of the agricultural sector to total GHG emissions 2018 across EU Member States (in %)



Source: Eurostat (2020c).

Between 2011 and 2017, Irish agricultural GHG emissions increased by 14.2%, mainly because of changes in dairy cow numbers and input reliance (Duffy et al., 2019). This trend is likely to continue as further growth in agricultural output, prominently from the dairy industry, is expected (Environmental Protection Agency, 2019a; Lanigan et al., 2018). Indeed, since emissions are primarily driven by animal numbers, and organic and synthetic fertiliser use[11], there exists an intrinsic relationship between levels of bovine agricultural activity and GHG emissions (Donnellan et al., 2018). Additionally, predicted declines in beef animals are unlikely to be sufficient to offset the expected increase in GHG emissions (Lanigan et al., 2018). The average Irish dairy farm emitted 3.6 times more GHG emissions than the average cattle or sheep farm in 2017 (Buckley et al., 2019), likely due to differences in production intensity.

Nevertheless, Ireland has an international obligation to decrease GHG levels as part of the 2015 Paris Agreement (COP21) and the EU Effort Sharing Decision (Environmental Protection Agency, 2019a; European Commission, 2019b, 2014). Specific GHG reduction targets are to be achieved by several sectors in the short to medium term. Under the EU Climate and Energy Framework, Ireland must decrease emissions from non-Emission Trading Scheme sectors[12] by 20% by 2020 and 30% by 2030 relative to 2005 levels. In 2018, agriculture accounted for 45% of non-Emission Trading Scheme GHG emissions (Sustainable Energy Authority of Ireland, 2020). As a major contributor to non-Emission Trading Scheme emissions, the agricultural sector is under pressure to participate in the reduction effort (Donnellan et al., 2018; Lanigan et al., 2018). Current projections also indicate that Ireland is unlikely to meet its carbon reduction targets over the 2013-2020 and 2021-2030 periods (Environmental Protection Agency, 2019a; European Commission, 2019a).

Given current ’Food Wise 2025’ agri-food strategy, widespread adoption of mitigation actions by individual farmers is required to lower GHG emissions (Donnellan et al., 2018; Lanigan et al., 2018). For the dairy sector, these include, among others, improving cow genetic merit, extending the length of the grazing season, introducing clover into grass swards, using sexed semen,

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[11] Main agricultural GHG emissions include methane from enteric fermentation by ruminant livestock, methane and nitrous oxide from the production and storage of livestock manures, and nitrous oxide from the application of manures and synthetic fertilisers to agricultural soils (Buckley et al., 2019).

[12] Non-Emission Trading Scheme sectors include agriculture, transport, residential, commercial, waste, and non-energy intensive industries.

or enhancing animal health (Lanigan et al., 2018). However, it is important to note that technology adoption will not be sufficient to reach GHG reduction targets and other alternatives such as a reduction of the suckler herd, a re-examination of agricultural growth targets, or a moderation of expectations of emission reduction from agriculture, will need to be considered (Donnellan et al., 2018).

Finally, it is worth mentioning that Irish dairy farms are becoming more carbon efficient. Since 2010, agricultural GHG emissions per kilograms (kg) of Fat-Protein-Corrected-Milk (FPCM) are steadily decreasing (Buckley et al., 2019). Intensification is a potential mitigation strategy if high levels of input application can be avoided and absolute emissions associated with the process are offset by higher levels of efficiency (Crosson et al., 2011). Additionally, temperate grass-based dairy production systems, such as the one in Ireland, have half the emission intensity compared with tropical or arid grassland dairy systems (Food and Agricultural Organization of the United Nations, 2010; Lanigan et al., 2018). Consequently, leakage of dairy production from temperate to other grass-based systems could result in a decrease in carbon efficiency of global milk production (Lanigan et al., 2018).

3.4.2. Risk to water quality

While dairy production is reliant on nitrogen and phosphorus inputs within fertilisers and concentrates, relatively low proportions of these nutrients are turned into milk, thereby leaving the rest available for loss to the environment (air and water bodies) (Burchill et al., 2016; Thomas et al., 2020). In general, dairy farming has low nutrient use efficiencies and high nutrient surpluses compared with other agricultural sectors (Quemada et al., 2020; Thomas et al., 2020). For instance, nitrogen surpluses were on average 2.7 times higher on Irish dairy farms than on cattle farms over the years 2015-2017 (Buckley et al., 2019).

Ongoing dairy expansion increases the risk to water quality by adding nutrient pressure. During the 2015-2017 time period, nitrogen surpluses increased by about 6% on dairy farms relative to the 2010-2012 average

(Buckley et al., 2019). Moreover, a recent report by the Environmental Protection Agency (2019b) revealed that between 2013 and 2018, nutrient concentration rose by 26% in rivers coinciding with areas of agricultural activity, thereby indicating a worrying trend. In certain areas of Ireland, levels of nitrogen and phosphorus losses from agriculture to the environment are already above the ‘safe operating space’, i.e., boundaries for anthropogenic perturbation of critical Earth-system processes (Steffen et al., 2015).

In the frame of the Nitrates Directive, the EU has warned that there would be repercussions from water quality deterioration in areas with high livestock density (European Commission, 2017). The Netherlands had first-hand experience of this in 2017. When facing an acute water quality issue mainly associated with dairy growth, the country had to cull 50,000 dairy cows (European Commission, 2017).

The EU Nitrates Directive was implemented in 1991 to protect water quality by preventing agricultural-related nutrients from polluting ground and surface waters. The policy promotes the use of good farming practices and imposes farm-level restrictions on nitrate and phosphate levels through strict monitoring of nutrient application and stocking rate limitations[13] (European Commission, 2010). In accordance with the Nitrates Directive, Ireland’s first Action Plan was introduced in 2006. Overall, it was successful in decreasing nitrogen and phosphorus surpluses on dairy farms before milk quota removal (Buckley et al., 2016a, 2016b). However, in recent years, increases in farm nutrient surpluses and water quality deterioration highlight the need to improve nutrient management and limit further environmental losses from dairy expansion.

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[13] Limitations are of 170 kg of organic nitrogen applied per ha. This is equivalent to a stocking rate of 2 dairy cows per ha. However, as part of the Nitrates Action Programme, Ireland has been granted a nitrates derogation for the fourth time for the years 2018-2021 (Nitrates, Biodiversity and Engineering Division, 2019). This allows the increase of the limitations up to 250 kg of organic nitrogen (i.e., equivalent to 2.94 dairy cows per ha) for farms that are highly stocked and more intensively driven. In 2018, a total of 7,000 Irish farms had a derogation, an increase by about 19% since 2014 (Nitrates, Biodiversity and Engineering Division, 2019).

In that regard, the adoption of improved farm management practices has a role to play in helping farmers reducing and/or getting higher responses to inputs. Quantities and forms of nutrient losses are highly dependent on farm management (Hoekstra et al., 2020). Reductions in fertiliser application could be gained from optimising soil nutrient status and adding nitrogen-fixing legumes (e.g., clover) onto swards (Hoekstra et al., 2020). Other grassland management strategies such as grass measurement and budgeting, soil testing and reseeding, lengthened grazing seasons, and the building of appropriate grazing infrastructures, could also increase grass growth and utilisation (Creighton et al., 2011; Hanrahan et al., 2019, 2017; Shalloo et al., 2011).

3.5. Overview of Irish extension services

As previously outlined, improved farm management and technology adoption can help farmers achieve sustainable intensification. Within this context, knowledge transfer through extension has a critical role to play in encouraging farmers' learning and implementing of improved farming practices. In Ireland, there exists a wide range of advisory services with which farmers can engage.

3.5.1. Teagasc mixed public-private extension model

Most of Ireland's agricultural extension services are delivered through Teagasc[14], the State Agriculture and Food Development Authority. Teagasc offers a unique model of integration between research, advisory, and education activities within one institution (Teagasc, 2015). In this way, knowledge transfer between all stakeholders is encouraged based on empirical-based advice and close research-advisory linkages. The primary purpose of Teagasc advisory is to "*maximise the income and sustainability of farm families*" (Teagasc, 2015, p. 2). The service operates from 51 locations throughout the country with about 240 advisors for 43,000 clients in 2018, giving an advisor-to-farmer ratio of 1 to 179 (all farming sectors

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[14] Which means "instruction" in the Irish Gaelic language.

included) (Teagasc, 2019). 87 of them were dairy advisors (Teagasc, 2019). Teagasc advisory exploits a wide range of communication methods including group extension under the form of farmers' discussion groups, one-to-one consultations and farm visits, large-scale events such as farm walks, open days and demonstrations, workshops, farm management newsletters, social media, and Teagasc Today's Farm magazine (Teagasc, 2015).

The Teagasc advisory service uses a mixed public-private model (Teagasc, 2015). More specifically, about 55% of the advisory budget is publicly funded while the remainder is covered by charges for services. The latter are generally invested in employing private consultants who complement the work of Teagasc advisors. Fees are calculated on the basis of farm size and the type of service that the farmer seeks[15] (Teagasc, 2020).

3.5.2. Access to private consultancy

Some farmers prefer to seek extension through the private sector. According to Kelly et al. (2013), there were about 250 private consultancy firms in 2013 (all farming sectors included). They predominantly offer advice on a one-to-one basis rather than group extension (Prager et al., 2016), even though private discussion groups have been growing in popularity in recent years. In general, the fees for services are set by the private consultant and vary depending on factors including farm size and the type of service that the farmer seeks.

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[15] For instance, the "Teagasc Technology" support package costs between €225 and €385 per annum and includes an office-based annual farm review (with support for the EU Basic Payment Scheme application), access to the Teagasc office by phone, invitations to mass events, a subscription to newsletters and Today's Farm magazine, access to the PastureBase Ireland software, office-based support for farm inspections, and a farm visit (Teagasc, 2020). PastureBase Ireland is "a web-based grassland management application incorporating a dual function of grassland decision support and a centrali[s]ed national database to collate commercial farm grassland data" (Hanrahan et al., 2017, p. 193). Farmers must pay an additional €150 if they wish to join a discussion group (Teagasc, 2020).

3.5.3. Participatory extension: farmers' discussion groups

Farmers' discussion groups are the primary channel of service delivery in Ireland and are the focus of this PhD thesis (Donnellan et al., 2015; Läpple et al., 2015; Teagasc, 2015). Discussion groups are a participatory form of extension. They foster a "bottom-up" approach to learning in a group setting, where participants exchange knowledge amongst themselves and are encouraged to learn from their peers. This is often seen as an improved extension model compared to traditional "top-down", one-to-one systems (Davis et al., 2012; Norton and Alwang, 2020; Prager and Creaney, 2017).

Discussion groups are composed of about 15 to 20 farmers and their discussion facilitator, a specialised dairy advisor. They meet on a monthly basis on one of the participants' farm and focus on three main principles of dairy farm management, i.e., breeding and herd fertility, grassland management and feeding strategy, and cost control and financial management (Department of Agriculture Food and the Marine, 2020).

While discussion groups were first introduced in the 1990s in Ireland, advisory priorities changed over the years to adapt to the market and policy context (Donnellan et al., 2015). Farmers' extension needs evolved as they moved from the strict quota regime, through the soft-landing period from 2010 until 2015, to the post-quota era. To support adjustments in the dairy industry, governmental schemes incentivised discussion group membership by paying participating farmers up to €1,000 per annum from 2010 until 2012 (i.e., DEP) and again from 2017 until 2019 (i.e., Knowledge Transfer Programme (KTP)) (Bogue, 2013; Department of Agriculture Food and the Marine, 2020; Läpple and Hennessy, 2014). In preparation for quota removal, the DEP specifically aimed at achieving efficiency gains in the dairy sector by increasing the level of participation in discussion groups and helping farmers to adopt best practices (Läpple and Hennessy, 2015, 2014). After quota removal, the KTP further encouraged efficiency and engagement in a process of continuous improvement so that farmers develop their own enterprises and contribute to the overall development of the agri-food sector (Department of Agriculture Food and the Marine, 2020).

The DEP cost €18 million (targeted only at the dairy sector) and was funded through the EU Common Agricultural Policy Single Payment Scheme[16]. As for the KTP, the total investment was €100 million (targeted at all farming sectors). The programme was co-funded by the National Exchequer and the European Agricultural Fund for Rural Development as part of Ireland's €4 billion Rural Development Programme (2014-2020) (Department of Agriculture Food and the Marine, 2020).

3.5.4. Impact of discussion groups: review of previous findings and participation rates

Previous research has been carried out to estimate the effect of discussion group participation on different outcomes in the Irish setting. Using cross-sectional data from 2009, Hennessy and Heanue (2012) found a positive relationship between discussion group participation and technology adoption (represented by artificial insemination with genomic bulls), and between participation and gross margin per ha. Nonetheless, a major concern in this study is that self-selection is not accounted for, thus limiting causal inferences. Läpple et al. (2013) overcame this issue and showed that the return to discussion group participation for an average member was €313 in gross margin per ha based on cross-sectional data from 2008.

Later studies by Läpple and Hennessy (2015, 2014) focused specifically on the DEP. Using cross-sectional data from 2010, Läpple and Hennessy (2014) found that the introduction of payments for participation was successful in attracting a new cohort of dairy farmers, i.e., older, less likely to be located in the South (traditional dairy region), and with smaller herds. Rates of participation increased from 24.8% in 2008 to 48.8% in 2010, as shown in Figure 3.10. However, Läpple and Hennessy (2015) revealed that discussion group participation did not lead to significant economic returns for new members, i.e., who joined after the subsidies were introduced. In contrast,

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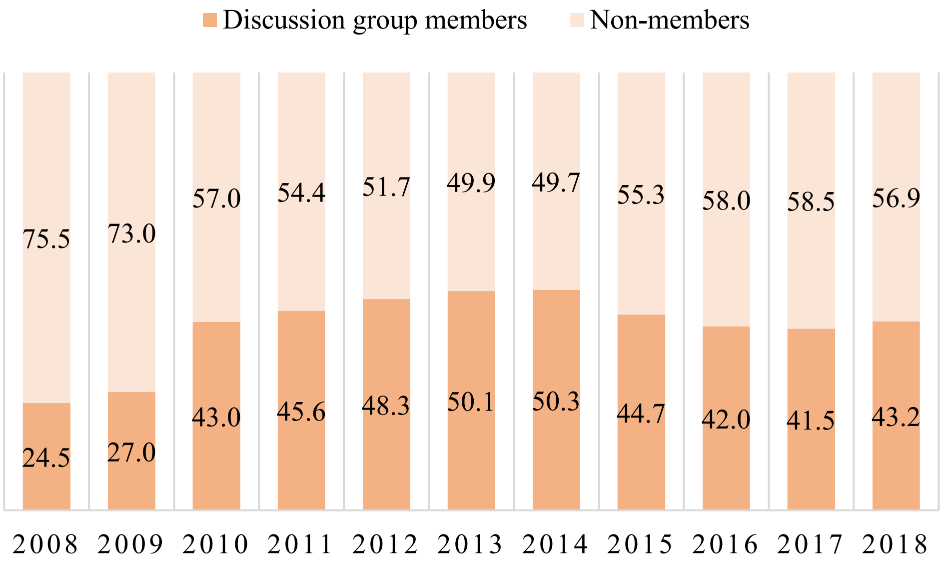
[16] Following the Health Check agreement, article 68(1) of Council Regulation (EC) 73/2009 makes provision for the use of unspent Single Payment Scheme funds to address specific disadvantages affecting farmers in the dairy sector (Department of Agriculture Food and the Marine, 2010b).

old members, i.e., who were already participating before financial support, received a return in gross margin by about €150 per cow. Their analysis was based on cross-sectional data from 2012.

Using panel data from 2008 until 2014 (i.e., covering the soft-landing period leading up to quota removal), Läpple et al. (2020) explored the role of discussion group participation in dynamic economic adjustments, as measured by changes in dairy herd size, stocking rate, and specialisation in dairy production. The authors found a positive, yet diminishing, return to participation. Their study suggests that discussion groups supported expansion and intensification at the farm level during the soft-landing period and were thus in line with the government's ambition to increase Irish milk production.

Finally, it is worth mentioning that after the DEP, participation rates remained relatively stable, as displayed in Figure 3.10. They ranged between about 43 and 48% in the 2013-2018 time period.

Figure 3.10: Rates of discussion group participation 2008-2018 (in %)



Source: Teagasc NFS data, weighted by Irish Central Statistics Office weights to ensure representativeness of the Irish dairy farming population.

3.6. Summary

Since milk quota removal in 2015, the EU dairy sector has been undergoing major structural changes. Heterogenous responses have been observed across Member States. Ireland has experienced major growth with a 53% increase in milk production between 2008 and 2018. This production growth was based on an expansion of the national herd and an improvement in cow milk yield.

The Irish dairy sector is relatively small in terms of farm and animal numbers within Irish agriculture. However, it is the most profitable farming system and strongest contributor to agri-food exports. Recent growth has reinforced this position. The Irish temperate climate is well suited for dairy farming and is the source of a competitive advantage on international markets. To capitalise on the long grass-growing season, dairy farmers mainly operate a spring-calving, pasture-based production system. Hence, grassland management and reproductive efficiency are important aspects of dairy management. As a result, Irish milk production is highly seasonal.

The intensification of Irish dairy farming raises significant sustainability challenges. Notably, changes in cow numbers and input reliance question the achievement of EU GHG reduction targets and threaten water quality. As the national dairy sector is expected to continue expanding and intensifying, Ireland faces a rising dilemma between agri-development and environmental commitments under EU and international directives and agreements.

Individual efforts to achieve sustainable intensification at the farm level are encouraged. In that regard, technology adoption and improved farm management practices have a role to play in increasing productivity and achieving greater sustainability. As they rely on the acquisition of new knowledge, Ireland has aligned agri-development goals with a dynamic agricultural extension environment. Teagasc and other private agencies provide learning opportunities to farmers through different communication channels. Amongst them, farmers' discussion groups are a popular way of delivering agricultural extension, with about half of the Irish dairy farming population involved in the last decade. These are a major topic of study within the current work.

The research undertaken for this PhD thesis contributes to the debate on how to achieve sustainable intensification on Irish dairy farms and has direct implications for the wider sector. It provides insights into the effectiveness of Irish extension in promoting improved farm management and the role of several farming practices in enhancing farm economic performance, while addressing sustainability challenges associated with dairy expansion. More specifically, Chapter 4 evaluates the suitability of a technology (i.e., milk recording) in simultaneously enhancing all dimensions of farm sustainability, i.e., increasing gross margins and milk yields, while improving milk GHG emission efficiency and herd health. Chapter 5 explores whether discussion group participation improves two main aspects of Irish dairy management, namely the share of homegrown grass in the diet of dairy cows and cow reproductive efficiency. It also examines how both aspects affect farm economic and environmental sustainability, represented by production costs, gross margins, farm nitrogen surplus, and milk GHG emission efficiency. Finally, Chapter 6 investigates whether discussion groups operated under the latest paid extension scheme (i.e., the KTP) and groups facilitated fully through the private sector attract different farmer cohorts. It also assesses their relationship with farm economic and environmental sustainability performances, measured by gross margins, milk yields, farm nitrogen surplus, and milk GHG emission efficiency.

Chapter 4 – Exploring the potential of a farm technology to achieve sustainable intensification: Evidence from milk recording on Irish dairy farms

4.1. Introduction

Sustainable intensification is seen as an important means of addressing major challenges faced by the global food system, such as food security, environmental degradation, and animal health and welfare concerns. As such, fostering its development has become an essential part of the agenda for policy makers and agri-food stakeholders (Department of Agriculture Food and the Marine, 2015; Food and Agricultural Organization of the United Nations, 2013). That is, attention has shifted from solely maximising agricultural productivity to optimising production across a wider set of economic, environmental, and social sustainability objectives (Pretty et al., 2010). In other words, the intention behind sustainable intensification is to increase food production while simultaneously enhancing all three sustainability pillars (i.e., economic, environmental, and social). This is not an easy task as it relies on systemic change at all levels of the food supply chain (Firbank et al., 2018) and conflicts between economic, environmental, and social sustainability may arise in the intensification process (Bos et al., 2013; Dawkins, 2017).

At the farm level, sustainable intensification translates into increasing agricultural yields while using the same or a lower amount of inputs so that adverse environmental effects of agricultural production are reduced (Franks, 2014). It also entails ensuring that food is produced within a wider ethical framework (Garnett et al., 2013). When applied to livestock production, sustainable intensification relies on diluting the environmental costs of animal maintenance (environmental pillar) through production efficiency gains (economic pillar) (Crosson et al., 2011; Guerci et al., 2013), with socially acceptable standards of animal welfare (social pillar) (Garnett et al., 2013; Lebacq et al., 2013). Farm-level solutions must be found to help farmers undertake this challenge and achieve sustainable intensification in comprehensive terms. This chapter explores the potential of an agricultural technology to concurrently increase farm efficiency and provide wider environmental and social benefits in the context of dairy farming.

Technology adoption has traditionally been considered as a key mechanism for increasing farm productivity (Ali et al., 2018; Läpple and Thorne, 2018; Manda et al., 2016), but a stronger emphasis on identifying 'win-win' strategies to simultaneously pursue several sustainability objectives has emerged more recently (Hocquette et al., 2014; Llonch et al., 2017). While it is reasonable to expect concurrent sustainability benefits from the adoption of certain agricultural technologies (Guerci et al., 2013; Huijps et al., 2010b; Lanigan et al., 2018), claims must be further verified through rigorous empirical assessments (Balafoutis et al., 2017; Tullo et al., 2019). However, the current empirical literature provides limited indication as to which technologies can help resolve the sustainable intensification challenge across all three sustainability dimensions and lead to a 'win-win-win' (Llonch et al., 2017) scenario.

In the present chapter, this issue is addressed by focusing on the case study of milk recording on Irish dairy farms. The need to find 'win-win-win' solutions to achieve sustainable intensification is particularly salient for the Irish dairy sector. Following European Union (EU) milk quota abolition in 2015, a process of dairy expansion and intensification was set in motion in Ireland (Eurostat, 2020a, 2020b) and poses significant sustainability concerns (Buckley et al., 2019; Lanigan et al., 2018). Milk recording is an agricultural technology, which provides per-cow information to farmers on a regular basis to support herd monitoring and decision making (Läpple et al., 2017). The use of milk recording information can help to improve herd productivity and health, and hence might reduce the environmental impact of milk production (Läpple et al., 2017). However, this ‘win-win-win’ potential has not yet been empirically verified.

Two main challenges arise from the estimation of technology impact on farm sustainability. On the one hand, new technologies can only be evaluated if their productive, environmental, and social performances can be reliably estimated (Fumagalli et al., 2012), thus emphasising the need for relevant metrics to measure sustainability outcomes (Bélanger et al., 2012). Additionally, the quantification of environmental and social sustainability is limited by data availability, and subjectivity and complexity in delineating these terms (Lebacq et al., 2013). This inevitably results in a greater representation of easily-defined and -recorded economic performance and thus an imbalance between sustainability dimensions in the literature (Lebacq et al., 2013). This problem is overcome by using the rich and original 2015 Teagasc National Farm Survey (NFS) dataset, which comprises a nationally representative sample of 296 Irish dairy farms. Based on this data, an indicator approach to measure farm sustainability is applied (Hennessy et al., 2013; Lynch et al., 2016), with dairy gross margin and milk yield per cow for economic sustainability, Greenhouse Gas (GHG) emission efficiency (i.e., GHG emitted per output unit) for environmental sustainability, and Bulk Tank Somatic Cell Count (BTSCC) of the milk produced for social sustainability.

On the other hand, as farmers ultimately decide whether or not to adopt a particular technology, self-selection must be accounted for when estimating technology impact. Drawing on previous theoretical and empirical literature, Propensity Score Matching (PSM) is applied to estimate treatment effects and assess milk recording’s ‘win-win-win’ potential (Dehejia and Wahba, 2002; Fentie and Beyene, 2019; Imbens and Wooldridge, 2009; Rosenbaum and Rubin, 1983; Schilling et al., 2014). As a robustness check, additional estimation methods (i.e., Inverse-Probability Weighting (IPW), Regression Adjustment (RA) and Inverse-Probability-Weighted Regression Adjustment (IPWRA)) are implemented. Moreover, as PSM is based on the strong assumption that selection occurs only on observed characteristics, Rosenbaum bounds are estimated to test the sensitivity of treatment-effects estimates to hidden bias (Becker and Caliendo, 2007; DiPrete and Gangl, 2004; Rosenbaum, 2002).

The present study has direct policy relevance by addressing the topical issue of sustainable intensification and adds value to the existing literature in at least two ways. Firstly, it provides important insights on the suitability of a technology to overcome sustainability challenges arising from ongoing agricultural intensification and can directly inform farmers' adoption decision. The study takes an original approach by simultaneously investigating economic, environmental, and social farm outcomes to explore the technology's 'win-win-win' potential. Secondly, the study also contributes to the literature on the development and application of sustainability indicators by extending their use for measuring the impact of new technologies. A set of indicators has already been created specifically for the Teagasc NFS dataset (Hennessy et al., 2013; Lynch et al., 2016) and is utilised in this study. Thus far, farm sustainability indicators have mostly been used to assess time trends in sustainability (Buckley et al., 2016; Dillon et al., 2016a) or to compare production systems (Buckley et al., 2015); consequently, this application is new. Subject to data availability, the approach could be replicated in other agricultural settings.

The remainder of the chapter is structured as follows: section 4.2 reviews relevant literature. Section 4.3 introduces background information on Irish dairy expansion and milk recording. Section 4.4 outlines the methodology, followed by a description of the sustainability indicators used in the study and the data in section 4.5. Section 4.6 presents and discusses the results, while the final section (4.7) provides the conclusions and policy implications.

4.2. Relevant literature

Agricultural technologies encompass a wide array of innovative practices implemented on farms. Among others, they can refer to new seed varieties, fertilisers or irrigation procedures (Doss, 2006; Kassie et al., 2018; Mutenje et al., 2016), new information and communication techniques to precisely inform management decisions (Barnes et al., 2019; Eastwood et al., 2012; Hennessy et al., 2016), milk meters (Eastwood et al., 2012; Hostiou et al., 2017), and growth hormones (Barham et al., 2004; McBride et al., 2004). In the literature, technology adoption has been identified as a main driver of farm productivity and profitability, and thus of farm economic sustainability (Ali et al., 2018; Läpple and Thorne, 2018; Manda et al., 2016). In the Irish context, Läpple and Thorne (2018) showed that innovation, as measured through an index that combines technology adoption, acquisition of knowledge, and continuous innovation (Läpple et al., 2015), enhances farm economic sustainability, represented by profitability, productivity of land, and market orientation.

However, technologies allowing for productivity gains might only resolve part of the sustainable intensification challenge. Not all technologies are equally suited to achieve this goal as their adoption might not always result in synergies but also in trade-offs across sustainability dimensions (Dawkins, 2017; Lanigan et al., 2018; Llonch et al., 2017). For instance, from the perspective of environmental synergies, Lanigan et al. (2018) identified several efficiency measures (e.g., inclusion of white clover in pastures, use of sexed semen, improved genetic merit) that simultaneously increase farm economic performance and mitigate GHG emissions from Irish milk production. Therefore, the adoption of these technologies can result in enhanced farm economic and environmental sustainability.

Additionally, technology-driven productivity gains can only show GHG mitigation benefits if emissions associated with intensification, particularly from off-farm sources, are offset by higher levels of efficiency (Crosson et al., 2011). In other words, increased productivity can mitigate GHG emissions of agricultural production if excessively high levels of external input application (e.g., concentrate feed and fertiliser) are avoided[17] (Basset-Mens et al., 2009; Crosson et al., 2011). This can be a concern in intensive pasture-based production systems such as the Irish one. In fact, since higher-yielding cows might have greater nutritional requirements, not always achievable from grazing alone (Charlton et al., 2011), increased productivity might also lead to enhanced reliance on external inputs (Foote et al., 2015). In the New Zealand context, Basset-Mens et al. (2009) found that high-input pasture-based systems emit more GHG emissions per kilogram (kg) of milk produced than low-input ones. Therefore, not all technology-driven productivity gains might enhance farm environmental sustainability. Similarly, Lanigan et al. (2018) proved that not all mitigation strategies can increase farm efficiency nor be profitable (e.g., low emission slurry spreading techniques), which questions their voluntary adoption by farmers and ability to simultaneously reach economic and environmental sustainability objectives at the farm level.

From an animal welfare perspective, mastitis provides an interesting example of sustainability synergies and trade-offs. Mastitis is a contagious production disease widely spread on dairy farms at global scale (Sharma et al., 2011) and in Ireland (Geary et al., 2012; More et al., 2012), with adverse effects on animal welfare (Medrano-Galarza et al., 2012). In the last thirty years, its incidence has risen due to genetic selection heavily focused on milk production traits (Algers et al., 2009; Oltenacu and Broom, 2010). These traits are genetically antagonistic towards mastitis resistance, which is now increasingly taken into account in breeding programmes (Algers et al., 2009; Oltenacu and Broom, 2010). Decreasing mastitis occurrence and improving herd health and welfare are a promising path towards more sustainable dairy systems (Dawkins, 2017; Llonch et al., 2017). Indeed, the disease leads to substantial milk yield losses, decreased raw milk quality, and avoidable culling decisions (Geary et al., 2012; Huijps et al., 2010b; Sharma et al.,

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[17] It is also important to highlight that environmental benefits achieved through productivity gains can be overturned if production scale is increased (Alcott, 2005; Barnes et al., 2019). In such cases, improvements in GHG emission efficiency may not be reflected in absolute GHG emissions.

2011). Beyond negative economic implications, mastitis also causes reduced GHG emission efficiency of dairy production (Özkan Gülzari et al., 2018; Özkan et al., 2015).

In that regard, routine hygiene measures such as carrying out post-milking teat disinfection were proven to be efficient to combat mastitis incidence in the Dutch (Huijps et al., 2010b) and Irish (Dillon et al., 2018a) contexts. Thus, these results indicate that the uptake of such technologies could lead to increased herd health and welfare status, and thus farm social sustainability (Lebacq et al., 2013). Huijps et al. (2010b, 2010a) also showed that these measures can be cost-efficient, notably by avoiding costs associated with mastitis, and suggest an economic benefit from implementing routine hygiene measures. Because of the association between mastitis, economic performance, and GHG efficiency (Geary et al., 2012; Huijps et al., 2010b; Özkan Gülzari et al., 2018; Özkan et al., 2015; Sharma et al., 2011), technologies reducing mastitis occurrence could have a subsequent 'win-win-win' effect across sustainability dimensions.

So far, the empirical literature focuses on identifying 'win-win' technologies, notably for joint improvements in economic performance and animal health (Huijps et al., 2010b), or concurrent enhancements of production efficiency and GHG emission efficiency (Lanigan et al., 2018). 'Win-win-win' potential is often discussed in review articles (Llonch et al., 2017; Tullo et al., 2019), but empirical proof is missing as to whether these technologies can indeed help to achieve sustainable intensification in comprehensive terms (i.e., economic, environmental, and social). This gap is filled by assessing milk recording's 'win-win-win' potential.

4.3. Background

4.3.1. Irish dairy expansion

The Irish dairy sector offers an excellent framework to explore sustainability issues associated with agricultural intensification, given large scale expansion following EU milk quota abolition. Between 2010 and 2017, dairy cow numbers and milk production increased by 33% and 40%, respectively (Eurostat, 2020a, 2020b). Ireland’s export-oriented dairy sector gains from a competitive advantage in international markets by relying on a low-cost pasture-based production system, with further scope for and expectations of continued growth (Donnellan et al., 2015; Lanigan et al., 2018).

However, significant sustainability concerns arise from ongoing, rapid growth (Buckley et al., 2019; Lanigan et al., 2018). Predicted growth in Irish agricultural output, mainly driven by increased dairy cow numbers and fertiliser use, is anticipated to result in a 9% rise in agricultural GHG emissions by 2030 relative to 2005 levels, thereby challenging the achievement of EU emission reduction targets (Lanigan et al., 2018). Agriculture is the largest single contributor to Irish GHG emissions by sector, accounting for about one-third of national emissions and half of emissions from non-Emission Trading Scheme sectors (Duffy et al., 2017). In the context of the EU Effort Sharing Decision, the country must decrease non-Emission Trading Scheme emissions by 30% by 2030 relative to 2005 levels (Environmental Protection Agency, 2018).

Moreover, even though the Irish grass-based milk production system is generally associated with high standards of animal welfare, dairy expansion and intensification could lead to challenges in that regard. There are international precedents for these concerns, notably in relation to udder and foot health (Lean and Playford, 2008; Algers et al., 2009).

Hence, this chapter addresses sustainability challenges at a critical time for the Irish dairy sector and is representative of situations faced by other agricultural sectors. It draws attention to the need to find ‘win-win-win’ technologies to achieve sustainable intensification and thus examines whether milk recording can provide solutions to alleviate sustainability conflicts.

4.3.2. Milk recording

Milk recording is an agricultural technology, which supports herd monitoring and farmers' decision making (Läpple et al., 2017). Through the use of milk meters, it measures milk volumes and samples milk from individual cows during milking. There exist two implementation options: 1) a manual option, for which a milk recording agent visits the farm to milk record, or 2) an electronic 'Do-It-Yourself' option, for which the farmer handles the recording himself/herself (in this case, appropriate training and support is provided by a technician) (Irish Cattle Breeding Federation, 2021). Milk samples are then collected by milk recording organisations to be analysed. Result reports are returned to farmers through an online service or on a paper version, with further support to interpret them. They include detailed per-cow information about milk yield, constituents, and Somatic Cell Count (SCC) levels. Historical data is also reported. If utilised, milk recording data allows for better-informed decisions in several areas of farm management (Läpple et al., 2017).

In terms of reproductive management, milk recording information can help farmers identify the most profitable animals (i.e., high yielding, producing high-quality milk, and with strong genetic merit) for breeding dairy replacements and informing culling decisions. In this way, farmers can increase milk quality and herd production performance (Läpple et al., 2017). Moreover, improved productivity through milk recording might be beneficial from a GHG mitigation perspective (Crosson et al., 2011; Guerci et al., 2013). Since agriculture is under pressure to reduce its emissions in Ireland (Buckley et al., 2019), active participation in the national GHG mitigation effort through the adoption of mitigation strategies by farmers is increasingly gaining in importance. However, some caution must be exercised in verifying milk recording's GHG mitigation potential. Because efficiency gains might lead to enhanced reliance on external inputs (Foote et al., 2015), off-farm reallocation of environmental burdens must be accounted for by applying a cradle-to-farm gate GHG estimation approach (O'Brien et al., 2014b).

In terms of animal health management, milk recording allows for the monitoring of mastitis by providing SCC readings for individual cows. Mastitis is mainly caused by bacterial infection in the udder and leads to elevated SCC (Geary et al., 2012; Huijps et al., 2010b; Sharma et al., 2011). The threshold of 200,000 cells per millilitre is generally accepted as an indicator of mastitis incidence (International Dairy Federation, 1997). Thus, SCC can be used to reliably detect mastitis incidence, even when clinical symptoms are not yet observable, and react accordingly (Animal Health Ireland, 2012; Sharma et al., 2011). Previous research has concluded that Irish dairy farmers tend to adopt a reactionary as opposed to a precautionary approach when managing mastitis, responding mainly to an indication of infection (Dillon et al., 2018a). This suggests that (subclinical) mastitis is not identified nor treated on time and underlines milk recording's potential herd health benefits.

From an implementation perspective, milk recording does not require any upfront investment. It costs approximately €12 per cow to milk record six times per year (Irish Cattle Breeding Federation, 2021), but farmers can do it as frequently as they wish. The technology is risk-free and easy to use because it necessitates little or no technical skills. Implementation does not generally disrupt the milking routine, although it does lengthen the milking task and requires the presence of an extra person in the parlour.

Finally, the use of milk recording is less prevalent in Ireland compared to some EU counterparts, with the technology utilised on 52% of Irish dairy cows in 2015 as opposed to 86% and 69% in Germany and in France, respectively (International Committee for Animal Recording, 2016). Reasons for these stark differences in adoption rates across countries are not fully understood, but one possible explanation may be that the benefits of milk recording are not clear or, alternatively, not effectively communicated in Ireland. This chapter contributes to resolving these issues by evaluating the technology's impact across all sustainability dimensions. Adopters are defined as farmers who milk record at least once per year and non-adopters as farmers who do not milk record at all.

4.4. Methodology

4.4.1. The impact evaluation problem

Ideally, the impact of technology adoption would be estimated by calculating the difference Δ in outcome at time t between a state where the farmer adopts the technology (Y_t^1) and a state where he/she does not adopt the technology (Y_t^0), as follows:

$$ATT = E(\Delta | T = 1) \tag{4.1}$$

where ATT is the Average Treatment Effect on the Treated (i.e., the average return only for the pool of adopters) and T indicates whether the technology has been adopted ($T = 1$) or not ($T = 0$). However, calculating Δ is impossible as farmers can only be observed in one of the two states (i.e., adopter or non-adopter), thus highlighting the need to construct counterfactuals (Blackman and Naranjo, 2012; Imbens and Wooldridge, 2009).

This problem could be solved by randomly assigning treatment, such that $E(Y_t^0, T = 0) = E(Y_t^0, T = 1)$, and equation (4.1) would become:

$$ATT = E(Y_t^1 | T = 1) - E(Y_t^0 |\, T = 0) \tag{4.2}$$

However, when using non-experimental data, individuals choose their treatment rather than being randomly assigned, which introduces well-known self-selection bias. In other words, technology adoption could lead to enhanced sustainability, but ‘better’ farmers are also more likely to adopt the new technology. This suggests the presence of initial differences between adopters and non-adopters, which may invalidate causal comparisons of outcomes by treatment status (Imbens and Wooldridge, 2009).

While several methods can be used to control for self-selection bias and estimate treatment effects (Imbens and Wooldridge, 2009), data availability often limits choice. In the absence of suitable panel data or credible instruments, PSM has emerged as a popular approach in agricultural contexts (Fentie and Beyene, 2019; Schilling et al., 2014).

4.4.2. Propensity score matching

In this study, PSM is applied to estimate the ATT of milk recording adoption on farm sustainability. Assuming that selection occurs only on observables, adopters and non-adopters with the same probability p of adopting the technology ($T = 1$), given a set of covariates X, can be compared and matched (Rosenbaum and Rubin, 1983). Under this assumption, the within-matched-pair difference in outcomes is then attributable to the technology's impact and treatment effects are estimated by averaging within-matched-pair differences in outcomes (Imbens and Wooldridge, 2009). Thus, equation (4.2) becomes:

$$ATT_{PSM} = E(Y_t^1 | T = 1, p) - E(Y_t^0 | \, T = 0, p) \tag{4.3}$$

Additionally, PSM is used to predict for each farmer both potential outcomes (Y_t^0 and Y_t^1), adjusted for observables, and estimate potential outcome means (POM) for the whole population, such that $POM^k = E(Y_t^k)$, where $k = \{0; 1\}$. In this way, ATTs can be expressed as a percentage of POMs.

The use of PSM involves a series of practical choices before estimating ATTs. First, propensity scores $p_i = P(T = 1|X_i)$ are estimated for each farmer i with a logit model (Dehejia and Wahba, 2002). X_i are a set of farm and farmers' characteristics that simultaneously affect milk recording adoption and farm sustainability, but are not impacted by adoption status (Caliendo and Kopeinig, 2008). This model is equivalent to an adoption decision model and is reported as Model 1 in Table A. 1 (Appendix A). Moreover, the model specification must meet two requirements: the overlap assumption and the balancing property (Caliendo and Kopeinig, 2008). For the overlap assumption, a match with similar propensity score value must be found for each adopter. It is ensured that, for each farmer i, p_i is included between 0 and 1 and that there is significant overlap between adopters' and non-adopters' propensity scores by plotting their distribution by treatment status (Dehejia and Wahba, 2002; Schreinemachers et al., 2016). The plot is presented in Figure A. 1 (Appendix A). For the balancing property, estimated propensity scores must balance the covariate distribution between adopters and non-adopters. The balance diagnosis is based on standardised differences. The aim is to reach post-matching values of at most 10% across covariates and on average over all covariates (Austin, 2009; Schreinemachers et al., 2016). Table A. 2 (Appendix A) displays these standardised differences before and after PSM and shows significant reduction in covariate imbalance after PSM[18].

Second, following the propensity score estimation, Nearest-Neighbour Matching (NNM) is performed to match adopters to their closest non-adopter(s) in terms of propensity score value. This method is common in PSM (Dehejia and Wahba, 2002; Schreinemachers et al., 2016). Its implementation relies on two practical choices that entail a trade-off between precision of treatment effect estimate and bias reduction (Dehejia and Wahba, 2002). One must select the number of matches for each adopter and whether to match with or without replacement (i.e., whether to match non-adopters more than once). To reach the best trade-off, two matches with replacement are chosen for the matching procedure[19].

Finally, the matching quality is evaluated by ordering propensity scores from lowest to highest and plotting them for adopters and matched non-adopters (Dehejia and Wahba, 2002). The plot is displayed in Figure A. 2 (Appendix A) and indicates that matching was performed successfully.

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[18] Age has a post-matching standardised difference of 10.01%. However, it is kept in the model as it improves the balance across other covariates that play a greater role in the adoption decision model, as suggested by Lee (2013).

[19] Other numbers of matches investigated during the exploration process included one to four non-adopters. Moreover, matching without replacement was not a viable option in this analysis as the reservoir of non-adopters relative to adopters is small (151 versus 145 observations, respectively).

4.4.3. Sensitivity analysis

As a robustness check, ATTs are estimated with alternative treatment-effects estimation methods, including IPW, RA and IPWRA (StataCorp, 2013). To check whether resulting ATTs differ significantly, the overall coefficient of variation is estimated (Schreinemachers et al., 2016). The latter measure shows the extent of variability around the mean and is calculated as the ratio of the standard deviation to the mean for the results of each outcome variable. This robustness check ensures that ATT results are insensitive to changes in the estimator (Schreinemachers et al., 2016).

Furthermore, one cannot directly assess whether bias is introduced by the presence of unobservables that (are likely to) affect the adoption decision (e.g., farmers' ability, motivation). In fact, one of the main shortcomings of PSM is that selection is assumed to occur only on observables and that this hypothesis cannot be formally tested. In this context, Rosenbaum bounds are meant to simulate the effect of unobservables on treatment effect estimates and to test the sensitivity of PSM results to hidden bias (Rosenbaum, 2002). Following Becker and Caliendo (2007), the adoption probability for each farmer i is given by:

$$p_i = P(T = 1|X_i) = F(\beta X_i + \gamma u_i) \tag{4.4}$$

where u_i is an unobserved variable and γ the effect of u_i on the adoption decision. If the analysis is free of hidden bias, γ will be zero and the adoption decision will be determined only by X_i. Conversely, if unobservables affect the adoption decision, farmers i and j with the same observed X will have different probabilities of adopting milk recording. Assuming F is the logistic distribution, the odds ratio Γ between both farmers i and j is given by:

$$\Gamma = \frac{p_i/(1-p_i)}{p_j/(1-p_j)} = \frac{p_i(1-p_j)}{p_j(1-p_i)} = \frac{\exp(\beta X_i + \gamma u_i)}{\exp(\beta X_j + \gamma u_j)} = \exp(\gamma(u_i - u_j)) \tag{4.5}$$

if farmers i and j have identical observed X (as assumed in PSM). In other words, both farmers i and j differ in their odds of adopting milk recording by a factor equal to Γ. If there are either no differences in unobserved variables $(u_i = u_j)$ or unobservables have no impact on the adoption probability ($\gamma = 0$), then Γ is 1, implying that PSM is successful in estimating unbiased effects. Conversely, if an unobserved characteristic impacts the adoption probability ($\gamma \neq 0$), it causes the odds ratio of the adoption decision to differ between farmers i and j by a factor Γ different than 1 and ATTs are likely to be biased. More formally, the Rosenbaum bounds approach is based on a Wilcoxon signed-rank test. At each Γ value, hypothetical significance levels are calculated and represent the upper and lower bounds of the ATT significance level in case of endogenous adoption decision (DiPrete and Gangl, 2004). Critical Γ values at which the p-values exceed the 10% threshold correspond to the magnitude of hidden bias required to alter PSM results and question causal inferences.

4.5. Outcome variables and data description

4.5.1. Choice of sustainability indicators and data

Evaluating the impact of milk recording on farm sustainability is a complex undertaking as it relies on the quantification of farm sustainability outcomes. Measuring farm sustainability through indicators has become a popular approach (Dillon et al., 2016a), which is applied in this study through the Teagasc NFS data from 2015. Sustainability indicators are “quantifiable and measurable attributes of a system that are judged to be related to its sustainability” and can help reveal movements in “the desired or undesired direction” in the data (Dillon et al., 2016a, p. 32). In this manner, they can provide useful insights to guide public policy (Bélanger et al., 2012; Dillon et al., 2016a; Fumagalli et al., 2012), such as exploring the sustainability potential of new technologies before encouraging widespread adoption.

The Teagasc NFS data is a rich and original enhancement of the data recorded for EU Farm Accountancy Data Network purposes (Dillon et al., 2016a). Professional farm recorders collect the data annually through face-to-face surveys over two to three farm visits. In conjunction with the Irish Central Statistics Office, a sample of approximately 900 farms is selected each year on a voluntary basis. Farms are then weighted to ensure nationally representativeness. Respondents are classified into six farming systems depending on the main source of farming income: dairy, cattle rearing, cattle other, sheep, arable, and mixed livestock. In this chapter, a subsample of 296 dairy farms from the 2015 survey is used by selecting farms for which the data required to calculate the selected farm sustainability indicators is recorded. They represent 87.8% of the original 2015 dairy sample.

Within the set of farm sustainability indicators available through the Teagasc NFS, the ones that are suitable in the context of milk recording are chosen based on Bélanger et al. (2012) selection criteria. More specifically, selected indicators must be able to capture changes in farm sustainability related to the technology's uptake. They must be linked with the overall objective of achieving sustainable intensification. They must also be relevant for potential users (e.g., farmers, extension agents, policy makers). Therefore, dairy gross margin and milk yield per cow are used to represent economic sustainability. GHG emission efficiency of milk production serves as an indicator of environmental sustainability. BTSCC of the milk produced is focused upon to measure social sustainability.

Dairy gross margin per cow is calculated as gross output minus direct production costs of the dairy enterprise on a per-cow basis. Milk yield per cow is measured as the total amount of milk produced on the farm, including milk sold and milk fed to other livestock, divided per cow.

GHG emission efficiency of milk production is the GHG emissions per kg of unit produced and thus a measure of farm environmental sustainability. For each farm, estimates of agricultural GHG emissions are derived by using a cradle-to-farm gate Life Cycle Assessment (LCA) approach developed by O'Brien et al. (2010, 2014a). The LCA methodology is internationally standardised (International Organization of Standardization, 2006a, 2006b) and specific guidelines have been developed to assess GHG emissions of milk production (British Standards Institute, 2011; Carbon Trust, 2010; International Dairy Federation, 2015). Following these guidelines[20], a

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[20] The LCA methodology was implemented according to the publicly-available PAS 2050:2011 specification from the British Standards Institute (British Standards Institute, 2011) and validated by the Carbon Trust, an accredited third party (O'Brien et al., 2014a).

holistic-systems approach to quantify GHG emissions throughout the production process is adopted (i.e., from off-farm production and acquisition of inputs to on-farm production of milk). All off- and on-farm GHG emissions associated with dairy production are modelled by combining the information from the Teagasc NFS dataset and emission factors estimated using the Intergovernmental Panel on Climate Change guidelines or other resources in the literature (Dong et al., 2006; Duffy et al., 2017)[21]. Emissions are then converted to total kg of Carbon Dioxide Equivalent (CO_2e) using the 100-year Global Warming Potential (Forster et al., 2007), as used for national emissions reporting. They are reported per kg of Fat-Protein-Corrected-Milk (FPCM)[22] (International Dairy Federation, 2015), which controls for differences in milk solids between individual farms.

BTSCC depicts risk for mastitis incidence at the herd level and thus general herd health status (Geary et al., 2012; More et al., 2012; Sharma et al., 2011). It reflects farm herd health management and animal welfare levels (Huijps et al., 2010b; Medrano-Galarza et al., 2012), which is an important component of the social sustainability of livestock-based agricultural systems (Lebacq et al., 2013). Through the Teagasc NFS, monthly data on herd-level SCC based on milk bulk tank readings is available and is utilised to calculate a yearly weighted average so that the seasonality in Irish milk production is accounted for (Dillon et al., 2015).

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[21] For a full description of the GHG emission sources and corresponding emission factors, please see O'Brien et al. (2014a).

[22] As explained by the International Dairy Federation (2015), using the FPCM basis allows for the comparison of farms with different breeds or feed systems. The formula to calculate it is as follows:

$$\begin{aligned} FPCM\ (kg\ per\ year) \\ &= Milk\ production\ (kg\ per\ year) \\ &\times [0.1226 \times Fat\% + 0.0776 \times Protein\% + 0.2534] \end{aligned}$$

4.5.2. Descriptive statistics

Difference in sustainability performance between milk recording adopters and non-adopters are assessed in Table 4.1 by dividing farms by adoption status and running a bivariate analysis. The results show that adopters have higher dairy gross margins and milk yields per cow, are more efficient in terms of GHG emissions, and achieve lower BTSCCs.

Table 4.1: Sustainability performance of Irish dairy farms, by technology adoption status

Outcome variable	Non-adopters (n = 151)	Adopters (n = 145)	All farmers (n = 296)	*t*-tests
Dairy gross margin per cow (€ / cow)	994.95 (283.61)	1132.40 (267.25)	1058.25 (284.08)	-4.29***
Milk yield per cow (l / cow)	5126.45 (972.58)	5774.45 (887.93)	5427.87 (987.20)	-5.99***
Agricultural GHG emissions per unit of output (kg of CO_2e / kg of FPCM)	1.20 (0.24)	1.11 (0.19)	1.16 (0.22)	3.56***
BTSCC (‘000 cells / ml)	194.22 (75.72)	155.76 (56.71)	176.32 (70.11)	4.96***

Note: Means and standard deviations in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively.

Table 4.2: Characteristics of Irish dairy farms, by technology adoption status

Variable	Description	Non-adopters (n = 151)	Adopters (n = 145)	All farmers (n = 296)	Differences
Farm characteristics					
Herd size	Number of dairy cows (cows)	59.34 (34.64)	87.02 (37.71)	72.22 (38.60)	-6.57***
Specialisation	Ratio of dairy cows to total livestock units (i.e., degree of specialisation in dairy production)	0.64 (0.14)	0.67 (0.11)	0.65 (0.13)	-2.20**
Soil	= 1 if good soil quality, 0 otherwise	0.58 (0.50)	0.61 (0.49)	0.59 (0.49)	0.35 (χ^2)
Stocking	Dairy livestock units per hectare (ha) (cows / ha)	2.03 (0.57)	2.05 (0.49)	2.04 (0.53)	-0.24
Concentrates	Concentrates fed per cow (kg / cow)	922.58 (399.24)	938.55 (454.51)	930.01 (425.20)	-0.32
Fertiliser	Nitrogen fertiliser applied per ha (kg / ha)	98.00 (52.11)	118.59 (54.68)	107.58 (54.21)	-3.31***

Variable *(Continued from previous)*	Description	Non-adopters	Adopters	All farmers	Differences
Farmers' characteristics					
Education	= 1 if the farm holder has completed some level of agricultural education, 0 otherwise	0.66 (0.47)	0.85 (0.36)	0.75 (0.43)	12.79*** (χ^2)
Age	Age of the farm holder (years)	49.91 (11.39)	48.28 (10.12)	49.15 (10.83)	1.31
Household	Number of household members (people)	3.25 (1.54)	3.72 (1.43)	3.46 (1.50)	-2.72***
Extension	Extension expenditure per cow (€ / cow)	31.55 (22.20)	28.57 (16.36)	30.17 (19.72)	1.32

Note: Means and standard deviations in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively. Statistical tests based on *t*-tests for continuous variables and chi-square tests for binary variables (distinguished by a χ^2).

The summary statistics reported in Table 4.2 reveal that adopters and non-adopters also differ in terms of farm and farmers' characteristics, which suggests that self-selection may be at play. Adopters have larger and more specialised dairy operations. They apply more fertiliser per ha, which indicates a higher reliance on external inputs. They are more likely to have completed some level of agricultural education and have larger households. Among the variables presented in Table 4.2, herd size, specialisation, soil, education, age, and household are included in the selection model to estimate propensity scores (see section 4.4.2 and Appendix A for more detail)[23].

4.6. Results and discussion

4.6.1. Results of the treatment effect estimation

PSM results are reported in Table 4.3. They indicate that milk recording has a positive impact on farm economic sustainability. Firstly, it increases dairy gross margin by €54 per cow, on average. Secondly, the technology increases milk yield by 406 litres per cow, on average. When expressing these results in terms of percentages of POMs (i.e., POM^1 in Table 4.3), Table 4.3 shows that milk recording increases dairy gross margin and milk yield by 5% and 7%, on average, respectively. When accounting for implementation costs (Irish Cattle Breeding Federation, 2021), the estimated net benefit is €42 per cow, which translates to a 4% net increase in dairy gross margin for adopters.

However, the findings reveal that milk recording does not have a significant effect on farm environmental sustainability. Although improved productivity was expected to concurrently lead to enhanced GHG emission efficiency (Crosson et al., 2011; Guerci et al., 2013), the technology does not change GHG emitted per unit of milk produced. This suggests that the difference in adopters' and non-adopters' environmental performance obtained in Table

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[23] Some variables from Table 4.2 are not included in the propensity score model specification as their inclusion does not lead to improved covariate balance. Nevertheless, another adoption decision model including all variables is estimated to assess whether hidden bias is of concern in section 4.6.2. It is reported as Model 2 in Table A. 1 (Appendix A).

4.1 is not attributable to the technology's impact, but is likely to be driven by the higher production intensity of adopters. Thus, the results show that, given current levels of data utilisation, milk recording does not directly help attenuate an environmental issue that is of increasing concern in agricultural production.

Finally, the findings in Table 4.3 show that milk recording is beneficial for farm social sustainability. More specifically, it has the largest effect on BTSCC, with a decrease by 38,860 cells per millilitre of milk, on average. When expressing this finding as a percentage of POM, milk recording results in a 25% reduction in BTSCC, hence improving herd health. This outcome is consistent with Dillon et al. (2016b). It is not surprising that the technology has the largest effect on herd health since its uptake is mostly promoted for the monitoring of elevated SCC (Animal Health Ireland, 2012). Indeed, farmers might be more aware and inclined to use milk recording information for herd health than for informed breeding decisions.

Table 4.3: Estimation of Average Treatment Effects of the Treated

Outcome variable	ATT	Standard error	POM^1	ATT as % of POM^1
Dairy gross margin per cow (€ / cow)[a]	54.22*	32.43	1,118.13	+4.85
Milk yield per cow (l / cow)	405.57***	121.67	5,741.08	+7.06
Agricultural GHG emissions per kg of output (kg of CO_2e / kg of FPCM)	-0.029	0.031	1.14	-2.54
BTSCC ('000 cells / ml)	-38.86***	11.02	155.21	-25.04

Note: Estimation based on PSM, with two nearest neighbours. ***, **, and * significant at the 1%, 5%, and 10% level, respectively. [a] Results from the PSM procedure, prior to subtracting implementation costs.

4.6.2. Results of the sensitivity analysis

As a robustness check, ATTs are estimated with alternative treatment-effects estimation methods and the coefficient of variation is calculated for each indicator. The findings are reported in Table 4.4. They reveal that ATT estimates do not substantially vary across IPW, RA, IPWRA, and PSM estimators and that the variation around the mean remains under 16% for all indicators.

Table 4.4: Sensitivity analysis to alternative treatment-effects estimation methods

Method	ATT estimates				CV (%)
	IPW	RA	IPWRA	PSM (2NN)	
Dairy gross margin per cow (€ / cow)	64.61** (32.26)	64.93* (33.20)	63.74** (31.74)	54.22* (32.43)	8.29
Milk yield per cow (l / cow)	513.23*** (121.14)	493.71*** (115.47)	507.72*** (112.72)	405.57*** (121.67)	10.48
Agricultural GHG emissions per kg of output (kg of CO_2e / kg of FPCM)	-0.020 (0.022)	-0.024 (0.023)	-0.028 (0.021)	-0.029 (0.031)	16.29
BTSCC (‘000 cells / ml)	-32.61*** (9.44)	-27.77*** (8.52)	-32.99** (8.89)	-38.86*** (11.02)	13.73

Note: ATTs and standard errors in parentheses. ***, **, and * significant at the 1%, 5%, and 10% level, respectively. Coefficients of variation (CV) calculated as a ratio of the standard deviation to the mean for the results of each indicator.

As PSM results may suffer from hidden bias, Rosenbaum bounds are estimated to investigate critical Γ values for dairy gross margin, milk yield, and BTSCC. The findings are reported in Table 4.5 and show that robustness to hidden bias varies across indicators, with milk yield being the most robust, BTSCC somewhat less robust, and dairy gross margin the least robust. The results suggest that the ATT estimates become sensitive to hidden bias if an unobserved characteristic causes the odds ratio of the adoption decision to differ between adopters and non-adopters by a factor of at least 2.35 for milk yield, 2.00 for BTSCC, and 1.55 for dairy gross margin.

To assess whether hidden bias is a serious concern, the critical Γ values displayed in Table 4.5 are equated with equivalent effects of observed characteristics from the propensity score estimation model (Model 1 in Table A. 1, Appendix A) (DiPrete and Gangl, 2004). The three significant predictors of milk recording adoption in Model 1 are herd size, herd size squared, and specialisation, with odds ratios of 1.05, 1.00, and 10.51, respectively. Concerns arise if this model specification omits important predictors that affect the adoption decision by a magnitude of at least 1.55. Given that Model 1 was not meant to perfectly predict technology adoption status and is constrained by the need to balance covariates (Caliendo and Kopeinig, 2008), it is likely to suffer from omitted variable bias if the goal is to predict the adoption decision. For this reason, a model with a wider selection of control variables[24] is estimated and compared to the critical Γ values. The model (reported as Model 2 in Table A. 1, Appendix A) includes stocking rate, concentrate feed use, fertiliser usage, and extension expenditure per cow, in addition to the covariates from Model 1 (see Table 4.2 for variable description). The results show that the odds ratios of the additional significant variables (stocking rate and fertiliser use) remain under 1.01, thus revealing that their exclusion from the propensity score estimation does not challenge PSM results.

Concerns can also arise from the exclusion of unobservables such as farmers' motivation and ability, but the effect of these characteristics is somewhat captured through education level, extension expenditure, and degree of dairy specialisation in a cross-sectional setting. This is based on the idea that better-informed, more-commercially oriented farmers are likely to be more motivated and inclined to adopt new technologies (Feder et al., 1985; Sauer and Zilberman, 2012). Effectively, it is unlikely that an unobserved

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[24] The model specification is based on previous literature focusing on technology adoption (Feder et al., 1985; Läpple et al., 2017; Sauer and Zilberman, 2012).

confounder would be a stronger predictor of the adoption decision than the variables included in Model 2. Therefore, while it cannot be ruled out that selection occurs also on unobservables, the study provides evidence of an impact of milk recording on economic and social farm sustainability.

Table 4.5: Estimated hypothetical p-values from Rosenbaum Bounds procedure, reported by Γ critical value

Dairy gross margin per cow		Milk yield per cow		BTSCC	
Γ	(+)	Γ	(+)	Γ	(-)
1.20	0.008	1.85	0.009	1.55	0.007
1.25	0.013	1.90	0.012	1.60	0.10
1.30	0.022	1.95	0.017	1.65	0.015
1.35	0.034	2.00	0.022	1.70	0.022
1.40	0.050	2.05	0.029	1.75	0.030
1.45	0.071	2.10	0.37	1.80	0.040
1.50	0.097	2.15	0.047	1.85	0.053
1.55	0.13	2.20	0.058	1.90	0.068
		2.25	0.071	1.95	0.085
		2.30	0.085	2.00	0.11
		2.35	0.10		

Note: (+) refers to the upper bound significance levels for the overestimation of treatment effects (for indicators impacted positively by milk recording) and (-) to the lower bound significance levels for the underestimation of treatment effects (for the indicator impacted negatively by milk recording). The opposite bound significance levels were not reported as they were always above the 1% level.

4.7. Conclusions and policy implications

In recent years, the sustainability of agricultural production has moved to the forefront of public concerns and the political agenda. While this is a topical issue for many agricultural sectors worldwide, lessons can be learnt from the Irish dairy sector, which is currently undergoing rapid growth initiated by EU milk quota abolition. This study evaluated the ‘win-win-win’ potential of an agricultural technology, i.e., milk recording, to simultaneously enhance all dimensions of farm sustainability and thereby foster sustainable intensification on Irish dairy farms. Matching methods were applied to a representative sample of 296 farms to control for observed farm and farmers’ characteristics that affect the adoption decision and estimate treatment effects on a wide set of sustainability indicators.

The empirical findings revealed that milk recording enhances farm economic and social sustainability through a 4% net increase in dairy gross margin, a 7% improvement in milk yield, and a 25% reduction in BTSCC. The technology's impact on BTSCC suggests a decrease in the risk of mastitis incidence due to the relationship between elevated SCC and mastitis (Geary et al., 2012; Huijps et al., 2010b; Sharma et al., 2011). Therefore, this study supports the idea that technology adoption can reconcile productivity and animal health objectives at the farm level (Dawkins, 2017).

Conversely, the analysis showed that milk recording does not have a significant impact on farm environmental sustainability, as measured by GHG emission efficiency of milk production. This result indicates that productivity gains reached through milk recording may not be sufficient to dilute the GHG costs of animal maintenance (Crosson et al., 2011; Guerci et al., 2013). Alternatively, these productivity gains might have been achieved through enhanced reliance on external inputs (Foote et al., 2015), which can counteract GHG benefits of improved efficiency (Basset-Mens et al., 2009). Increases in productivity per additional unit of external inputs need to be larger so that GHG emission efficiency is overall improved (Crosson et al., 2011). Consequently, considering the current application of milk recording, this study does not confirm the technology's 'win-win-win' potential to foster a sustainable intensification of Irish milk production.

Important policy implications arise from this study. The results suggest that increasing milk recording's adoption rates would be valuable to increase output and enhance animal health for farmers who are not currently milk recording. The technology implies an out-of-pocket expenditure, whose return on investment can be difficult to assess for farmers. While milk recording adoption does not imply a direct cash return, the findings confirm clear economic benefits. In that sense, the study offers interesting insights in terms of methodological approach by extending the application of farm sustainability indicators for the measuring of technology impact. The estimation of treatment effects on sustainability indicators is a means of isolating the impact of farm strategies and provides evidence-based, self-explanatory figures (e.g., 25% decrease in BTSCC) that can subsequently inform farmers' adoption decisions. The diffusion of the research findings to farmers through veterinarians and extension agents would be useful to encourage milk recording's uptake. These actors are important sources of knowledge for farmers (Genius et al., 2014; Sligo and Massey, 2007; Vrain and Lovett, 2016) and are already actively involved in the promotion of best practices in Ireland (see for instance: Animal Health Ireland, 2016a; Department of Agriculture Food and the Marine, 2020).

While milk recording is a support technology, farmers remain the central piece in the system as they are the ones making decisions and acting upon the delivered information (Berckmans, 2014; Hostiou et al., 2017). Nonetheless, the data does not help to determine the extent or manner in which milk recording information is utilised to inform farm management decisions. Further research is needed investigate this topic. Even though milk recording organisations provide training and support to implement the technology and interpret results, concerns may arise from the large amount of information returned to farmers (Progressive Genetics, 2020) since it might be difficult to select which of it is key for decision making (Hostiou et al., 2017; Schewe and Stuart, 2015).

Previous research has indicated that farmers adopt a short-term reactionary (versus precautionary) approach towards mastitis management and as such, milk recording technology might not be widely used for breeding decisions (Dillon et al., 2018a). Using the information for this purpose might potentially require a much deeper understanding of the figures and expected impacts on cow offspring. If it were improved, herd productivity could be further enhanced. Increases in GHG emission efficiency could also be expected with significant improvements in herd genetic merit (Lanigan et al., 2018), if excessively high levels of external inputs are avoided (Crosson et al., 2011). This accentuates the role of individual decision making based on milk recording information and need of further training (notably through extension). More emphasis on all potential applications of milk recording information (including breeding) may improve current depth of use by milk recorders as there seems to be scope for improvement. ‘Information intensive technologies’ (i.e., which provide information to support decision making) (Barnes et al., 2019) tend to require further investments in training and learning so that farmers use them at full potential (Barnes et al., 2019; Eastwood et al., 2012).

In the absence of proven GHG benefits, it might be difficult to justify public intervention to support the promotion of milk recording for environmental purposes alone (Barnes et al., 2019). Nevertheless, it is still likely to gain policy interest in the short-term future in the frame of the new EU regulation addressing the public risk of antimicrobial resistance (European Parliament and Council of the European Union, 2019; Irish Co-operative Organisation Society, 2019). This regulation will come into force in January 2022. One of its goals is to reduce preventative antibiotic use in livestock production. As a result, strict restrictions on the use of ‘blanket dry cow therapies’ will be implemented at dry-off so that only dairy cows for which it is an absolute necessity to use dry cow antibiotics will receive the treatment (Irish Co-operative Organisation Society, 2019). Farmers will have to move towards ‘selective dry cow therapies’ and distinguish cows that qualify for dry cow strategies free from antibiotics (i.e., internal teat sealants) (Animal Health Ireland, 2016b). Milk recording is one tool that can help farmers identify cows with low risks of infection at dry-off (through individual SCC readings) and thus comply with the new regulation (Animal Health Ireland, 2016b; Irish Co-operative Organisation Society, 2019). Hence, the technology might contribute even more to the sustainability of Irish milk production by helping to prevent antimicrobial resistance. Up until January 2022, adoption rates must increase (Irish Co-operative Organisation Society, 2019), thereby justifying public intervention, for instance, through subsidised trials. If farmers are to fully bear the costs of this new regulation, more research is needed to understand barriers to the adoption of milk recording. In the meantime, the figures estimated in this study can be used to encourage voluntary uptake.

Finally, sustainable intensification is likely to rely on more controlled agricultural systems, with minimal waste along the supply chain. As dairy farmers upgrade their milking equipment, there will be opportunities to encourage a move away from traditional types of support technologies like milk recording, on to more sophisticated precision livestock farming technologies like automated milking facilities (Eastwood et al., 2012). These can provide daily information for herd monitoring and thus real-time decision aid, with expectations of economic, environmental, and social sustainability benefits (Barnes et al., 2019; Berckmans, 2014; Eastwood et al., 2012). Just as for milk recording, the realisation of their ‘win-win-win’ potential will depend on the actual use of the information they provide to inform daily decision making (Berckmans, 2014; Eastwood et al., 2012; Hostiou et al., 2017). Therefore, more research is needed to improve the link between technology adoption and farm management decisions.

Chapter 5 - Extension and management pathways for enhanced farm sustainability: Evidence from Irish dairy farms

5.1. Introduction

The total world population is expected to reach over 9 billion people by 2050 (United Nations, 2017). Moreover, changing dietary trends and higher demand for animal-based products increasingly add pressure on the food supply system and natural resources (Godfray et al., 2010). Production levels must thus be increased, but without causing further deterioration to the environment or even while reversing some existing damage (Garnett et al., 2013; Pretty, 2018). In response to this challenge, the concept of "sustainable intensification" was developed and draws significant attention in policy agendas (Council of the European Union, 2014; Department of Agriculture, Food and the Marine, 2015). While there is no commonly accepted definition of the term, it is centred around an efficiency-based paradigm that more food can be produced given a fixed, or declining, natural resource base (Barnes et al., 2016; Garnett et al., 2013). In fact, one can argue that fostering a more efficient conversion of inputs into outputs could lead to a simultaneous increase in food supply and reduction in environmental costs per output unit (Crosson et al., 2011).

The adoption of new farming practices can help producers to achieve sustainable intensification at the farm level (Kassie et al., 2018; Lanigan et al., 2018; Teklewold et al., 2013). However, uptake is often delayed, notably due to limited access to information regarding benefits, costs, and implementation of new practices (Takahashi et al., 2020; Weersink and Fulton, 2020). To address information constraints and foster widespread adoption, agricultural extension services aim at facilitating knowledge transfer within the farming community and thereby farmers' learning (Anderson and Feder, 2004; Davis et al., 2012). From a farmer's perspective, expected outcomes from extension participation encompass the development of analytical skills and critical thinking for improved resource utilisation and better decision-making (Davis et al., 2012). By focusing on key production components on which system efficiency relies (Hanrahan et al., 2019), extension can play a role in raising farming incomes and productivity, and in enhancing comparative advantage at the farm level (Davis et al., 2012; Läpple et al., 2020). Extension can also decrease on-farm environmental pressure by promoting improved land management practices and a more efficient use of inputs (Nordin and Höjgård, 2017).

The effectiveness of extension programmes has been extensively examined, with mixed records of success (e.g., Läpple and Hennessy, 2015; Mullally and Maffioli, 2015; Ragasa and Mazunda, 2018). Within this context, several review articles have explored reasons why extension is not always effective and how it can be improved (e.g., Anderson and Feder, 2004; Norton and Alwang, 2020; Takahashi et al., 2020). These reasons include, among others, difficulty in attributing causal impacts, weak accountability of extension agents, inconsistent financial support, and farmers' behavioural or cognitive biases towards extension messages. Nevertheless, despite the wide body of literature, there is still a lack of understanding of the conditions for successful extension systems. Gaining insights into the mechanism through which extension participation affects farm performance could contribute to overcoming this issue. Notably, while it is speculated that extension can affect farm performance by helping farmers to improve the management of their enterprises (e.g., Davis et al., 2012; Mullally and Maffioli, 2015; Ragasa and Mazunda, 2018), this link has yet to be empirically verified using farm-level data.

In this chapter, management pathways between extension participation and farm economic and environmental sustainability are assessed in the context of Irish dairy farming. More specifically, the impact of extension on specific farm management indicators is examined, followed by an estimation of their impact on farm sustainability. This study is timely for Ireland as the dairy sector is currently undergoing major structural changes following the abolition of European Union (EU) milk quotas in 2015. This policy change has set in motion substantial expansion and intensification of Irish dairy production. Significant challenges arise from ongoing growth as farmers require new management skills to transition to and operate larger holdings in a sustainable manner (Dillon et al., 2008; Hoekstra et al., 2020; Lanigan et al., 2018; Läpple et al., 2020). In this light, Irish extension has a critical role to play in supporting farmers' learning so that they achieve sustainable intensification (Department of Agriculture, Food and the Marine, 2015; Teagasc, 2015). To promote peer-to-peer knowledge exchange and get farmers actively involved in the learning process, Irish advisory services are mainly provided in a participatory manner under the form of farmers' discussion groups (Läpple et al., 2020; Läpple and Hennessy, 2015).

Previous research in an Irish context has demonstrated that extension participation can improve milk yields and gross margins of dairy farmers (Läpple et al., 2013; Läpple and Hennessy, 2015). Extension efforts were also successful in assisting farmers to gear up for quota removal by stimulating adjustments in herd size, dairy specialisation, and farm intensification (Läpple et al., 2020). However, as previously found in other settings in the international literature (e.g., Ragasa and Mazunda, 2018; Takahashi et al., 2020), the magnitude and significance of Irish extension effects were proven to vary within the pool of participants (Läpple et al., 2020; Läpple and Hennessy, 2015). Thus, the Irish context provides an excellent context to delve deeper into management pathways between extension and farm sustainability, which is the main contribution of this study.

In so doing, another literature gap is addressed in this chapter by incorporating farm management and environmental sustainability outcomes into the empirical analysis. Although Irish extension has integrated improved farm management and environmental sustainability as specific goals of the programme (Department of Agriculture Food and the Marine, 2020; Teagasc, 2015), the effect of participation on these outcomes has not yet been formally examined. Lack of evidence of extension impact on farm management and environmental sustainability is a common issue in the literature, with the exception of Mullally and Maffioli (2015) and Nordin and Höjgård (2017), respectively.

Farm management relates to the choosing between alternative uses of resources and the implementing of decisions involved in operating a farm (Malcolm, 2004). Difficulties arise from measuring it for two main reasons. First, microdata about farmers' practices is rarely available, which is an issue notably faced in the Mullally and Maffioli (2015) study on extension impact. Second, changes in decisions and practices are generally measured by dichotomous variables that cannot represent incremental on-farm adjustments (Weersink and Fulton, 2020). These limitations are overcome by utilising a rich farm-level dataset that allows for the development of continuously defined indicators of farm management. Drawing upon the specificities of the Irish grass-based production system, the extension programme focuses mainly on two areas of dairy management, namely grassland management and reproductive efficiency (Department of Agriculture Food and the Marine, 2020; Donnellan et al., 2015). Hence, this study uses the share of homegrown grass in the diet of dairy cows as indicator of grassland management (Hanrahan et al., 2018; O'Brien et al., 2018) and calving rates as indicator of reproductive efficiency (Butler, 2014; Crowe et al., 2018; Lane et al., 2013).

Regarding farm environmental sustainability, data availability and complexity in defining the term are often limiting factors to quantify environmental outcomes (Lebacq et al., 2013). Comparatively, economic sustainability, represented by gross margins and direct production costs in the current study (Kassie et al., 2018; Läpple and Hennessy, 2015), is overrepresented in the literature (Lebacq et al., 2013). It may in fact be unrealistic to expect farmers to engage with information and new practices if they do not perceive it as cost-efficient. As environmental sustainability is increasingly gaining importance in public policies and extension programmes, more research is needed to further assess environmental outcomes in empirical work. Consequently, two distinct aspects of environmental sustainability are focused upon in this study, i.e., Greenhouse Gas (GHG) emission efficiency and nitrogen surplus (Buckley et al., 2019). GHG emissions and nutrient pressure are issues of growing concern for dairy farmers, with high policy relevance in Ireland (Environmental Protection Agency, 2019b; European Commission, 2010; Hoekstra et al., 2020; Lanigan et al., 2018). They have thus been drawing the attention of Irish extension services (Department of Agriculture Food and the Marine, 2020; Teagasc, 2015). While Nordin and Höjgård (2017) use a measure of nutrient surplus as the variable of interest in their study of extension impact, no work has been carried out on GHG emissions within the extension literature yet.

An unbalanced panel dataset of extension participation from 2010 until 2017 from the Teagasc National Farm Survey (NFS) is used in this study. Based on advisory guidelines from the extension programme and previous literature on farm sustainability (Dillon et al., 2008; Garnsworthy, 2004; Lanigan et al., 2018; Llonch et al., 2017; O'Brien et al., 2014a; Shalloo et al., 2014; Teagasc, 2016), extension participation is expected to affect gross margins and direct production costs (i.e., economic sustainability), and GHG emission efficiency and nitrogen surpluses (i.e., environmental sustainability) through two main management pathways: 1) the grassland management pathway and 2) the reproductive efficiency pathway. Hence, a system of simultaneous equations is built and estimated through two-way Fixed Effects (FE) Seemingly Unrelated Regressions (SUR) models, with several estimators (De Mey et al., 2016; Wooldridge, 2010; Zellner, 1962). Moreover, to test for coefficient stability and achieve partial identification, a bounding approach, originally developed by Altonji et al. (2005) and further expanded by Oster (2019), is implemented. This method is referred to as the Oster procedure thereafter.

The remainder of this chapter is structured as follows: in section 5.2, the contextual background is outlined. In section 5.3, the regression framework and econometric strategy is presented. In section 5.4, the data and descriptive statistics are described. In section 5.5, the results are reported and discussed, followed by the conclusion in section 5.6.

5.2. Contextual background

5.2.1. Irish dairy growth and sustainability challenges

After EU milk quota removal was confirmed, the Irish government announced in 2010 'Food Harvest 2020' growth targets of a 50% increase in milk production by 2020 relative to the 2007-2009 average (Department of Agriculture Food and the Marine, 2010a). These targets were achieved in 2018, two years ahead of schedule (Eurostat, 2020a). Further expansion is expected in the context of the governmental 'Food Wise 2025' agri-food strategy (Department of Agriculture Food and the Marine, 2015; Lanigan et al., 2018).

However, ongoing, rapid growth adds environmental pressure, which highlights the need to achieve sustainable intensification. Agricultural GHG emissions increased by 14.2% between 2011 and 2017, mostly due to dairy herd expansion and enhanced reliance on external inputs (Duffy et al., 2019). These changes challenge the achievement of GHG reduction targets to which Ireland has agreed as part of the EU Effort Sharing Decision (Environmental Protection Agency, 2019a; European Commission, 2014). Another problem is the compliance with the EU Nitrates Directive regulations, which requires a strict monitoring of nitrogen applied at the farm level (through organic and inorganic sources). This links to the EU Water Framework Directive, which aims at achieving high ecological status across watercourses (European Commission, 2010). Nonetheless, since milk quota removal, farm nutrient surpluses and river nutrient concentrations have been on the rise in Ireland (Buckley et al., 2019; Environmental Protection Agency, 2019b).

5.2.2. Irish grass-based milk production system and dairy farm management

The Irish dairy sector gains from a competitive advantage on international markets by relying on a low-cost grass-based production system, where cows graze outdoors from early spring until late autumn (Dillon et al., 2008). The temperate climate allows for the growth of a large amount of grass, which represents the main feed source of dairy cows, as well as the cheapest (Hanrahan et al., 2018; Läpple et al., 2012). Best practice for Irish dairy farmers is to maximise homegrown grass in the diet of dairy cows with appropriate supplementation from concentrates when grass supply and grazing conditions are not suitable (O'Brien et al., 2018). This implies that farmers mainly operate spring-calving systems to synchronise seasonal grass growth, herd feeding requirements, and reproductive cycles (Butler, 2014). Therefore, the relative importance of dairy fertility is greater than for non-seasonal production systems as spring pasture growth and cow intake demands must be matched (Shalloo et al., 2014).

The functioning of such a production system can be challenging and highly depends on individual skills and knowledge in grassland management and reproductive efficiency (Dillon et al., 2008). These two areas of farm management are key to achieving 365-day compact calving patterns and capitalising on long grass-growing seasons (Butler, 2014; Hanrahan et al., 2019, 2018; Lane et al., 2013; Läpple et al., 2012; Shalloo et al., 2014). While weather and agronomic conditions can restrict grass growth and grazing, they can be overcome by continued grassland management throughout the production year (Hanrahan et al., 2017; Teagasc, 2016). In that regard, daily management and decision-making at paddock level are fundamental (Hanrahan et al., 2017). As for reproductive efficiency, while many factors influence dairy fertility (e.g., breed, age, cow health), the combination of high submission and conception rates is essential and relies on precise assessment and monitoring, particularly just before and during the breeding season (i.e., April - June) (Butler, 2014; Lane et al., 2013). Moreover, breeding (or buying) replacement heifers with higher genetic merit for fertility traits can help farmers to achieve greater reproductive efficiency (Coleman et al., 2009; Cummins et al., 2012).

Benefits for farm economic and environmental sustainability can be expected from enhanced management in the areas of grassland management and reproductive efficiency. Previous literature suggests that improved grassland management is associated with an increase in farm economic performance (Läpple et al., 2012; Hanrahan et al., 2018), may reduce requirements for external inputs (e.g., fertiliser, concentrates) and thus nitrogen pressure at the farm level (O'Brien et al., 2014a; Basset-Mens et al., 2009; Foote et al., 2015), and also has potential for GHG mitigation (Lanigan et al., 2018; O'Brien et al., 2014c). Additionally, reproductive inefficiency associated with poor management can lead to large economic losses such as increased culling costs, adverse effects on labour costs resulting from suboptimum calving dates, and higher artificial insemination and intervention costs (Lane et al., 2013; Shalloo et al., 2014). Poor fertility also implies that more cows are required to meet production targets, which might ultimately increase avoidable environmental costs associated with feeding unproductive animals (Garnsworthy, 2004; Llonch et al., 2017).

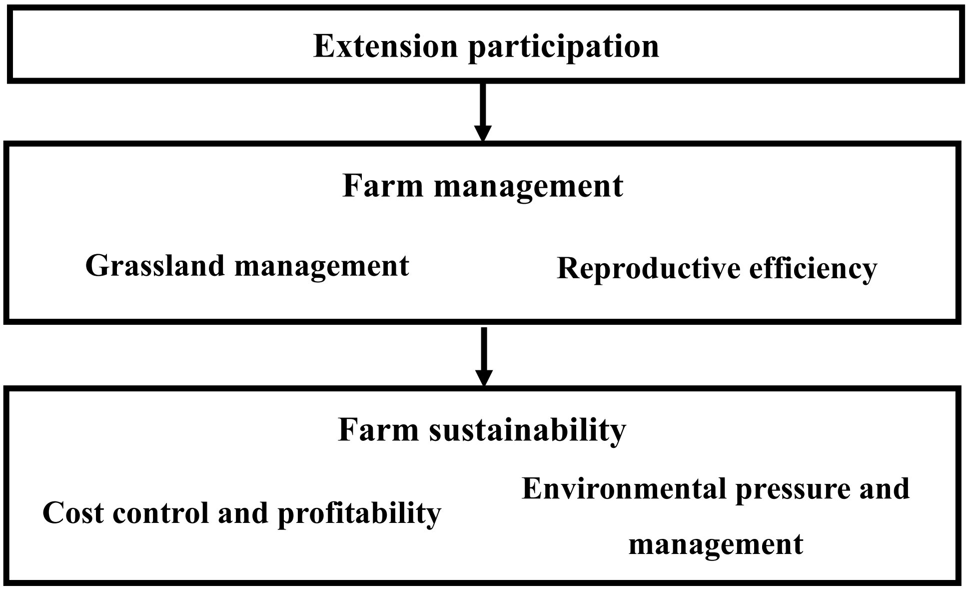
5.2.3. Hypothesised management pathways between extension participation and farm sustainability

Irish extension supports the view that better dairy sustainability can be achieved through an improved conversion of inputs into outputs. Hence, the programme focuses on "*the general principles of dairy farm management*" (Department of Agriculture Food and the Marine, 2020), i.e., the key components on which the efficiency of the Irish grass-based production system relies (Hanrahan et al., 2019; Shalloo et al., 2014). More specifically, strong emphasis is placed on improving farmers' skills in grassland management and feeding strategy, breeding and herd fertility and, as a consequence, cost control (Department of Agriculture Food and the Marine, 2020; Donnellan et al., 2015).

To this end, discussion groups, composed of 15 to 20 farmers and their discussion facilitator (i.e., an extension agent specialised in dairy production), gather on a monthly basis. Meetings are usually held on one of the participants' farm and cover a variety of issues embedded in the main aspects of dairy management. For grassland management and feeding strategy, these may include, for instance, nutrient application response, soil fertility, grazing infrastructures, and the choice of sward species, with the overarching goal of improving grass growth and utilisation (Teagasc, 2016, 2015). For breeding and herd fertility, potential issues can range from improvements in herd genetic merit, the tightening of calving rates, sire selection, and heat detection to ensure high reproductive efficiency and the achievement of production targets (Teagasc, 2016, 2015). Topics discussed in meetings are chosen by groups to match seasonal farming tasks, host farmer's specific conditions, and programme guidelines.

Consequently, building upon the previously mentioned literature and the characteristics of Irish extension and milk production system, it is hypothesised that extension participation exerts an effect on farm economic and environmental sustainability through two main management pathways, i.e., 1) the grassland management pathway and 2) the reproductive efficiency pathway. These are represented in Figure 5.1.

Figure 5.1: Hypothesised management pathways between extension participation and farm sustainability



5.3. Regression framework and econometric strategy

When translating Figure 5.1 into a regression framework, the following equations are obtained:

$$G = f_1(DG; X_1) \tag{5.1}$$

$$R = f_2(DG; X_2) \tag{5.2}$$

$$S = f_3(G; R; X_3) \tag{5.3}$$

where G is an indicator of grassland management, R is an indicator of reproductive efficiency, and S represents a farm economic or environmental sustainability indicator. DG stands for the years of discussion group participation. X_1, X_2, and X_3 are sets of farm and farmers' characteristics that affect G, R, and S, respectively.

Difficulties arise in estimating equations (5.1-3) as error terms are likely to be correlated across equations (Wooldridge, 2012). This problem can be seen in different ways. Firstly, although the extension programme follows specific guidelines regarding the content to be covered in discussion group meetings throughout the year (e.g., Department of Agriculture Food and the Marine, 2020), the amount of learning time dedicated to each principle of dairy farm management is chosen by discussion group members. Decisions of time allocation between learning about grassland or reproduction can be affected by endogenous characteristics, including observables (e.g., stocking rate) and unobservables (e.g., motivation to learn about the different topics). They can also be influenced by exogenous factors, including observables (e.g., EU milk quota removal) and unobservables (e.g., short-term weather shocks). Secondly, while G and R are dependent variables in equations (5.1-2), they are independent variables in equation (5.3). Thirdly, $X_{j,j\in[1;3]}$ might not only contain equation-specific characteristics, but also overlapping ones (e.g., farm size is likely to affect the different areas of farm management, as well as economic and environmental performances). Finally, farmers make concurrent choices regarding discussion group participation, farm management, and performance. Therefore, equations (5.1-3) must be considered as a system of simultaneous equations to be jointly determined (Wooldridge, 2012).

5.3.1. Endogeneity concerns

Estimating equations (5.1-3) is a complex task because of self-selection bias (Imbens and Wooldridge, 2009). Extension participation is voluntary, and thus more motivated, better farmers with higher sustainability performances might seek to participate in discussion groups. Because farmers self-select into the extension programme, profiles of members and non-members are likely to be systematically different (Imbens and Wooldridge, 2009). Systematic differences in profiles may in turn invalidate causal comparisons of outcomes by participation status, thus leading to biased estimates of extension effect (Imbens and Wooldridge, 2009).

Therefore, self-selection bias caused by unobserved heterogeneity must be accounted for[25]. The panel nature of the data is exploited by controlling for individual and time FE and clustering standard errors at the farm level (Allison, 2009; McCullagh and Nelder, 1989). Nonetheless, time-varying unobserved heterogeneity remains a concern to draw causal conclusions. This is legitimate as farmers' ability and motivation is likely to vary over time, especially when participating in extension. Even though researchers often try to limit time-varying unobserved heterogeneity by controlling for observables that are likely to capture its effect, this approach is not always convincing as observables may be incomplete proxies of true omitted variables (Altonji et al., 2005; Oster, 2019). To address this concern, the alternative Oster bounding strategy is implemented. It is presented later in this section (5.3.3).

Another important source of endogeneity to consider is the simultaneity between our dependent variables and their corresponding set of regressors (Wooldridge, 2012). While regressors can affect the outcome, the outcome can also influence some of the regressors. For instance, extension contact can

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[25] It is worth mentioning that the dataset does not include valid instruments of extension participation and farm management, thus ruling out instrumental variable approaches.

improve farm management, but farm management can also inform the decision to participate in discussion groups. Simultaneous causality can introduce bias and is difficult to control for in the absence of valid instruments (Wooldridge, 2012). These concerns are reduced by including years of discussion group participation and some other regressors as one-year lags (for those likely to be affected by the dependent variables) (De Mey et al., 2016; Fan et al., 2000). Indeed, the simultaneity between current dependent variables and past regressors is likely to be small or even non-existent (Fan et al., 2000). This approach also allows for time adjustment lags between learning about and implementing new practices (Fan et al., 2000; Wooldridge, 2012), which is relevant in an extension context. One-year lags are chosen as level of lags to limit loss of information as only seven time periods are observed.

5.3.2. Estimation approach

Based on these premises, equations (5.1-3) are rewritten as follows:

$$G_{it} = \beta_{1,1}DG_{it-1} + \beta_{1,2}X_{1,\,it-1} + \beta_{1,3}Z_{1,\,it} + \alpha_{1,i} + u_{1,it} \tag{5.4}$$

$$R_{it} = \beta_{2,1}DG_{it-1} + \beta_{2,2}X_{2,\,it-1} + \beta_{2,3}Z_{2,\,it} + \alpha_{2,i} + u_{2,it} \tag{5.5}$$

$$S_{it} = \beta_{3,1}G_{it} + \beta_{3,2}R_{it} + \beta_{3,3}X_{3,\,it-1} + \beta_{3,4}Z_{3,\,it} + \alpha_{3,i} + u_{3,it} \tag{5.6}$$

where the subscript i refers to the individual being observed and the subscript t denotes the time period at which individual i is observed. $(\alpha_{j,i} + u_{j,it})_{j\in[1;3]}$ are the error terms, where $\alpha_{j,i}$ represent the time-invariant unobserved effects and $u_{j,it}$ are disturbances assumed to be identically and independently distributed. The sets of farm and farmers' characteristics which are not included as one-year lags are labelled $Z_{j,\,it}$. Finally, the β parameters are to be estimated, with particular interest for $\beta_{1,1}$ and $\beta_{2,1}$ (i.e., effect of (past) extension participation on grassland management and reproductive efficiency, respectively), and $\beta_{3,1}$ and $\beta_{3,2}$ (i.e., effect of grassland management and reproductive efficiency on farm sustainability, respectively).

The system of equations (5.4-6) can be jointly estimated through two-way FE SUR models, with clustered standard errors at the farm level (Zellner, 1962). While equations (5.4-6) can be consistently estimated equation by equation with Ordinary Least Squares (OLS), SUR estimation traditionally uses Feasible Generalised Least Squares (FGLS) to account for correlation across error terms and gain in efficiency (Zellner, 1962). However, in FE settings, FGLS can also result in inconsistent standard errors and other estimators may be preferred (Hansen, 2007; Wooldridge, 2010). As an alternative to FGLS, De Mey et al. (2016) implemented the Generalised Method of Moments Three-Stage Least Squares (GMM 3SLS) estimator (Wooldridge, 2010). The GMM 3SLS estimator is an improved extension of the regular 3SLS estimator (Zellner and Theil, 1962) in cases where the set of explanatory variables varies across equations and cluster-robust standard errors are required (Wooldridge, 2010).

Therefore, equations (5.4-6) are estimated equation by equation with OLS and jointly with FGLS and GMM 3SLS to ensure the robustness of the results[26]. Although no differences are expected in coefficient magnitudes across estimators, standard errors and thus significance levels may vary. Four systems are estimated in total, i.e., one per sustainability indicator.

5.3.3. Sensitivity analysis and partial identification strategy

While the magnitude of bias, potentially introduced by time-varying unobserved heterogeneity, cannot be formally examined, coefficient stability can be tested through the Oster procedure. Based on the assumption that observable selection gives information about unobservable selection[27], the methodology explores whether unobserved heterogeneity is likely to affect estimation results and thereby causal inferences (Altonji et al., 2005; Oster, 2019). To allow for partial identification, it simulates the effect of unobservables and calculates bounds for treatment effects conditional on

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[26] For the FGLS estimator, clustered standard errors were obtained through bootstrapping with 1,000 replications.

[27] This assumption is reasonable as one can expect observables that affect the decision to participate in discussion groups (e.g., farm size) to be to some extent related to unobservables that also affect this decision (e.g., farmer’s motivation and ability). Similarly, observables that influence farm management skills are expected to be somewhat related to unobservables that influence these skills too.

varying levels of proportional unobservable selection. Hence, the Oster procedure is implemented to check the robustness of extension effect on farm management and management effect on farm sustainability to unobservable selection[28]. In this way, causal conclusions can be drawn.

Following Oster (2019), let us denote Y, the outcome (i.e., G and R in equations (4-5), S in equation (6)), T, the treatment (i.e., DG in equations (4-5), G and R in equation (6)) , X, a set of observables, and W, a vector of unobservables. X and W are orthogonal. The proportional selection relationship can be defined as $\frac{\sigma_{XT}}{\sigma_X^2} = \frac{\sigma_{WT}}{\sigma_W^2}$, where $\sigma_{XT} = cov(X,T)$, $\sigma_{WT} = cov(W,T)$, $\sigma_X^2 = var(X)$, $\sigma_W^2 = var(W)$, and δ is the degree of proportionality between observable and unobservable selections. δ takes the value of 0 if unobservable selection is non-existent (which is speculated in 'naïve' FE SUR models). δ takes the value of 1 if observables and unobservables equally affect the selection decision. Consider now the following regression models:

$$Y = \dot{\beta}_1 T + \dot{u} \tag{5.7}$$

$$Y = \widetilde{\beta_1} T + \widetilde{\beta_2} X + \tilde{u} \tag{5.8}$$

$$Y = \beta_1 T + \beta_2 X + \beta_3 W + u_{max} \tag{5.9}$$

$\dot{\beta}$ is the coefficient resulting from the simple regression of Y on T, and $\dot{R}$ its R-squared. $\tilde{\beta}$ are the coefficients obtained from the multiple regression of Y on T and X, and $\tilde{R}$ its R-squared. Finally, β are the coefficients obtained from the multiple regression of Y on T, X and W, and R_{max} its R-squared. In other words, R_{max} is the R-squared from a hypothetical regression of the outcome on the full set of observables and unobservables. Building upon the omitted variable bias formula, Oster (2019) proves that the magnitude of bias from

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[28] Please note that the method can only be run when the system of equations (4-6) is estimated equation by equation with OLS. This is not an issue as consistent results across estimators are expected, and coefficient movement is the focus of the Oster procedure.

omitting W is equal to $\delta(\dot{\beta}_1 - \widetilde{\beta_1})\frac{R_{max}-\tilde{R}}{\tilde{R}-\dot{R}}$, and a bias-adjusted treatment effect β_1^* can thus be approximated with $\widetilde{\beta_1} - \delta(\dot{\beta}_1 - \widetilde{\beta_1})\frac{R_{max}-\tilde{R}}{\tilde{R}-\dot{R}}$.

As calculating unbiased estimates of treatment effects requires the unknown values of δ and R_{max}, bounds for treatment effects that account for the uncertainty in these two entities are determined instead. One bound is defined by $\widetilde{\beta_1}$, the value of the treatment effect when $R_{max} = \tilde{R}$ or $\delta = 0$. That is, one bound is determined by the coefficient estimated in the ‘naïve’ FE SUR model, which assumes that unobservable selection is non-existent. To calculate the other bound $\beta_1^*(\delta, R_{max})$, values of δ and R_{max} must be inputted into the estimator. The assumptions made on these values are the basis for partial identification. Oster (2019) suggests a value of $\delta = 1$ as an appropriate cut-off since empirical researchers aspire to choose observables that are at least as important as unobservables in the selection decision. As for the R_{max} value, the most conservative assumption of 1 is considered, which implies that the outcome would be entirely explained if the full set of observables and unobservables was controlled for. This assumption is plausible in a FE setting.

A bounding set $\Delta = [\widetilde{\beta_1};\ \beta_1^*(1,1)]$ is then constructed. It collects a range of coefficient values taken by treatment effects when unobservable selection moves from non-existent to equally as important as observable selection. Once Δ is calculated, the conclusions drawn from the bounding approach must be examined to see whether they challenge the ones inferred from the FE SUR estimation. In that regard, Oster (2019) recommends verifying whether Δ includes 0 or not. If it does, time-varying unobserved heterogeneity could potentially cancel treatment effects or change their sign, thus indicating a lack of robustness. Oster (2019) also suggests comparing Δ to the 95% confidence interval of treatment effects computed in baseline models. If they overlap, the range of treatment effect estimates under varying levels of proportional unobservable selection consist in the same set of potential values of the unknown true treatment effect computed in FE SUR models. This would point out that time-varying unobserved heterogeneity does not question causal inferences based on the FE SUR estimation, and hence that causal conclusions can be drawn.

5.4. Data and descriptive statistics

The main source of data is the Teagasc NFS data, which is an enhancement of the financial and technical data recorded to fulfil Ireland's EU statutory requirements through the Farm Accountancy Data Network (Dillon et al., 2016a). The data is collected on a yearly basis through face-to-face surveys by a team of professional data recorders. In conjunction with the Central Statistics Office, a sample of approximately 900 farms is selected to represent Irish farms[29]. Respondents 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 chapter, farms with a dairy enterprise are focused upon, including dairy specialists, and arable and mixed livestock farms. An unbalanced panel dataset from 2010 until 2017 is compiled by selecting farms that do not have missing values for the key variables of interest. The sample contains 2,458 observations accounting for 431 farms and represents about 90% of the original 2010-2017 dairy sample. Farms remain on average 5.7 years in the panel. As regressions include one-year lagged variables, the sample size is reduced to 1,945 observations for the main analysis to include farms that are present in the dataset during at least two consecutive years.

5.4.1. Variable description

The key variables of interest include extension participation, farm management indicators, and farm economic and environmental sustainability indicators. Following Läpple et al. (2020), extension participation is assessed through the length of participation in discussion groups, measured in years.

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[29] Please note that in this chapter, Central Statistics Office weights are not accounted for in the analysis for two main reasons. First, the weights vary over time for each farm, which is not supported in panel data models. Second, the GMM estimator does not achieve convergence when the data is weighted. Hence, the analysis is performed on the unweighted Teagasc NFS data.

The year of initial participation is observed in the data for members who joined after 2010. For members who joined prior to 2010, the year of initial participation is self-declared. For non-members, the variable takes the value of 0.

Grassland management is measured through the share of homegrown grass in the diet of dairy cows (Hanrahan et al., 2018; O'Brien et al., 2018). According to Irish advisory guidelines, 74% of dry matter fed to dairy cows should come from grazed grass and 19% from grass silage (Teagasc, 2016). Best practice is to grow all the grass on the farm. Therefore, the advisory guidelines translate into a target of 93% of homegrown grass in the diet of dairy cows. The indicator is calculated following the methodology developed by O'Brien et al. (2018) for the Teagasc NFS dataset. Through a back calculation based on dairy cow energy demand requirements, kilograms (kg) of dry matter[30] fed from homegrown grazed grass and grass silage can be estimated by subtracting energy supply coming from other feed sources from the total energy demand. Energy demand includes maintenance and activity, milk production, pregnancy, and body weight change and growth. The share of homegrown grass in the diet of dairy cows is then deduced by dividing kg of dry matter fed from homegrown grass by total kg of dry matter fed.

Reproductive efficiency is represented by calving rate, i.e., the proportion of dairy cows calving in the herd (Butler, 2014; Crowe et al., 2018; Lane et al., 2013). The Irish extension target of a 90% in-calf rate at the final pregnancy diagnosis (Teagasc, 2016) translates into a 90% target for calving rate. Calving rate is not directly recorded in the Teagasc NFS, but this information is retrieved by dividing the amount of calf births by the opening stock of dairy cows, adjusted for potential still and twin birth rates. As these data are not included in the dataset, national averages for Irish dairy herds are used: the prevalence of still births is about 4% (Mee et al., 2008) and the average twinning rate is approximately 2% (Fitzgerald et al., 2014).

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[30] In order to account for differences in energy fed by feed type, all dry matters are converted to an energy unit called Unité Fourragère Lait (Jarrige, 1989) for the calculation. Please see O'Brien et al. (2018) for more detail.

As for farm sustainability indicators, economic sustainability is measured through direct production costs per unit of output for cost control and gross margin per cow for profitability. These are common indicators of farm economic performance (Kassie et al., 2018; Läpple and Hennessy, 2015). A Fat-Protein-Corrected-Milk (FPCM) correction is applied to the unit-of-output measure to control for differences in milk solids and energy requirements across farms (International Dairy Federation, 2015).

Environmental sustainability is assessed through nitrogen surplus per hectare (ha) and GHG emitted per kg of FPCM (Buckley et al., 2019). Nitrogen surplus gives a farm-level estimation of nitrogen, potentially available for loss to water bodies, and hence serves as an indicator of nutrient management and farm environmental pressure (Buckley et al., 2016b, 2015; Schröder et al., 2003). It is calculated following an input-output accounting methodology, i.e., as inputted (e.g., fertiliser, concentrate feed) minus outputted (e.g., milk, livestock) quantities of nutrient on a per-hectare basis (Buckley et al., 2019). In this way, the analysis is restricted within the farm gate to include inputs and outputs of nutrients over which the farmer has direct control (Buckley et al., 2016b, 2015).

GHG emitted per FPCM reflects milk GHG emission efficiency and is thus used as an indicator of farm environmental efficiency (Crosson et al., 2011). Agricultural GHG emissions are estimated by using a cradle-to-farm gate Life Cycle Assessment (LCA) approach (O'Brien et al., 2014b, 2010)[31]. All GHG emissions associated with dairy production are modelled (including on- and off-farm) using emission factors that follow the Intergovernmental Panel on Climate Change guidelines or come from other resources in the

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[31] This approach is internationally standardised (International Organization of Standardization, 2006a, 2006b) and specific guidelines are available for milk production (British Standards Institute, 2011; Carbon Trust, 2010; International Dairy Federation, 2015). The LCA approach implemented in this chapter was developed according to the publicly-available PAS 2050:2011 specification from the British Standards Institute (British Standards Institute, 2011) and validated by the Carbon Trust, an accredited third party (O'Brien et al., 2014b). Please refer to O'Brien et al. (2014b) for the full list of GHG emission sources and corresponding emission factors.

literature (Dong et al., 2006; Duffy et al., 2017). Emissions are converted to kg of Carbon Dioxide Equivalent (CO_2e) using the 100-year Global Warming Potential (Forster et al., 2007). They are reported per kg of FPCM (International Dairy Federation, 2015). The data necessary to calculate GHG emissions is available only after 2013 in the dataset, and the sample thus is reduced from 2013 until 2017 for the analysis with this indicator.

Other farm and farmers' characteristics are included in regressions as control variables to limit time-varying unobserved heterogeneity within farms (Altonji et al., 2005; Oster, 2019). They are selected through a literature review. Farm area allocated to the dairy enterprise, degree of specialisation in dairy production, stocking rate, and farmers' age are commonly controlled for in extension and sustainability contexts (e.g., Läpple et al., 2020; Nordin and Höjgård, 2017; Ragasa and Mazunda, 2018) and thus overlap across equations (5.4-6).

Length of grazing season, proportion of leased land to total farmed land, and farmers' household size are only used in equation (5.4). In order to increase homegrown grass intake, it is seen as best practice to start the grazing season early in the spring until late autumn, if weather conditions allow it (Läpple et al., 2012; Teagasc, 2016). The proportion of leased land can suggest the level of investments in grazing infrastructures (e.g., roadways, paddock system) and land fragmentation (Orea et al., 2015; Teagasc, 2016). As for household size, it serves as a proxy for available family labour, a limiting factor of continued grassland management (O'Donovan et al., 2008).

Artificial insemination expenditure, Bulk Tank Somatic Cell Count (BTSCC), and milk recording expenditure are included in equation (5.5). Artificial insemination usage is seen as best practice in Irish extension to improve genetic merit and increase in-calf rate (Teagasc, 2016). BTSCC is an indicator of milk bacterial contamination and risk of mastitis incidence (Dillon et al., 2015). It reflects general herd health status, which is fundamental to reproductive efficiency (Lane et al., 2013; Shalloo et al., 2014). Regular milk recording allows to monitor cow health and inform breeding decisions (Läpple et al., 2017).

Control variables likely to introduce simultaneity bias (Wooldridge, 2012) are inserted as one-year lags (De Mey et al., 2016; Fan et al., 2000). These include farm area, degree of dairy specialisation, and stocking rate. Length of grazing season is also lagged because it can have adverse effects on grass availability in the coming grazing season if paddock closure is delayed for too long in late autumn (Lawrence et al., 2017).

5.4.2. Descriptive statistics

Table 5.1 reports variable definition and descriptive statistics for the 2010-2017 pooled sample. Discussion group members represent about 49.4% of the sample and have been involved in extension for about 9 years, on average. The proportion of discussion group members gradually increased from 2010 (46.1%) until 2015 (53.4%) but dropped back in 2017 (43.6%).

Table 5.1 suggests that discussion group members achieve higher shares of homegrown grass and calving rates than non-members. However, both discussion group members and non-members are below advisory targets of 93% of homegrown grass in the diet of dairy cows and 90% in-calf rates (Teagasc, 2016).

Table 5.1 also indicates that farm economic sustainability is higher for members than non-members. In terms of farm environmental sustainability, while discussion group members achieve lower GHG emissions per unit of output than non-members, they also have larger nitrogen surpluses per ha. In other words, group members produce milk with a better GHG efficiency but apply more nutrient pressure at the farm level. This is probably due to higher scale and intensity of dairy production.

Finally, when considering farm and farmers' characteristics in Table 5.1, differences are observed between members and non-members. This suggests the presence of self-selection into discussion groups and reinforces the importance of accounting for unobserved heterogeneity in the econometric analysis.

Table 5.1: Variable definition and descriptive statistics (2010-2017 pooled sample)

Variable	Definition	Discussion group members (n = 1,214)	Non-members (n = 1,244)	All farmers (n = 2,458)
Extension participation				
Extension	Years of participation in discussion groups (years)	9.01 (6.88)	0	4.45 (6.61)
Farm management				
Homegrown grass	Share of dry matter fed from homegrown grass (grazed grass and grass silage) in the diet of dairy cows (%)	79.04 (10.50)	78.47 (11.42)	78.75 (10.98)
Calving rate	Proportion of cows calving in the herd (%)	83.57 (11.06)	81.61 (12.61)	82.58 (11.91)
Farm economic sustainability				
Costs	Direct production costs per unit of output (cents / kg of FPCM)	13.72 (3.37)	14.50 (4.25)	14.11 (3.86)
Margin	Gross margin per cow (€ / cow)	1173.65 (312.38)	1032.01 (345.73)	1101.96 (337.13)
Farm environmental sustainability				
Nitrogen	Nitrogen surplus per ha (kg / ha)	171.66 (64.47)	144.90 (68.33)	158.12 (67.77)
GHG $_a$	Agricultural GHG emissions per unit of output (kg of CO_2e / kg of FPCM)	1.09 (0.20)	1.16 (0.26)	1.12 (0.23)

Variable *(Continued from previous)*	Definition	Group members	Non-members	All farmers
Equation-specific farm and farmers' characteristics				
Grazing	Length of grazing season (days)	245.28 (29.52)	233.72 (27.21)	239.43 (28.95)
Leased land	Proportion of leased land to total farmed land (%)	24.02 (20.03)	19.37 (20.81)	21.67 (20.56)
Household	Number of household members (people)	3.74 (1.60)	3.74 (1.60)	3.53 (1.58)
AI	Artificial insemination expenditure per cow (€ / cow)	28.37 (17.58)	20.74 (18.58)	24.51 (18.33)
BTSCC	Bulk tank somatic cell count ('000 cells / ml)	184.95 (74.52)	233.04 (117.14)	209.29 (97.82)
Milk recording	Milk recording expenditure per cow (€ / cow)	8.59 (7.85)	2.89 (5.71)	5.71 (7.42)
Non-equation specific farm and farmers' characteristics				
Farm area	Farm area allocated to the dairy herd (ha)	44.91 (21.94)	31.06 (16.57)	37.90 (20.60)
Specialisation	Share of dairy cows to total livestock units (%)	63.20 (11.26)	59.93 (16.41)	61.54 (14.20)
Stocking rate	Dairy livestock units per ha (cows / ha)	2.03 (0.48)	1.87 (0.52)	1.95 (0.51)
Age	Age of the main farm holder (years)	53.38 (10.99)	56.83 (9.98)	55.12 (10.63)

Note: Means and standard deviations in parentheses. $_a$ Sample reduced from 2013 until 2017, with a total of 1,512 observations accounting for 380 farms.

5.5. Results and discussion

5.5.1. Results of the fixed effects seemingly unrelated regression models

The results of the FE SUR estimation with the GMM 3SLS estimator are presented in Table 5.2 for the economic indicators and Table 5.3 for the environmental indicators. Only the main variables of interest are reported. Please refer to Table B. 1, Table B. 2, Table B. 3, and Table B. 4 (Appendix B) for the full regressions. The findings from the FE OLS equation-by-equation and FGLS estimations are also presented in these tables (Appendix B). Please note that the analysis was also conducted on the balanced panel dataset to ensure that attrition bias was not at play and hence verify the robustness of estimation results, as suggested by Cheng and Trivedi (2015). The findings on the balanced panel are reported in Table B. 5, Table B. 6, and Table B. 7 (Appendix B) and lead to similar conclusions than the results on the unbalanced panel.

As a first impression of the models in Appendix B, findings are consistent across estimators. Standard errors slightly vary, but without affecting significance levels of the variables of interest. Since all estimators yield similar results, the GMM 3SLS estimator is focused upon in Table 5.2 and Table 5.3. While causal conclusions cannot be drawn from the results in Table 5.2 and Table 5.3, they point out correlations that can be used as the basis for partial identification in the sensitivity analysis (reported in Table 5.4).

Regarding the effect of extension on farm management, the findings in Table 5.2 and Table 5.3 show that (past) extension is positively associated with calving rate, which represents reproductive efficiency. Conversely, it does not have a significant effect on the share of homegrown grass in the diet of dairy cows, which suggests a lack of extension impact on that indicator. Additional analyses (not reported in this chapter) were carried out with two other measurements of feeding strategy and grassland management to verify this finding. The indicators were length of grazing season and feed conversion efficiency (i.e., kg of FPCM produced per kg of concentrates fed to the dairy cows (a substitute of grass)) (Beever and Doyle, 2007; Hanrahan et al., 2018; Läpple et al., 2012). SUR estimation results with these two indicators revealed that (past) extension does not have a significant effect on grassland management, as measured by any of the indicators under consideration.

In terms of the effect of farm management on economic sustainability, the results in Table 5.2 show that higher proportions of homegrown grass and improved calving rates are positively correlated with a cost reduction per unit of output and larger gross margins per cow.

In relation to the effect of farm management on environmental sustainability, the findings in Table 5.3 reveal that higher proportions of homegrown grass are positively associated with reductions in farm nitrogen surplus and GHG emitted per unit of output. Calving rate does not have a significant effect on nitrogen surplus and is negatively associated with a GHG reduction. This suggests that efficiency gains achieved through increased calving rates do not reduce environmental pressure.

Table 5.2: FE SUR estimation results exploring management pathways between extension and farm economic sustainability (GMM 3SLS estimator)

Variables	Direct production costs per unit of output			Gross margin per cow		
	Homegrown grass	Calving rate	Costs	Homegrown grass	Calving rate	Margin
Extension $_{t-1}$	0.0023 (0.077)	0.36*** (0.10)		0.0023 (0.077)	0.36*** (0.10)	
Homegrown grass			-0.15*** (0.013)			5.82*** (0.72)
Calving rate			-0.021*** (0.0073)			4.80*** (0.52)

Note: n = 1,945 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. Individual and time fixed effects, and farm and farmers’ characteristics controlled for.

Table 5.3: FE SUR estimation results exploring management pathways between extension and farm environmental sustainability (GMM 3SLS estimator)

Variables	Nitrogen surplus per ha			GHG emitted per unit of output [a]		
	Homegrown grass	Calving rate	Nitrogen	Homegrown grass	Calving rate	GHG
Extension $_{t-1}$	0.0023 (0.077)	0.36*** (0.10)		-0.044 (0.078)	0.31*** (0.11)	
Homegrown grass			-1.34*** (0.22)			-0.0017** (0.00085)
Calving rate			0.025 (0.10)			0.0011** (0.00058)

Note: n = 1,945 observations. [a] for the GHG indicator, data available only from 2013-2017 and thus n = 1,371 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. Individual and time fixed effects, and farm and farmers' characteristics controlled for.

5.5.2. Results of the Oster bounds estimation

Oster bounds are estimated for the significant variables of interest. These are used to draw causal conclusions under the Oster bounds assumptions (i.e., proportional unobservable selection and $R_{max} = 1$). Results are reported in Table 5.4 and are compared to FE SUR results (GMM 3SLS). Overall, the findings reveal that most Oster bounds do not include 0, except for the effect of homegrown grass and calving rate on cost control, and the effect of homegrown grass on GHG emission efficiency. When 0 is excluded, the percentage of Oster bounds included in the SUR estimated 95% confidence intervals is calculated to assess the degree to which they overlap.

The findings in Table 5.4 show that Oster bounds for the estimated coefficient of calving rate on gross margin per cow are [4.80; 5.60] and fully overlap with the 95% confidence interval (i.e., [3.78; 5.82]). It implies that the range of treatment effect estimates under varying levels of proportional unobservable selection consists in the same set of potential values of the unknown true treatment effect computed in the FE SUR model. This gives strong confidence in the robustness of the result and partial identification can be achieved. Therefore, based on the findings from Table 5.4 and under the Oster bounds assumptions (Oster, 2019), it can be concluded that an increase of 1% in calving rate is likely to lead to an increase of between €4.8 and 5.6 per cow in gross margin per year. If discussion group members were to bridge the gap between their average calving rate (83.6%, see Table 5.1) and the advisory target (90%, see Teagasc (2016)), this would likely result in an increase between €30.7 and 35.8 per cow in gross margin per year. Hence, for the average discussion group member (with 89.3 dairy cows), bridging the gap between current calving rate performance and advisory target would likely lead to an increase between about €2,741 and 3,197 in yearly gross margin. These results corroborate previous studies, which highlighted the economic benefits of improved reproductive efficiency (Lane et al., 2013; Shalloo et al., 2014).

Table 5.4 also shows that Oster bounds and SUR estimated 95% confidence intervals do not fully overlap for the effects of (past) extension on calving rate, of homegrown grass on gross margin and nitrogen surplus, and of calving rate on GHG emission efficiency. Under varying levels of proportional unobserved selection, these findings indicate coefficient movements beyond the set limits of potential values of the unknown true treatment effect computed in SUR models. Thus, they challenge the sensitivity of the FE SUR estimation results. Interestingly, in these four cases, unobservable selection may lead to an underestimation of treatment effects.

In the calving rate equation, only 14.7% of the Oster bounds for (past) extension are included in the SUR estimated 95% confidence interval ([0.36; 1.69] versus [0.16; 0.56], respectively). Consequently, under the Oster bounds assumptions (Oster, 2019), it can be concluded that an additional year of discussion group participation is likely to increase calving rate by at least 0.4% in the following year (i.e., lower bound estimated by the Oster procedure). When considering the average calving rate of discussion group members (83.6%, see Table 5.1), the result suggests that bridging the gap between current performance and advisory target (90%, see Teagasc (2016)) would require an additional 16 years of discussion group participation in the 'worst case' scenario (i.e., if unobservable selection is not at play at all). While this scenario suggests that the effect of extension participation on reproductive efficiency is limited, further research should explore in greater detail the causal impact with appropriate data. Depending on the actual influence of unobservable selection, the conclusion of limited extension effectiveness on calving rates may need to be revised. Specifically, if unobservables turned out to have a small effect on the decision to participate in discussion groups compared to observables, then the causal impact would be close to the lower Oster bound estimated in this study (about 0.4%), thereby confirming limited extension effectiveness. Conversely, if unobservables played a relatively important role in the participation decision compared to observables, then the causal impact could be larger.

In the gross margin equation, 79.7% of the Oster bounds for the homegrown grass indicator are included in the SUR estimated 95% confidence interval ([5.82; 7.59] versus [4.41; 7.23], respectively). Similarly, in the nitrogen surplus equation, only 18.2% of the Oster bounds for homegrown grass are included in the SUR estimated 95% confidence interval ([-3.71; -1.34] versus [-1.77; -0.91], respectively). Therefore, under the Oster bounds assumptions (Oster, 2019), the results imply that an increase of 1% in homegrown grass in the diet of dairy cows is likely to result in an increase by at least €5.8 per cow in gross margin (i.e., lower bound estimated by the Oster procedure) and a decrease by at least 1.3 kg per ha in farm nitrogen surplus (i.e., upper bound estimated by the Oster procedure). If discussion group members were to bridge the gap between their average share of homegrown grass in the diet of dairy cows (79.0%, see Table 5.1) and the advisory target (93%, see Teagasc (2016)), this would likely result in an increase by at least €81.2 per cow in yearly gross margin and a decrease by at least 18.4 kg per ha in nitrogen surplus. In other words, for the average discussion group member (with 89.3 dairy cows and a farm size of 75.1 ha), bridging the gap between current grass performance and advisory target would likely lead to an increase by at least €7,243 in yearly gross margin and a reduction by at least 1,382 kg of nitrogen surplus. These findings are in line with previous literature (Basset-Mens et al., 2009; Foote et al., 2015; Hanrahan et al., 2018; O'Brien et al., 2014a).

In the GHG emission efficiency equation, only 34.4% of the Oster bounds for calving rate are included in the SUR estimated 95% confidence interval ([0.0011; 0.0044] versus [-0.000037; 0.0022], respectively). Consequently, under the Oster bounds assumptions (Oster, 2019), the findings suggest that an increase by 1% in calving rate is likely to increase GHG emissions by at least 1.1 grams of CO_2e per unit of output (i.e., lower bound estimated by the Oster procedure). The potential of improved fertility to increase GHG emission efficiency is thus not confirmed in this study, which stands in contrast to previous literature (Garnsworthy, 2004; Llonch et al., 2017). While this result is unexpected, it may be related to the time period under consideration (2010 – 2017). Due to EU quota abolition, the size of the national herd has expanded by 34% between 2008 and 2018 (Eurostat, 2020b). In order to increase cow numbers, farmers may have increased the share of heifers in dairy herds, as well as having strategically kept older cows. As both heifers and older cows have lower milk yields, potential changes in herd age profile may have resulted in a reduction in GHG emission efficiency. More research will be needed when the dairy expansion process reaches its end.

Finally, significant concerns arise regarding the robustness of the effect of both farm management indicators on cost control and of homegrown grass on GHG emission efficiency. Regarding the cost control equation, as shown in Table 5.4, the Oster bounds are [-0.15; 0.060] for the homegrown grass indicator and [-0.021; 0.0021] for the calving rate indicator. The inclusion of 0 in these bounds indicates that unobservable selection may lead to insignificant effects, or even a reversed direction of the effects, of homegrown grass and calving rate on direct production costs estimated by the SUR models. Similarly, in the GHG emission equation, the findings in Table 5.4 show that Oster bounds are [-0.0017; 0.00018] for the homegrown grass indicator. As 0 is included in these bounds, unobservable selection may lead to an insignificant effect, or even a reversed direction of the effect, of homegrown grass on GHG emission efficiency estimated by the SUR model[32]. Thus, SUR estimated coefficients of both farm management indicators on cost control and of homegrown grass on GHG emission efficiency are largely unstable with respect to unobservables. Given available data and methods, causal conclusions about their impact cannot be drawn in this study.

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[32] The estimation results on the balanced panel dataset reported in Table B. 6 (Appendix B) reinforce this concern as the effect of homegrown grass on GHG emission efficiency becomes insignificant in the FE SUR model.

Table 5.4: Sensitivity analysis based on Oster (2019)

Equations	Sensitivity tested for	FE SUR (GMM 3SLS) results		Oster procedure		
		$\widehat{\beta}$ (SE)	95% confidence interval	Bounds $\Delta = [\widetilde{\beta_1};\ \beta_1^*(1,1)]$	Includes 0?	% included in 95% confidence interval
Calving rate	Extension $_{t-1}$	0.36*** (0.10)	[0.16; 0.56]	[0.36; 1.69]	No	14.7
Costs	Homegrown grass	-0.15*** (0.013)	[-0.18; -0.12]	[-0.15; 0.060]	Yes	12.1
Costs	Calving rate	-0.021*** (0.0073)	[-0.035; -0.0067]	[-0.021; 0.0021]	Yes	61.9
Margin	Homegrown grass	5.82*** (0.72)	[4.41; 7.23]	[5.82; 7.59]	No	79.7
Margin	Calving rate	4.80*** (0.52)	[3.78; 5.82]	[4.80; 5.60]	No	100
Nitrogen	Homegrown grass	-1.34*** (0.22)	[-1.77; -0.91]	[-3.71; -1.34]	No	18.2
GHG $_a$	Homegrown grass	-0.0017** (0.00085)	[-0.0034; -0.000034]	[-0.0017; 0.00018]	Yes	88.6
GHG $_a$	Calving rate	0.0011** (0.00058)	[-0.000037; 0.0022]	[0.0011; 0.0044]	No	34.4

Note: n = 1,945 observations ($_a$ except for the GHG equations that has 1,371 observations). ***, ** and * significant at the 1, 5 and 10% levels.

5.6. Conclusion

Extension services have an important role to play in fostering farmers' learning and helping them to achieve sustainable intensification. Yet, little is known about the mechanism through which extension participation affects farm sustainability. Thus, this chapter examined two management pathways between extension participation and farm economic and environmental sustainability in the context of Irish dairy farming. As the efficiency and competitive advantage of Irish dairy production relies on grassland management and reproductive efficiency (Butler, 2014; Dillon et al., 2008; Läpple et al., 2012), these aspects of farm management are focused upon within the extension programme (Department of Agriculture, Food and the Marine, 2020; Donnellan et al., 2015) and were analysed in this study. Grassland management was measured by the share of homegrown grass in the diet of dairy cows (Hanrahan et al., 2018; O'Brien et al., 2018) and reproductive efficiency by calving rates (Butler, 2014; Crowe et al., 2018; Lane et al., 2013). Economic sustainability was represented by gross margin per cow and direct production costs per unit of output (Kassie et al., 2018; Läpple and Hennessy, 2015), while environmental sustainability was assessed by nitrogen surplus per ha and GHG emission efficiency (Buckley et al., 2019). Using panel data, several systems of simultaneous equations were estimated and a bounding approach based on Oster (2019) was implemented to achieve partial identification (referred to as the Oster procedure).

Regarding the effect of extension participation on farm management, the study first indicated that extension has a positive impact on reproductive efficiency. Each additional year of participation is likely to result in at least a 0.4% increase in calving rate in the following year. However, the Oster procedure revealed that unobserved heterogeneity could actually lead to an underestimation of the causal effect of extension on calving rate. Hence, while the 'worst case' scenario points out limited effectiveness of Irish extension on reproductive efficiency, further analysis with improved data and econometric techniques is needed to confirm this finding. Within this context, it is also worthwhile to mention that improving herd genetic merit for fertility traits is a very slow process and can explain why extension may have a small impact on reproductive efficiency. In Ireland, age at first calving is generally between 24 and 36 months (Berry and Cromie, 2009), which suggests a significant time lag between current breeding decisions and resulting improvements in cow reproductive efficiency. Second, estimation results revealed that extension participation does not have any effect on grassland management, which is surprising given the focus of the programme (Department of Agriculture Food and the Marine, 2020; Donnellan et al., 2015). A potential explanation for lack of extension effectiveness could be that many factors, which influence grass growth and grazing (e.g., weather and agronomic conditions), are outside of the farmer's direct control (Hanrahan et al., 2017).

The results confirmed findings from previous literature by demonstrating clear economic benefits to improved grassland management and reproductive efficiency (Hanrahan et al., 2018; Lane et al., 2013; Shalloo et al., 2014). For the average extension participant, bridging the gap between current share of homegrown grass in the diet of dairy cows and advisory target (Teagasc, 2016) would likely lead to an improvement by at least €7,243 in yearly gross margin. Similarly, catching up with the advisory target for calving rates would likely result in an increase between about €2,741 and 3,197 in yearly gross margin. While the Oster procedure confirmed partial identification for the effect of selected farm management indicators on gross margin, their effect on cost control proved to be unstable.

In addition, the findings suggested that the effect of farm management on farm environmental sustainability is mixed. A clear negative effect of homegrown grass was found on nitrogen surplus and confirmed by the Oster procedure. More specifically, for the average extension participant, bridging the gap between current share of homegrown grass in the diet of dairy cows and advisory target (Teagasc, 2016) would likely lead to a reduction by at least 1,382 kg of nitrogen surplus at the farm level. This result corroborates previous studies, which highlight the role of improved grassland management in reducing nitrogen pressure (O'Brien et al., 2014a; Basset-

Mens et al., 2009; Foote et al., 2015). However, no GHG benefits associated with improved farm management were confirmed in this study, which stands in contrast to previous literature (Garnsworthy, 2004; Lanigan et al., 2018; Llonch et al., 2017; O'Brien et al., 2014b). As for calving rate, the results suggested that it has a negative impact on GHG emission efficiency, likely due to the time period under consideration (2010 – 2017) and ongoing, rapid expansion of the Irish dairy sector. It is also worthwhile to mention that GHG benefits as measured in terms of efficiency (i.e., GHG emitted per output unit) do not necessarily lead to improvements in absolute GHG emissions if production scale is increased (Alcott, 2005; Barnes et al., 2019). Hence, if the Irish dairy sector continues to expand and intensify, other farming strategies may need to be considered to decrease GHG emissions at industry level and meet the EU GHG reduction targets (Donnellan et al., 2018; Environmental Protection Agency, 2019a; European Commission, 2014).

Overall, the chapter specifically confirmed the reproductive efficiency pathway between extension participation and farm gross margin. This result highlights the economic benefits expected from an improvement of extension effectiveness on calving rates. Additionally, while the grassland management pathway was not validated in the study, benefits in terms of gross margin and nitrogen surplus are expected if extension effectiveness on the share of homegrown grass in the diet of dairy cows was improved.

The findings suggest that a potential reason why extension services sometimes fail to enhance farm performance could be their restricted effectiveness in enhancing farm management. Nonetheless, positive farm performance outcomes can only be obtained if farmers adopt better practices and improve in managing agricultural holdings. This justifies paying more attention to the effect of extension participation on changes in farming practices, instead of directly examining farm performance outcomes. In the literature, the impact of extension services on the binary uptake of new technologies has been widely explored (Ainembabazi et al., 2017; Buehren et al., 2019; Nakano et al., 2018b; Pan et al., 2018; Raghunathan et al., 2019). However, dichotomous measures of technological progress give limited information about farmers' decision making and overlook the dynamic aspect of the learning process (Weersink and Fulton, 2020). Among the bundle of technologies recommended by extension services, farmers are likely to adopt those which will give them a relative advantage and are suitable for their own farming conditions (Montes de Oca Munguia and Llewellyn, 2020; Norton and Alwang, 2020; Pannell et al., 2006). When focusing on binary indicators of technology adoption as outcome variables, these considerations are ignored, and the conclusions drawn about extension effectiveness can be sensitive to the practices selected in the analysis. Future research may focus on continuously defined measures of farm management, such as the ones used in this chapter. These allow for the comparison of farmers based on acquired skills and reduce the influence of unobserved heterogeneity in farming conditions and technological choice. In other words, continuous indicators of farm management allow for flexibility in the choice of practices adopted by individual farmers to focus on skill acquisition and farm management implications.

Finally, it is important to emphasise that the results of this study do not represent the overall effectiveness of the Irish extension programme. Previous literature showed that the programme was successful in meeting other goals, such as widening their audience and helping farmers adjust to policy changes (Läpple et al., 2020; Läpple and Hennessy, 2014). When evaluating extension effectiveness, studies are limited by the outcomes that they consider, and the overall effect of the programme can be difficult to examine. In this chapter, partial effects were explored by focusing only on two indicators of farm management, but other potential pathways may indeed exert an impact on farm performance.

Chapter 6 - Mixed public-private and private extension systems: A comparative analysis using farm-level data from Ireland

6.1. Introduction

Public investments into extension service provision are a traditional policy instrument to encourage widespread technology adoption, and thereby foster productivity growth and more sustainable agricultural production (Anderson and Feder, 2004; Nordin and Höjgård, 2017; Norton and Alwang, 2020; Pannell and Claassen, 2020; Takahashi et al., 2020). Accordingly, the impact of extension services has been widely explored, with a mixed record of success (Anderson and Feder, 2004; Birkhaeuser et al., 1991; Takahashi et al., 2020). As a result, a growing body of literature questions how suitable the public sector is for providing such services (Feder et al., 2011; Ragasa and Mazunda, 2018). Fundamental issues related to public extension include the limited adaptability to farmers' priorities, the lack of accountability of extension agents, the heterogeneity in farmers' profiles and farming conditions, and the evolution and expansion in farmers' information needs (Anderson and Feder, 2004; Feder et al., 2011; Knierim et al., 2017; Norton and Alwang, 2020; Sutherland et al., 2013). This comes in a context where consistent funding for extension can be difficult to secure (Anderson and Feder, 2004; Faure et al., 2012; Feder et al., 2011; Norton and Alwang, 2020).

Greater involvement of the private sector in extension service provision can reduce the need for public funding and make use of the market mechanism for farmers to express their information needs and service preferences (Feder et al., 2011; Norton and Alwang, 2020). Nevertheless, sole reliance on the private sector for extension provision could exclude some farmers, who are unwilling or unable to pay for services, from having access to information (Feder et al., 2011; Ferroni and Zhou, 2012; Norton and Alwang, 2020). It could also shift extension's focus towards fulfilling only farmer-clients' private benefits (Klerkx et al., 2006; Norton and Alwang, 2020; Sutherland et al., 2013). As farmers who are able to pay fees are more likely to have large, commercial farms (Feder et al., 2011; Ferroni and Zhou, 2012; Norton and Alwang, 2020), the private sector may indeed favour advice related to economic and lifestyle objectives rather than environmental and societal concerns (Klerkx et al., 2006; Norton and Alwang, 2020; Sutherland et al., 2013).

To overcome these limitations, public and private sectors can coordinate by coexisting and forming mixed public-private arrangements (Feder et al., 2011; Norton and Alwang, 2020). Effective coordination would encourage demand-driven services, reduce the financial burden on the public sector, and ensure that the information needs of all farmers are met regarding both public and private goods. Despite being a promising approach, there is a lack of empirical evidence that public and private sectors can play complementary roles in extension service provision in a successful manner (Eastwood et al., 2017; Feder et al., 2011; Klerkx, 2020; Norton and Alwang, 2020). As highlighted by Norton and Alwang (2020), evaluation allows for the identification of which extension systems or combination of extension systems are effective. When new models are implemented, their assessment relies on the use of extension measures, which distinguish the type of service provision and notably delivery and financing mechanisms (Norton and Alwang, 2020; Ragasa and Mazunda, 2018).

Within this context, this chapter compares mixed public-private and private extension services using farm-level data from Irish dairy farms. Two main questions are explored. First, the study examines the disparities in farm and farmers' characteristics between three cohorts, i.e., farmers involved in mixed public-private extension, farmers involved in private extension, and non-participants. Second, the relationship between farmer cohorts and farm economic and environmental sustainability is assessed.

The study uses data collected from Irish dairy farmers in 2018. In Ireland, extension is commonly delivered in a participatory manner, under the form of farmers' discussion groups (Donnellan et al., 2015; Läpple et al., 2020; Läpple and Hennessy, 2014). From 2017 until 2019, the Irish government and the European Union (EU) co-funded the €100 million Knowledge Transfer Programme (KTP), which paid farmers to participate in State or private discussion groups (Department of Agriculture Food and the Marine, 2020). Alternatively, farmers could choose to participate in a private discussion group, completely external to the paid scheme. Hence, this study compares KTP and fully private discussion groups. KTP groups are categorised as mixed public-private extension. They are publicly funded by the Irish government and the EU, and publicly and/or privately delivered by State advisory or private consultancy. Private groups are categorised as private extension. They are privately funded by farmers, and privately delivered by private consultancy.

The Irish context is well suited to investigate the role of public and private sectors in the provision of extension services with respect to public and private goods (represented by farm environmental and economic sustainability in this study, respectively). Irish dairy farms are currently undergoing significant expansion and intensification following EU milk quota removal in 2015 (Eurostat, 2020a, 2020b). The Irish government has been fostering growth over the last decade through two main agri-development strategies, i.e., Food Harvest 2020 and Food Wise 2025 (Department of Agriculture Food and the Marine, 2015, 2010a). Despite positive economic outcomes (Bord Bia, 2018; Buckley and Donnellan, 2020), environmental concerns arise from the process (Donnellan et al., 2018; Hoekstra et al., 2020; Lanigan et al., 2018). Notably, adverse environmental effects challenge the compliance with the EU Nitrates Directive and the achievement of EU Greenhouse Gas (GHG) emission reduction targets (Environmental Protection Agency, 2019b, 2019a; European Commission, 2019a, 2010). Helping farmers to achieve sustainable growth is thus key to the continued development of the Irish dairy sector and one of the main KTP goals (Kelly et al., 2020; Läpple et al., 2020; Teagasc, 2015).

In addition to conducting a comparative analysis between mixed public-private and private extension services, this study contributes to the literature in four complementary ways. First, a limited number of articles have considered differences in the type of service provision, but they did not approach this question using farm-level data nor were they based on quantitative evidence (Eastwood et al., 2017; Knierim et al., 2017; Prager et al., 2016; Sutherland et al., 2013). While the literature suggests that public and private extension services can target various profiles of farmers and play different roles in the provision of public and private goods (Feder et al., 2011; Ferroni and Zhou, 2012; Klerkx et al., 2006; Norton and Alwang, 2020; Sutherland et al., 2013), a farm-level empirical assessment is provided in this chapter.

Second, even though many empirical studies on extension effectiveness have been published, evidence mostly comes from developing countries, where public extension is the predominant service provider (e.g., Buehren et al., 2019; Nakano et al., 2018a; Ragasa and Mazunda, 2018; Raghunathan et al., 2019). As for developed countries, the private sector may play a larger role in service provision, but lack of data availability can make it difficult to evaluate private extension systems (Cawley et al., 2018). Consequently, most research on extension in developed country settings focuses on programmes funded, at least partially, through the public sector (e.g., Jin and Huffman, 2016; Läpple et al., 2020; Nordin and Höjgård, 2017). The lack of evidence on private extension systems is addressed in this study.

Third, although several articles have examined the effect of Irish extension, differences in types of service provision and environmental outcomes have not yet been examined (Cawley et al., 2018; Hennessy and Heanue, 2012; Läpple et al., 2020, 2013; Läpple and Hennessy, 2015, 2014). Lack of data availability on types of service provision and environmental sustainability is a common problem in the literature and can limit the analysis of the relationship between extension systems and public goods (Lebacq et al., 2013; Ragasa and Mazunda, 2018). This issue is overcome in the current study by using a rich farm-level dataset from the Teagasc National Farm Survey (NFS). This data includes detailed information about farm and farmers' characteristics, extension participation behaviours, and farm sustainability performance, which allows for the implementation of non-linear and linear regression models to explore the two research questions.

Finally, this study builds on and expands previous work on publicly funded, paid extension in the Irish context (Läpple and Hennessy, 2015, 2014). The KTP was not the first subsidised scheme in Ireland. The Dairy Efficiency Programme (DEP) ran from 2010 until 2012. It was operated under a similar mixed public-private arrangement as the KTP and cost €18 million (Department of Agriculture Food and the Marine, 2010b). However, its objectives differed, with a strong focus on increasing rates of participation in discussion groups, in addition to encouraging dairy efficiency gains. The DEP was successful in attracting a new cohort of participants, including older farmers, located outside of the traditional dairy region (i.e., the South), with smaller herds and less heavily stocked farms (Läpple and Hennessy, 2014). While DEP participation resulted in higher milk yields and gross margins for farmers who were already participating in discussion groups before the start of the DEP, farmers who joined after the introduction of payments did not significantly benefit from the programme (Läpple and Hennessy, 2015).

The Läpple and Hennessy (2015, 2014) articles raise questions as to whether the new cohort of discussion group members were mainly attracted by the financial reward rather than the learning experience. These mixed results justify further investigating the effect of paid extension in Ireland, especially because an additional €100 million were invested in the new paid scheme (Department of Agriculture Food and the Marine, 2020). The KTP context differs from the DEP one for three main raisons. Firstly, environmental concerns have gained more attention (Donnellan et al., 2018; Hoekstra et al., 2020; Lanigan et al., 2018). Secondly, increasing participation rates is not an objective of the new scheme (Department of Agriculture Food and the

Marine, 2020). Thirdly, private extension is growing in popularity among farmers (Prager et al., 2016).

The remainder of this chapter is structured as follows: first, background information on Irish extension is provided in section 6.2. Second, the methodology is described in section 6.3. Third, the results and discussion are reported in section 6.4. The chapter ends with conclusions and policy implications in section 6.5.

6.2. Background

Farmers' discussion groups were first introduced in Ireland in the 1990s and have grown in popularity ever since (Donnellan et al., 2015; Läpple et al., 2020; Läpple and Hennessy, 2014). It is estimated that about 43% of specialist dairy farmers[33] were involved in a discussion group in 2017 (Buckley et al., 2019). This participatory model is based on a bottom-up approach to extension, where the advisor acts as a discussion facilitator rather than a "lecturer" and farmers are encouraged to learn from their peers (Davis et al., 2012; Läpple et al., 2020; Prager and Creaney, 2017). Groups are composed of 15 to 20 farmers, who meet on a monthly basis on one of the participants' farm to walk the farm, discuss potential issues that the host farmer is facing, and identify solutions together.

There typically exist two channels of service delivery in Ireland. On the one hand, Teagasc, the State Agriculture and Food Development Authority, provides most extension services and operates under a mixed public-private model (Teagasc, 2015). About 55% of the Teagasc advisory budget is publicly funded, while the remainder is covered by farmers' fees. The latter are invested in employing private consultants who complement the work of Teagasc advisors through occasional interventions. On the other hand, farmers can engage directly with the private sector, which, by nature, is more heterogenous than State extension (Cawley et al., 2018; Prager et al., 2016).

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[33] Classification based on relative Standard Outputs of the different farming subsectors present on the farm.

Farmers can thus choose whether they want to participate in a State or a private discussion group.

In 2017, the publicly funded KTP was introduced to incentivise discussion group participation for 3 years (Department of Agriculture Food and the Marine, 2020). Both State and private groups were eligible[34]. Farmers could receive €750 per year for joining a KTP discussion group (or €1,000 for being a member of two discussion groups in different farming sectors). The payment was subject to terms and conditions, including a 60% attendance-at-meeting rule and the completion of a 'Farm Improvement Plan' with specific yearly tasks. Farmers still had to pay regular service fees to Teagasc or their private consultant to be a client[35]. These were thus deduced from the KTP payment. Advisors and consultants had to be approved by the Department of Agriculture, Food and the Marine to become a KTP discussion group facilitator. They were then paid €500 per year per participant for facilitating the groups (and an additional €250 if their farmers were involved in a secondary group).

The KTP was targeted at several sectors, including dairy, beef, sheep, poultry, tillage, and equine (Department of Agriculture Food and the Marine, 2020). It had the overarching goal "*to up-skill Irish farmers, to encourage efficiency and effectiveness of work and ensure they engage in a process of continuous improvement which will not only develop their enterprise but also contribute to the overall development of the agri-food sector*" (Department of Agriculture Food and the Marine, 2020). More specific objectives and schedule were then detailed by sector.

For dairy farmers, the KTP focused on the general principles of dairy management, including grassland management, breeding and herd fertility, and cost control (Department of Agriculture Food and the Marine, 2020). It

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[34] It is worthwhile to mention that all State discussion groups were operated under the KTP during the duration of the scheme.

[35] Teagasc service fees are publicly available and depend on farm size and the type of services that the farmer seeks (Teagasc, 2020). Conversely, fees for private consultancy are not standardised and vary by consultant, farm size, and service type.

aimed at increasing the profitability and efficiency of dairy farms, while reducing adverse environmental effects of milk production (Department of Agriculture Food and the Marine, 2020; Teagasc, 2015). Particular attention was paid to nutrient management and the identification of GHG mitigation options. To be operated under the KTP scheme, discussion group meetings had to cover a list of topics related to the overall goals of the programme.

Overall, farmers could choose between being paid to join the KTP scheme or paying to participate in a fully private group. Consequently, differences are expected in the farmer cohorts attracted by both types of discussion groups. Previous literature suggests that more motivated farmers operating larger, more commercial dairy farms are likely to be willing to pay for private extension, while publicly funded extension may attract resource-poorer farmers (Feder et al., 2011; Ferroni and Zhou, 2012; Norton and Alwang, 2020). Additionally, the KTP has strict guidelines and a schedule to follow that does not only incorporate private, economic benefits but also environmental outcomes (Department of Agriculture Food and the Marine, 2020). Therefore, the paid scheme is likely to be more supply driven than private group extension, in which participants focus on whichever issues they want (Feder et al., 2011; Norton and Alwang, 2020; Ragasa and Mazunda, 2018). Conversely, private discussion groups are likely to follow a demand-driven model, with farmers favouring mostly (if not exclusively) advice related to productive and economic outcomes instead of having a more public-good, environmental focused approach (Klerkx et al., 2006; Norton and Alwang, 2020; Sutherland et al., 2013).

6.3. Methodology

6.3.1. Data description

This study is based on the 2018 Teagasc NFS data. The Teagasc NFS is operated in the frame of the EU Farm Accountancy Data Network. It fulfils Ireland’s statutory requirements as an EU Member State to provide technical and financial data to the European Commission. The data is collected on a yearly basis through face-to-face interviews by a team of professional data recorders. In conjunction with the Irish Central Statistics Office, a nationally representative sample of approximately 900 farms is selected annually. Each farm is assigned a weighting factor to ensure representativeness of the Irish farming population. Respondents are classified into six farming systems according to their main source of gross output: dairy, cattle rearing, cattle other, sheep, arable, and mixed livestock. This analysis uses a subsample of 253 dairy farms (including dairy specialists, and arable and mixed livestock farms), which represent 77.6% of the original Teagasc NFS sample with a dairy enterprise.

Information about discussion group participation has been recorded since 2008 in the Teagasc NFS, including the initial year in which farmers joined and hence total length of participation. However, the dataset does not normally provide detail about the type of discussion group in which farmers are involved. For the purpose of this study, additional data was thus collected in 2018 to find out whether discussion group members were involved in a group operating under the KTP and/or a private group[36]. Hence, Teagasc NFS farmers can be divided into three cohorts: farmers not involved in discussion groups (known as 'non-members') (53.0% of the sample), members only involved in a KTP group (referred to as 'members of a KTP group') (27.7%), and members involved in a private group (20.2%). The latter cohort includes farmers who are involved in both KTP and private groups (8.3% of the sample) and farmers involved only in a private group (11.9%). Due to the low observation count, all farmers involved in a private group are combined into one cohort, as they are likely to share similar characteristics for being willing to pay for private extension.

The Teagasc NFS dataset includes information about the farm and family farming household, which can help to characterise the three farmer cohorts and explore their relationship with farm economic and environmental sustainability. Based on previous literature on extension participation, this study uses detail on farm size, degree of specialisation in dairy production

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[36] Please note that KTP farmers are not distinguished between farmers involved in a State or private KTP discussion group.

(i.e., ratio of dairy cows to total livestock units), stocking rate, farmers' age, and completion of agricultural education (Feder et al., 2011; Ferroni and Zhou, 2012; Läpple and Hennessy, 2014; Norton and Alwang, 2020). Household size, a proxy for family labour availability, and regional differences across farms are also considered in this analysis (Läpple and Hennessy, 2014; Lee, 2005).

Level of farm management is used as a proxy for farmers' motivation to innovate and ability (Läpple et al., 2020; Montes de Oca Munguia and Llewellyn, 2020). In the Irish extension context, two variables are focused upon, including Bulk Tank Somatic Cell Count (BTSCC) and the proportion of homegrown grass in the diet of dairy cows. BTSCC is an indicator of milk bacterial contamination and mastitis incidence, which can have negative implications for milk yields, and herd reproductive efficiency and health (Geary et al., 2012; Lane et al., 2013; More et al., 2017; Shalloo et al., 2014). A BTSCC above 200,000 cells per ml is generally used as an indicator of clinical mastitis incidence (International Dairy Federation, 1997). BTSCC is recorded on a monthly basis in the Teagasc NFS.

The proportion of homegrown grass in the diet of dairy cows is estimated based on the O'Brien et al. (2018) methodology by using activity and feed data included in the Teagasc NFS (Hanrahan et al., 2018; O'Brien et al., 2018). Due to the grass-based nature of Irish milk production systems, advisory guidelines recommend achieving a 93% rate of homegrown grass in the diet of dairy cows through precise grassland management (Teagasc, 2016).

Farm sustainability outcomes are chosen based on their policy relevance and KTP focus (Buckley and Donnellan, 2020; Department of Agriculture Food and the Marine, 2020; Environmental Protection Agency, 2019b, 2019a; European Commission, 2019a, 2010). The economic dimension is measured by gross margin and milk yield per cow to represent profitability and productivity (Buckley and Donnellan, 2020; Läpple and Hennessy, 2015).

The environmental dimension is represented by nitrogen surplus per hectare (ha) and GHG emitted per unit of output. Nitrogen surplus serves as an indicator of nutrient management and farm environmental pressure (Buckley and Donnellan, 2020; Schröder et al., 2003). It is calculated following an input-output accounting method, i.e., inputted (e.g., fertiliser, concentrate feed) minus outputted (e.g., milk, livestock) quantities of nitrogen per ha (Buckley and Donnellan, 2020). This formula restricts the analysis within the farm gate so that only inputs and outputs over which the farmer has direct control are considered.

GHG emitted per unit of output gives an indication of milk GHG emission efficiency and hence farm environmental efficiency[37] (Crosson et al., 2011). GHG emissions are estimated by using a cradle-to-farm gate Life Cycle Assessment (LCA) approach, which includes on- and off-farm emission sources[38] (O'Brien et al., 2014b, 2010). Emission factors used for the estimation follow the Intergovernmental Panel on Climate Change guidelines or come from other resources in the literature (Dong et al., 2006; Duffy et al., 2017). Emissions are then converted to kilograms (kg) of Carbon Dioxide Equivalent (CO_2e) using the 100-year Global Warming Potential (Forster et al., 2007). They are reported per kg of Fat-Protein-Corrected-Milk (FPCM) to account for differences in cow breeds and feeding systems (International Dairy Federation, 2015).

To summarise, a description of the variables used in this study is provided in Table 6.1, as well as descriptive statistics by farmer cohort.

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[37] Please note that improvements in GHG emission efficiency may not necessarily lead to a reduction in absolute GHG emissions if production scale is increased (Alcott, 2005; Barnes et al., 2019). Hence, it is important to recognise that GHG emission efficiency serves as an indicator of environmental efficiency, as opposed to environmental pressure.

[38] This approach is internationally standardised (International Organization of Standardization, 2006a, 2006b) and specific guidelines are available for milk production (British Standards Institute, 2011; Carbon Trust, 2010; International Dairy Federation, 2015). The LCA approach implemented in this chapter was developed according to the publicly-available PAS 2050:2011 specification from the British Standards Institute (British Standards Institute, 2011) and validated by the Carbon Trust, an accredited third party (O'Brien et al., 2014b). Please refer to O'Brien et al. (2014b) for the full list of GHG emission sources and corresponding emission factors.

Table 6.1: Descriptive statistics, by farmer cohort

Variable	Definition	KTP discussion group (n = 70)	Private discussion group (n = 51)	Non-members (n = 132)	All farmers (n = 253)
Farm economic sustainability					
Gross margin	Gross margin per cow (€ / cow)	1233.98 (247.24)	1320.89 (289.95)	1067.27 (341.29)	1156. 71 (326.19)
Milk yield	Milk yield per cow (l / cow)	5798.29 (808.72)	5996.81 (935.61)	5216.85 (1111.80)	5509.93 (1060.42)
Farm environmental sustainability					
Nitrogen surplus	Nitrogen surplus per ha (kg / ha)	217.28 (86.09)	218.39 (77.81)	187.95 (80.08)	201.13 (82.34)
GHG efficiency	GHG emissions per unit of output (kg of CO_2e / kg of FPCM)	1.06 (0.16)	1.03 (0.16)	1.14 (0.24)	1.10 (0.21)

Variable *(Continued from previous)*	Definition	KTP discussion group	Private discussion group	Non-members	All farmers
Farm characteristics					
Herd size	Number of dairy cows (cows)	96.90 (50.89)	108.75 (47.16)	63.96 (40.11)	80.67 (48.25)
Farm area	Farm area allocated to the dairy herd (ha)	44.97 (20.77)	52.49 (21.65)	31.29 (17.23)	38.70 (20.87)
Stocking rate	Stocking rate (cows / ha)	2.15 (0.46)	2.10 (0.43)	2.07 (0.56)	2.09 (0.51)
Specialisation	Percentage of dairy cows to total cattle (%)	68.79 (11.38)	70.28 (9.65)	63.75 (15.20)	66.25 (13.66)
South	= 1 if the farm is located in the south (i.e., traditional dairy region in Ireland), 0 otherwise	0.53 (0.50)	0.78 (0.42)	0.65 (0.48)	0. 65 (0.48)

Variable *(Continued from previous)*	Definition	KTP discussion group	Private discussion group	Non-members	All farmers
Farmers' characteristics					
Participation [a]	Years of participation in farmers' discussion groups (years)	12.28 (8.11)	14.24 (7.41)	0	4.80 (7.91)
Age	Age of the main farm holder (years)	51.93 (10.61)	52.52 (11.11)	54.43 (9.79)	53.43 (10.28)
Education	= 1 if the farmer has completed agricultural training, 0 otherwise	0.81 (0.39)	0.89 (0.31)	0.70 (0.46)	0.76 (0.43)
Household members	Household size (number)	3.52 (1.54)	3.57 (1.29)	3.16 (1.46)	3.33 (1.46)
BTSCC	Bulk Tank Somatic Cell Count ('000 cells / ml)	156.57 (56.75)	141.89 (63.31)	193.62 (84.60)	174.58 (84.60)
Homegrown grass	Share of homegrown grass in the diet of dairy cows (i.e., grazed grass and grass silage) (%)	69.79 (11.93)	74.67 (9.39)	70.32 (13.20)	70.96 (12.35)

Note: Means and standard deviations in parentheses. [a] Variable available only for 221 observations (i.e., 132 non-members, 50 members of a KTP discussion group, and 39 members of a private group) when farmers also participated in the 2017 Teagasc NFS data collection.

6.3.2. Analytical framework

The first step of the analysis focuses on exploring whether members of a KTP discussion group, members of a private group, and non-members differ in terms of farm and farmers' characteristics using non-linear regression models. Specifically, farmers are divided into three cohorts and particular interest lies in the effect of various characteristics on each one of them. Farmers choose whether or not to join a discussion group, as well as the type of service delivery. Therefore, differences across the three farmer cohorts can be examined with discrete choice models, where farmers make a single choice among multiple and unordered alternatives (Greene, 2012; Hensher and Greene, 2003; Läpple and Hennessy, 2014; Niggol Seo, 2010).

The outcome variable, farmer cohort, y includes three alternatives and can thus take the values $j \in [\![1;3]\!]$, where $j = 1$ if the farmer is not in a discussion group, $j = 2$ if the farmer is involved in a KTP discussion group, and $j = 3$ if the farmer is involved in a private group. Discrete choice models predict the probability of each cohort given a set of farm and farmers' characteristics X. As alternatives are multiple and unordered, the determinants of each cohort are compared to a base alternative. In this chapter, both non-members and members of a KTP group are considered consecutively as base alternative to investigate the differences between discussion group members and non-members, as well as between members of KTP and private groups. The probability that the outcome variable y takes the value of k (where k is one of the alternatives $j, j \in [\![1;3]\!]$) is determined by the following equation:

$$P(y = k|X) = \frac{\exp(\beta_k X)}{\sum_{j=1}^{3} \exp(\beta_j X)} \tag{6.1}$$

A normalisation of β_1 is necessary so that coefficients can be identified against the base alternative. Hence, equation (6.1) becomes:

$$\begin{cases} P(y = k|X) = \frac{\exp(\beta_k X)}{1 + \sum_{j=2}^{3} \exp(\beta_j X)} \text{ if } k > 1 \\ P(y = 1|X) = \frac{1}{1 + \sum_{j=2}^{3} \exp(\beta_j X)} \text{ if } k = 1 \end{cases} \tag{6.2}$$

Equation (6.2) is commonly estimated with a multinomial logit model (Greene, 2012; Läpple and Hennessy, 2014). However, this model relies on the strong assumption of Independence of Irrelevant Alternatives (IIA) (Greene and Hensher, 2003). More precisely, the probability of choosing an alternative relative to another must remain unchanged if a third option is added or dropped from the analysis. The multinomial logit model forces the IIA by assuming that error terms are uncorrelated. The Hausman-McFadden test can be conducted to detect a violation of the IIA assumption (Hausman and McFadden, 1984), although reliance on its result has often been criticised in the literature (Cheng and Long, 2011; Vijverberg, 2011). Thus, in addition to carrying out the Hausman-McFadden test, reflecting upon the IIA within the study's conceptual framework is an important procedure for assessing its suitability.

In the current analysis, the IIA assumption can be challenged for two main reasons. First, members of a KTP discussion group were paid up to €1,000 per annum to participate (Department of Agriculture Food and the Marine, 2020), which may have shifted their preferences regarding extension participation (Läpple and Hennessy, 2014). In the absence of the subsidised scheme, it is difficult to know for sure whether farmers would have preferably joined a private group or dropped out altogether[39]. In other words, the removal of the KTP scheme may affect the probability of choosing to participate in a private group over non-participation. Second, it is known that some members of private discussion groups also participate in a KTP group, thus questioning again the IIA assumption.

Consequently, equation (6.2) is not only estimated with a multinomial logit model but also with a mixed logit model, which relaxes the IIA assumption[40]

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[39] Most farmers involved in the KTP in 2018 were participating in discussion groups before the scheme was introduced, but according to the Teagasc NFS data, participation rates have overall decreased by about 16% between 2014 and 2018.

[40] Please note that the marginal utilities associated with alternative-specific characteristics can vary between individuals in mixed logit models. In such a case, the distribution of random coefficients must be specified. This is a not a concern in this study as the interest lies only in individual-specific variables and alternative-specific variables are not included in the model.

(Hensher and Greene, 2003; Niggol Seo, 2010). For both models, estimated coefficients are reported as relative-risk ratios. After model estimation, likelihood-ratio tests are carried out between the three farmer cohorts to verify whether groups should be considered separately or combined (Läpple and Van Rensburg, 2011).

The second step of the analysis aims at examining the relationship between farmer cohorts and farm economic and environmental sustainability. Since sustainability indicators are continuously defined, this relationship can be assessed using linear regression models, as follows:

$S = \alpha_0 + \ \alpha_1 KTP\ members + \alpha_2 Private\ members + \alpha_3 Z$ if $Non - members$ is the base dummy variable (6.3)

$S = \ \gamma_0 - \ \alpha_1 Non - members + \gamma_2 Private\ members + \alpha_3 Z$ if $KTP\ members$ is the base dummy variable (6.4)

where S is one of the four sustainability indicators (i.e., gross margin, milk yield, nitrogen surplus, or GHG efficiency). $KTP\ members$ is a dummy variable, which takes the value of 1 if the farmer is a KTP member and 0 otherwise. Similarly, $Private\ members$ takes the value of 1 if the farmer is a private group member and 0 otherwise. $Non - members$ takes the value of 1 if the farmer is not participating in a discussion group and 0 otherwise. Z is a set of farm and farmers' characteristics affecting S. The effect of each cohort is interpreted relative to the base dummy variable excluded from the model (i.e., non-members or members of a KTP group).

The parameters in equations (6.3-4) are estimated using Ordinary Least Squares (OLS). Heteroskedasticity is tested for using the Breusch-Pagan test, where a rejection of the null hypothesis indicates the need for robust standard errors (Breusch and Pagan, 1979; Wooldridge, 2012). Moreover, several model specifications are tested to limit the effect of potential confounders and select models with the highest goodness of fit. To this end, likelihood-ratio tests are conducted between models with varying sets of farm and farmers' characteristics (Lewis et al., 2011). Attention is also paid to the

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with lower values indicating a better fit (Kuha, 2004).

6.4. Results and discussion

6.4.1. Comparison between farmer cohorts

While the sample averages reported in Table 6.1 suggests that there are differences between the three farmer cohorts, statistical tests are required to confirm this. Consequently, *t*-tests are performed to explore differences in continuous variables between groups and are reported in Table 6.2. Differences in binary variables (i.e., south and education) are not formally tested due to the small percentage of farmers in each category[41].

Overall, the results in Table 6.2 confirm that there are significant differences between discussion group members and non-members for many characteristics under consideration (except stocking rate and age). Conversely, only a few variables vary significantly between both cohorts of discussion group members (i.e., gross margin, farm area, and homegrown grass).

More specifically, the three groups differ in terms of sustainability performance. Discussion group members have significantly higher gross margins, milk yields, nitrogen surpluses, and GHG emission efficiencies than non-members. Significant differences between both cohorts of discussion group members are only obtained for the gross margin variable.

In terms of farm and farmers' characteristics, Table 6.2 shows that discussion group members have significantly larger farms than non-members, represented by herd size and area dedicated to the dairy herd. Farm area also significantly differs between members of KTP and private discussion groups. Moreover, discussion group members have significantly higher degrees of

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[41] For the same reasons, these binary variables are not included in non-linear regression models predicting farmer cohorts.

specialisation in dairy production than non-members. Members of a private discussion group have significantly larger households than non-members.

Finally, it is worthwhile to highlight that members of public-private and private discussion groups do not vary in terms of years of extension participation.

Table 6.2: Comparison of characteristics between farmer cohorts with *t*-tests

Comparison between	Non-members (n = 132)	Non-members (n = 132)	KTP discussion group (n = 70)
	KTP discussion group (n = 70)	Private discussion group (n = 51)	Private discussion group (n = 51)
Gross margin	**-3.98*****	**-5.04*****	**-1.73***
Milk yield	**-4.25*****	**-4.79*****	-1.22
Nitrogen surplus	**-2.36****	**-2.35****	-0.070
GHG efficiency	**3.05*****	**3.69*****	0.98
Herd size	**-4.70*****	**-6.00*****	-1.32
Farm area	**-4.72*****	**-6.27*****	**-1.92***
Stocking rate	-1.10	-0.49	0.53
Specialisation	**-2.65*****	**-3.45*****	-0.78
Participation [a]	NA	NA	-1.19
Age	1.63	1.07	-0.29
Household members	-1.61	**-1.86***	-0.20
BTSCC	**3.44*****	**4.24*****	1.32
Homegrown grass	0.29	**-2.49****	**-2.52****

Note: *t*-statistics reported in the table. ***, ** and * significant at the 1, 5 and 10% levels. [a] Variable available only for 50 members of a KTP discussion group and 39 members of a private group. Significant differences reported in bold font in the table. NA = Non-Applicable.

6.4.2. Results of non-linear regression models

Differences in terms of farm and farmers' characteristics across farmer cohorts are further examined with a mixed logit model in Table 6.3. Results are reported as relative-risk ratios. The multinomial logit model can be found in Table C. 1 (Appendix C) as robustness check[42]. As no significant differences were found for stocking rate and farmers' age in Table 6.2, these two variables are excluded from the mixed logit model. Moreover, only one measure of farm size (i.e., farm area) is included in the model to avoid multicollinearity issues. Before analysing the findings from Table 6.3, likelihood-ratio tests are conducted after model estimation to ensure that the three farmer cohorts are stand-alone groups (Läpple and Van Rensburg, 2011). The test rejects the null hypothesis at the 1% level that non-members and members of a KTP group can be combined ($\chi^2(5) = 32.02, p = 0.00$). The null hypothesis that non-members and members of a private group can be merged is also rejected at the 1% level ($\chi^2(5) = 57.63, p = 0.00$), while it is rejected at the 5% level for members of KTP and private groups ($\chi^2(5) = 11.38, p = 0.044$).

When using non-members as the base alternative, the findings in Table 6.3 reveal that farm area and specialisation are positively associated with the likelihood of participating in discussion groups. More precisely, an increase by one ha in farm area is associated with increases by 3% and 5% in the likelihood of being a KTP or private member over a non-member, respectively. An increase by 1% in the proportion of dairy cows to total livestock units is associated with increases by 2% and 4% in the likelihood of being a KTP or private member over a non-member, respectively. When further exploring differences between both cohorts of discussion group

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[42] The Hausman-McFadden test of the IIA assumption was rejected in this analysis (Hausman and McFadden, 1984), which reinforces the choice of the mixed logit model over the multinomial logit model for result description and interpretation. The multinomial logit model yields similar findings than the mixed logit model, except for the magnitude of the effect of the BTSCC variable on the likelihood of being a KTP member over a non-member. The relative-risk ratio of 1 for this variable in Table C. 1 (Appendix C) indicates no changes in the likelihood of being a KTP member over a non-member based on BTSCC level.

members for these two farm characteristics (with KTP group as base alternative), only farm area is significant. An increase by 1 ha in farm area is associated with an increase by 2% in the likelihood of choosing private discussion group over the KTP scheme. As for household size, it is not a significant predictor of discussion group membership.

The results displayed in Table 6.3 further confirm the pairwise comparisons of farm management level reported in Table 6.2. BTSCC is negatively associated with the likelihood of participating in discussion groups. An increase by 1,000 cells per ml is associated with a decrease by 1% in the likelihood of being both a KTP or private member relative to a non-member. Additionally, BTSCC is not a significant predictor of private group participation relative to KTP participation.

Homegrown grass is not a significant predictor of KTP participation relative to non-participation. Conversely, it is positively associated with the likelihood of participating in a private group relative to a KTP group or non-participation. More specifically, an increase by 1% in the share of homegrown grass in the diet of dairy cows is associated with increases by 4% and 5% in the likelihood of participating in a private group relative to a KTP group or non-participation, respectively. Hence, the findings suggest that there exists a spectrum of managerial ability across farmers, with members of a private group being the most advanced, followed by members of a KTP group, and then non-members.

Overall, the results in Table 6.3 are in line with previous literature. Farmers in contact with group extension are likely to be better farm managers and have larger, more specialised farms than non-participants (Anderson and Feder, 2004; Läpple et al., 2020; Läpple and Hennessy, 2014). The findings also corroborate the idea that publicly funded and private extension services can target different pools of farmers (Feder et al., 2011; Ferroni and Zhou, 2012; Norton and Alwang, 2020). Farmers with larger, more commercial holdings are likely to be preferably drawn to private extension, while publicly funded extension attracts resource-poorer farmers.

Table 6.3: Estimated relative-risk ratios for the mixed logit model exploring the determinants of farmer cohorts

Base alternative	Non-members		KTP discussion group	
Farmer cohort	KTP group	Private group	Non-members	Private group
Farm area	1.03*** (0.0082)	1.05*** (0.0094)	0.97*** (0.0077)	1.02** (0.0079)
Specialisation	1.02* (0.012)	1.04** (0.016)	0.98* (0.012)	1.01 (0.017)
Household members	1.12 (0.12)	1.05 (0.13)	089 (0.094)	0.94 (0.12)
BTSCC	0.99** (0.0023)	0.99*** (0.0030)	1.01** (0.0023)	1.00 (0.0031)
Homegrown grass	1.00 (0.012)	1.05** (0.020)	1.00 (0.012)	1.05** (0.020)
Log-likelihood	-222.54			
AIC	469.09			
BIC	511.49			

Note: n = 253 observations. ***, ** and * significant at the 1, 5 and 10% levels. Relative-risk ratios and standard errors reported in parentheses. AIC = Akaike Information Criterion and BIC = Bayesian Information Criterion.

6.4.3. Results of linear regression models

The relationship between farmer cohorts and farm sustainability is explored with linear regression models. To select model specification, three sets of independent variables are tested using likelihood-ratio tests, and AIC and BIC values (Kuha, 2004; Lewis et al., 2011). The three sets are as follows: 1) Farmer cohorts, farm area, specialisation, and household size; 2) BTSCC and homegrown grass in addition to the first set; and 3) stocking rate, southern region, age, and education in addition to the second set. The results are reported in Table C. 2 (Appendix C) for economic outcomes and in Table C. 3 (Appendix C) for environmental outcomes. They show that the second set of explanatory variables is preferred in all sustainability regressions, except for nitrogen surplus for which the third set performs better. In the latter case, the findings for the variables of interest (i.e., farmer cohorts) are not affected by the addition of stocking rate, south, age, and education. Hence, for all four sustainability outcomes, the regression models which include the second set of independent variables are reported and interpreted. The results are presented in Table 6.4 for economic outcomes and in Table 6.5 for environmental outcomes[43]. After carrying out the Breusch-Pagan test, robust standard errors are used for the gross margin, nitrogen surplus and GHG emission efficiency regression models (Breusch and Pagan, 1979; Wooldridge, 2012). Overall, the models explain 21% of the variance for gross margin, 29% for milk yield, 23% for nitrogen surplus, and 38% for GHG emission efficiency.

When using non-members as the base dummy variable in Table 6.4, the results show that discussion group participation is positively associated with farm economic sustainability. More specifically, participation in a KTP group relative to non-participation is associated with increases by about €94 per cow in gross margin and 297 litres per cow in milk yield. Participation in a private group relative to non-participation is associated with increases by about €132 per cow in gross margin and 483 litres per cow in milk yield. Therefore, discussion group participation is associated with improved economic performance, as previously found in the literature (Cawley et al., 2018; Läpple and Hennessy, 2015). It should be highlighted that self-selection is not accounted for in the current cross-sectional study because of the small observation count in each farmer cohort and the absence of instrumental variables (Imbens and Wooldridge, 2009). Despite controlling for a wide set of observed variables in regression models, there may still be

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[43] To conduct a multicollinearity diagnostic, Variance Inflation Factors (VIF) are estimated for each individual covariate and means are calculated for the overall models (Salmerón Gómez et al., 2016). That is because multicollinearity concerns may arise from the inclusion in the same linear regression model of farmer cohorts and farm and farmers' characteristics used in the mixed logit model. When non-members are used as base dummy variable, the highest covariate VIF and the mean VIF are equal to 1.38 and 1.16, respectively. When KTP discussion group is used as base dummy variable, the highest covariate VIF and the mean VIF are equal to 1.58 and 1.22, respectively. These values indicate no salient multicollinearity issues between independent variables.

some confounding variables and the relationship between discussion group participation and economic performance is thus not causal.

The findings in Table 6.4 also reveal that there are no significant differences in farm economic performance between members of KTP and private groups. Participation in a private discussion group relative to a KTP group was expected to be associated with higher economic sustainability due to the more demand-driven nature of private extension (Feder et al., 2011; Norton and Alwang, 2020; Ragasa and Mazunda, 2018). However, this was not verified in the analysis. Several explanations can be suggested. First, private groups may not be as effective as expected in enhancing farm economic sustainability, or, alternatively, the KTP programme may be more effective than expected. Second, there may be some confounders, which capture the effect of private groups relative to KTP groups. Of particular concern are unobserved discussion-group specific characteristics that potentially affect both farm economic sustainability and the type of discussion group in which farmers choose to participate (e.g., motivation and ability of group peers and the facilitator). Third, some survey participants were categorised in the 'private group' cohort but were simultaneously participating in a KTP group[44]. Hence, the effect of KTP and private groups may not be fully separated when grouping together farmers involved only in a private group and farmers involved in both KTP and private groups.

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[44] Farmers involved only in a private group represent 11.9% of the sample (n = 30), while farmers involved in both KTP and private groups account for 8.3% (n = 21).

Table 6.4: Results of linear regression models exploring the relationship between farmer cohorts and farm economic sustainability

Outcome	Gross margin		Milk yield	
Farmer cohort used as baseline	Non-members	KTP discussion group	Non-members	KTP discussion group
Non-members		**-93.86* (49.46)**		**-296.75** (144.13)**
KTP discussion group	**93.86* (49.46)**		**296.75** (144.13)**	
Private discussion group	**132.30** (51.71)**	**38.44 (57.54)**	**483.06*** (174.05)**	**186.31 (177.82)**
Farm area	1.66* (0.93)	1.66* (0.93)	8.64*** (3.06)	8.64*** (3.06)
Specialisation	2.21 (1.51)	2.21 (1.51)	6.55 (4.33)	6.55 (4.33)
BTSCC	-0.93*** (0.29)	-0.93*** (0.29)	-3.24*** (0.71)	-3.24*** (0.71)
Homegrown grass	3.71* (1.94)	3.71* (1.94)	-22.56*** (4.71)	-22.56*** (4.71)
Household members	17.99 (12.82)	17.99 (12.82)	4.49 (39.68)	4.49 (39.68)
F statistic	6.16***		14.39***	
R^2	0.21		0.29	
AIC	3602.38		4170.84	
BIC	3630.65		4199.11	
Breusch-Pagan test	12.26***		1.94	

Note: n = 253 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and robust standard errors reported in parentheses for the gross margin indicator; coefficients and standard errors reported in parentheses for the milk yield indicator. Results for variables of interest in bold font. Breusch-Pagan test used to test for heteroskedasticity, with significance indicating the need for robust standard errors (Breusch and Pagan, 1979; Wooldridge, 2012).

The results in Table 6.5 reveal that discussion group participation is not associated with improved nitrogen surplus and GHG emission efficiency, which represent farm environmental sustainability. Additionally, no significant differences are obtained between the two cohorts of discussion group members, as already suggested by pairwise comparisons in Table 6.2.

Consequently, discussion group participation is not associated with improved farm environmental sustainability. Because of the more demand-driven nature of private extension (Feder et al., 2011; Sutherland et al., 2013), it is not surprising to find no environmental effect of private discussion groups. However, positive environmental outcomes were expected from KTP participation as the publicly funded programme had incorporated environmental objectives into its schedule (Department of Agriculture Food and the Marine, 2020). Unless some confounders capture the effect of discussion group participation in the environmental regression models, the results may be due to the lack of effectiveness in enhancing farm environmental performance. This suggests that improvements in environmental sustainability, as measured by GHG emission efficiency and nitrogen surplus, are not achieved at farm level through the publicly funded extension scheme.

Table 6.5: Results of linear regression models exploring the relationship between farmer cohorts and farm environmental sustainability

Outcome	Nitrogen surplus		GHG efficiency	
Farmer cohort used as baseline	Non-members	KTP discussion group	Non-members	KTP discussion group
Non-members		**-10.83 (13.85)**		**0.029 (0.024)**
KTP discussion group	**10.83 (13.85)**		**-0.017 (0.023)**	
Private discussion group	**16.18 (13.16)**	**5.34 (15.73)**	**-0.0097 (0.027)**	**0.0077 (0.026)**
Farm area	0.26 (0.22)	0.26 (0.22)	-0.0014** (0.00056)	-0.0014** (0.00060)
Specialisation	1.11*** (0.36)	1.11*** (0.36)	-0.0085*** (0.00097)	-0.0089*** (0.0010)
BTSCC	-0.14*** (0.052)	-0.14*** (0.052)	0.00022 (0.00022)	0.00033 (0.00024)
Homegrown grass	-2.12*** (0.47)	-2.12*** (0.47)	-0.0021* (0.0011)	-0.0013 (0.0011)
Household members	8.09** (3.65)	8.09** (3.65)	-0.0015 (0.0077)	-0.0044 (0.0081)
F statistic	13.96***		13.36***	
R^2	0.23		0.38	
AIC	2897.31		-163.86	
BIC	2925.58		-135.60	
Breusch-Pagan test	20.82***		37.59***	

Note: n = 253 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and robust standard errors reported in parentheses. Results for variables of interest in bold font. Breusch-Pagan test used to test for heteroskedasticity, with significance indicating the need for robust standard errors (Breusch and Pagan, 1979; Wooldridge, 2012).

6.5. Conclusions and policy implications

There is an ongoing debate in the literature over the ability of the public and private sectors to effectively coordinate and deliver extension services to the farming population with respect to sustainable agricultural production (Eastwood et al., 2017; Feder et al., 2011; Knierim et al., 2017; Norton and Alwang, 2020). This study compared extension services delivered under a mixed public-private arrangement and services provided only by the private sector using a cross-sectional dataset of Irish dairy farms in 2018. Farmers' discussion groups are the participatory learning model used in Ireland and were thus analysed in this study (Department of Agriculture Food and the Marine, 2020; Donnellan et al., 2015). In 2018, farmers could choose between two types of service provision: mixed public-private discussion groups operated under a publicly funded scheme (i.e., the KTP), which paid farmers up to €1,000 per year to participate, or fully private discussion groups. Two main research questions were addressed. First, differences in farm and farmers' characteristics between three farmer cohorts (i.e., members of mixed public-private and private groups, and non-members) were examined with non-linear regression models. Second, the relationship between farmer cohorts and farm economic and environmental sustainability were assessed using linear regression models.

The findings from non-linear regression models revealed that the three farmer cohorts differ in terms of farm size, specialisation in dairy production, and level of farm management. Farmers involved in private extension are likely to operate the largest farms and achieve the highest levels of farm management. Farmers involved in mixed public-private extension are likely to operate smaller farms and achieve a lower level of farm management than farmers in private extension. Farmers who were not involved in group extension are likely to be the resource-poorest farmers with the lowest level of farm management. Therefore, these results confirmed previous literature, which suggested that publicly funded and private extension services could target different profiles of farmers (Feder et al., 2011; Ferroni and Zhou, 2012; Norton and Alwang, 2020).

The results from linear regression models showed that while discussion group participation is associated with higher economic performance, there are no significant differences between mixed public-private and private members. Additionally, neither participation in mixed public-private nor private groups is associated with enhanced environmental sustainability. However, it is important to note that self-selection was not accounted for in this study (Imbens and Wooldridge, 2009).

Important policy implications arise from this study. In the sample, farmers who were participating in the paid scheme in 2018 had been involved in discussion groups for 12 years, on average, thus previously showing willingness and ability to pay for services. Hence, without a clear change in objectives of and outcomes from extension, one may question the cost-effectiveness of subsidising participation as farmers are paid for a behaviour that they have already adopted. This issue has been extensively investigated in the context of agri-environmental schemes, where adverse selection is a common concern (Cullen et al., 2018). In fact, farmers who join paid schemes tend to have low compliance costs and a minor intensity of changes in practices required (Barreiro-Hurlé et al., 2010).

In that regard, cost-benefit analyses and impact evaluations that compare programme outcomes against objectives are required. These rely on the collection of data before, during, and after the publicly funded extension programme on participating farms (and non-participating farms as a counterfactual). In the current study, secondary, nationally representative data, with a strong inferential power, was used to analyse the relationship between types of discussion groups and farm outcomes. The data and selected farm sustainability indicators may not have been sensitive enough to capture the specific effects of mixed public-private and private extension services (Bélanger et al., 2012).

The data collected in the frame of this study also revealed that some farmers benefitted from the KTP payment and simultaneously satisfied their extension needs through fully private discussion groups. In other words, the data suggests that public funding was used for a segment of the farming population that also paid private consultants for additional group extension. Thus, thought must be dedicated as to whether stricter selection criteria should be introduced to avoid the overlap between mixed public-private and fully private extension participants. Notably, this argument is worth considering if there is no farm-level added-value to mixed public-private extension participation relative to private extension (i.e., proven additional economic or environmental outcomes).

Nonetheless, it could also be argued that farmers who are involved in both types of discussion groups actively participate in meetings. As they are private group members, they are likely to be more progressive than regular mixed public-private participants and potentially have more positive contributions to the relational and learning dynamics of publicly funded groups. Previous research has shown that while farmers learn from their peers, not all farmers are predominant and effective sources of information (BenYishay and Mobarak, 2019; Maertens, 2017; Nakano et al., 2018b; Shikuku et al., 2019; Songsermsawas et al., 2016). Within this context, evidence from randomised control trials in developing countries have proven that paying progressive farmers to diffuse information to other farmers can be an effective channel of knowledge and technology transfer (BenYishay and Mobarak, 2019; Shikuku et al., 2019). Hence, understanding which role farmers who are involved in both types of service provision play in their group peers' learning would enable a more informed policy decision as to whether their group participation should be publicly funded.

In developed countries, it might be difficult to justify consistent public funding for agricultural extension without a proven environmental or societal benefit (Barnes et al., 2019). Previous research has shown that mixed public-private extension can be successful in improving farm environmental sustainability (Nordin and Höjgård, 2017). In the Swedish context, Nordin and Höjgård (2017) showed that a publicly funded extension programme, which was free of charge for farmers and delivered under a mixed public-private arrangement, resulted in a decrease in farm nitrogen surpluses. One salient difference between the KTP and the Swedish programme analysed in Nordin and Höjgård (2017) is that the former paid farmers to participate while the latter was free of charge. Läpple and Hennessy (2015) had previously questioned the effectiveness of a paid scheme if it attracts farmers who are more interested in the financial reward than the learning experience. Thus, favouring mixed public-private extension schemes that are free of charge for participants may ensure that farmers who join are truly interested in the learning outcomes.

Alternatively, using results-based agri-environmental schemes as an example (Bartolini et al., 2020; Cullen et al., 2018), paying farmers based on their sustainability improvements over the length of the extension programme could be an interesting approach to increase the effectiveness of publicly funded extension. In Ireland, both subsidised schemes implemented so far (i.e., the DEP from 2010 to 2012 and the KTP from 2017 to 2019) paid farmers mostly based on their attendance record (Department of Agriculture Food and the Marine, 2020, 2010b).

This study focused on the Irish dairy sector, even though the KTP was targeted at six farming sectors (Department of Agriculture Food and the Marine, 2020). In Ireland, the dairy sector is not only the most profitable but also the only one which was targeted by the first paid extension scheme (i.e., the DEP) (Buckley and Donnellan, 2020; Department of Agriculture Food and the Marine, 2010b). Moreover, the private sector is likely to play a smaller role for other farming sectors in Ireland due to differences in farm profitability. Consequently, a larger share of non-dairy farmers may be attracted by publicly funded schemes. As a result, the KTP may have had different effects in each farming sector, which could be examined in future research.

In addition to differences between farmer cohorts, only farm economic and environmental outcomes were considered in this study. However, group extension may have other, more social benefits, which could explain why Irish farmers have been participating in discussion groups for years. Social aspects of group extension are also likely to impact how motivated and likely farmers are to learn from each other and hence effectiveness in enhancing farm performance (e.g., Macken-Walsh, 2019; Prager and Creaney, 2017). Exploring such components is an important task for future research.

Chapter 7 - Conclusion

7.1. Contributions of the thesis

Increasing food supply while achieving greater sustainability is one of the most pressing issues faced by the agricultural sector. This PhD thesis contributed to resolving this challenge by assessing the role of extension services and technology adoption in enhancing farm sustainability. Specifically, it focused on bringing empirical evidence into the sustainable intensification debate. In the last decade, sustainable intensification has attracted significant attention as a policy goal (Council of the European Union, 2014; Department of Agriculture Food and the Marine, 2015; Food and Agricultural Organization of the United Nations, 2020a), despite being built on a relatively weak empirical foundation (Godfray, 2015; Petersen and Snapp, 2015; Struik and Kuijper, 2017). Hence, this PhD thesis addressed numerous shortcomings in the literature in order to demonstrate the sustainability benefits of efficiency-focused farming strategies and to develop more effective extension systems (Balafoutis et al., 2017; Barnes et al., 2019; Feder et al., 2011; Godfray, 2015; Norton and Alwang, 2020; Petersen and Snapp, 2015; Struik and Kuijper, 2017; Tullo et al., 2019).

The thesis adopted a multidimensional approach to measure farm sustainability and incorporated a wide set of economic, environmental, and social sustainability indicators into the examination of technology and extension effects. In this way, the twofold challenge of meeting farmers' private needs while simultaneously providing wider public benefits in relation to agricultural production was analysed. The thesis investigated productive and economic outcomes and key policy-relevant issues to inform both farmers' adoption decisions and policy making for the use of public support in agricultural extension. In that regard, the PhD thesis also delved deeper into the effectiveness of extension systems in two ways. First, it examined pathways between extension participation, farm management, and sustainability performance. Second, it explored how public and private sectors can cooperate to deliver extension services for greater agricultural sustainability.

The research was conducted using data from dairy farms in the Republic of Ireland (referred to as Ireland in this PhD thesis) and has important implications for the Irish dairy sector. Following European Union (EU) milk quota removal in 2015, Irish dairy farms are undergoing major expansion and intensification (Eurostat, 2020a, 2020b). Addressing sustainability concerns associated with ongoing growth is critical to the continued development of the dairy industry (Kelly et al., 2020). To do so, a sustainable intensification of milk production has been put forward as the dominant strategy from a policy perspective (Department of Agriculture Food and the Marine, 2020, 2010b; Teagasc, 2015). Within this context, this PhD thesis verified the sustainability-enhancing potential of several farming practices that are recommended as best practices. It also analysed in detail Irish extension systems, including the publicly funded Knowledge Transfer Programme (KTP), which paid farmers to participate in discussion groups.

The current chapter summarises the main findings and recommendations of this PhD thesis in section 7.2. Then, the limitations and potential avenues for future research are discussed in section 7.3.

7.2. Main findings and recommendations

7.2.1. Sustainability benefits associated with technology adoption

When exploring the effect of technology adoption on the economic, environmental, and social dimensions of farm sustainability, this PhD thesis found mixed results. First, it demonstrated clear economic sustainability benefits resulting from the adoption of the analysed farming practices. The findings in Chapter 4 showed that milk recording, a support technology that can inform breeding and herd health decisions (Läpple et al., 2017), had a positive impact on gross margins and milk yields. In Chapter 5, the results proved that reaching farm management targets recommended by Irish extension in grassland management and reproductive efficiency could lead to an increase in gross margins (Department of Agriculture Food and the Marine, 2020; Donnellan et al., 2015; Teagasc, 2016). Therefore, the PhD results reinforced previous findings in the literature that emphasised the role of technological progress in enhancing farm profitability and productivity (Ali et al., 2018; Manda et al., 2016; Nakano et al., 2018a; Pan et al., 2018).

Second, the evidence provided in Chapter 4 validated that technology adoption can lead to synergies between farm economic and social sustainability. More precisely, the findings showed that milk recording adoption decreased Bulk Tank Somatic Cell Count (BTSCC). BTSCC is an indicator of milk bacterial contamination, and herd health and welfare, which are an important component of farm social sustainability (Geary et al., 2012; Lebacq et al., 2013; Medrano-Galarza et al., 2012; More et al., 2017). Hence, Chapter 4 supports the idea that efficient farming and better animal health standards can be reconciled, as previously suggested by Dawkins (2017).

Third, the effect of technology adoption on farm environmental sustainability was proven to be less evident. On the one hand, Chapter 5 indicated that improving farmers' grassland management skills could decrease nitrogen surpluses at the farm level, a measure of environmental pressure and risk to water quality (Buckley et al., 2016b; Department of

Agriculture Food and the Marine, 2020; Schröder et al., 2003; Teagasc, 2016). On the other hand, greater reproductive efficiency did not have a significant effect on nitrogen surpluses in Chapter 5, even though it was expected to reduce avoidable environmental costs of feeding unproductive animals (Department of Agriculture Food and the Marine, 2020; Garnsworthy, 2004; Llonch et al., 2017; Teagasc, 2016).

Similarly, Greenhouse Gas (GHG) benefits expected from the adoption of efficiency-focused farming practices were not confirmed in this thesis, which is not in line with previous literature (Garnsworthy, 2004; Lanigan et al., 2018; Llonch et al., 2017; O'Brien et al., 2014c; Özkan Gülzari et al., 2018; Özkan et al., 2015). In fact, Chapter 4 showed that milk recording uptake did not have a significant effect on GHG emission efficiency, as measured by GHG emissions emitted per kilogram (kg) of Fat-Protein-Corrected-Milk (FPCM). In Chapter 5, the positive effect of grassland management proved to be unstable to unobserved heterogeneity, while improved reproductive efficiency led to a decrease in GHG emission efficiency.

Consequently, the empirical proof provided in this PhD thesis suggests that the analysed farming practices can resolve only part of the sustainable intensification challenge, namely the productive and economic aspect[45]. In other words, the technologies under consideration can mainly provide private benefits for farmers, while their ability to deliver public goods in terms of GHG emissions and nutrient pressure is not evident. Hence, even though only a few examples of technologies were explored in this thesis, the findings do not support the pursuit of intensification strategies for greater sustainability in agricultural production. Nonetheless, it is important to recognise that these results cannot be generalised to all efficiency-focused technologies because of local specificities. Rather, they highlight the need to adopt an evidence-based approach to find technologies that can promote a move towards more sustainable agriculture.

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[45] Please note that additional analyses focused on farm social sustainability would be needed to reach a more definite conclusion regarding this sustainability dimension.

Additionally, most of the PhD results showed no environmental deterioration associated with the analysed farming practices (except for the negative effect of reproductive efficiency on GHG emission efficiency in Chapter 5, most likely due to the time period and dairy expansion). If the goal of sustainable intensification is merely to produce more with no additional environmental cost, then efficiency-focused strategies, such as the ones considered in this PhD thesis, can fit this definition. Inversely, the PhD empirical results suggest that intensification strategies cannot substantially help in improving environmental outcomes and hence in reversing prior environmental damage. This may rule out sustainable intensification as a means to restore deteriorated ecosystem services. Hence, this PhD thesis is in line with previous calls in the literature to clarify the definition and goals of sustainable intensification and consider supplementary strategies to overturn existing environmental damage (Godfray, 2015; Petersen and Snapp, 2015; Struik and Kuijper, 2017). For instance, these may include a move towards lower-emitting land uses (e.g., forestry, crop-based agricultural) at farm- and/or industry-level, and stricter environmental regulations (e.g., forbidding nitrates derogations).

From a public policy perspective, it is also important to consider that the sustainable intensification strategy is often justified by the claim that environmental costs of agricultural production can be reduced on a per-unit basis (Crosson et al., 2011; Salou et al., 2017). However, environmental commitments set at global, regional, and national scales are expressed in terms of absolute environmental costs (European Commission, 2019b, 2019a), thereby questioning how viable an intensification strategy is to meet these goals.

A final point to highlight in the case of Irish milk production is that the size of the national dairy herd increased by 34% between 2008 and 2018, in addition to the 16% improvement in milk yields (Eurostat, 2020a, 2020b). Inevitably, the increase in cow numbers implies additional environmental costs, even if milk is produced more efficiently (Buckley and Donnellan, 2020; Donnellan et al., 2018; Duffy et al., 2019; Environmental Protection Agency, 2019b). To feed the world's growing population, the problem of increasing production levels may go beyond the sustainable intensification challenge, thereby raising two questions. The first one relates to whether Ireland can produce more environmentally friendly milk than other regions of the world, which could justify further dairy specialisation. The second one concerns the sustainability of meeting the rising demand for animal-based products if technological progress is not sufficient in the medium- to long-run to substantially decrease environmental costs of livestock-based agriculture.

7.2.2. Extension effectiveness for greater farm sustainability

When delving deeper into the effectiveness of extension systems in enhancing farm sustainability, the PhD findings were also mixed. A first observation is that farming practices recommended by Irish extension and analysed in this thesis led to evident private benefits for farmers, while their public good dimension was less clear.

Additionally, Chapter 5 found reduced effectiveness in influencing pathways between extension, farm management, and sustainability, not only because of the limited sustainability benefits of selected farm management indicators, but also due to the insufficient improvements in farmers' management skills. Despite revealing that extension participation had a positive impact on dairy cow reproductive efficiency, the results suggested that farmers had not reached advisory targets yet (Teagasc, 2016). The findings in Chapter 5 also showed that extension participation did not have a significant effect on grassland management.

In line with the rest of the PhD findings, Chapter 6 revealed that participation in both KTP and private discussion groups was directly associated with higher gross margins and milk yields but did not have any effect on nitrogen surplus and GHG emission efficiency. Because of the more demand-driven nature of private extension (Feder et al., 2011; Sutherland et al., 2013), it was not surprising to find no environmental effect of private discussion groups. However, as the publicly funded KTP had incorporated environmental objectives into its schedule (Department of Agriculture Food and the Marine, 2020), positive environmental outcomes were expected from KTP participation. Therefore, Chapter 6 raises concerns regarding the ability of paid extension schemes in enhancing farm environmental sustainability. In a context where reduced environmental damage is one of the main reasons for providing publicly funded extension services, it may be difficult to justify continued public support without a proven public benefit (Barnes et al., 2019; Klerkx et al., 2006; Norton and Alwang, 2020; Sutherland et al., 2013).

Overall, the PhD findings have two main implications regarding extension systems. First, extension services must focus on technologies with proven environmental benefits to substantially increase farm sustainability. Second, more thought should be dedicated to the improvement of extension effectiveness for greater farm sustainability. This is a particularly challenging task as it relies on the development of extension systems that can strike the balance between providing immediate private benefits to farmers (to ensure their participation) and meeting wider sustainability goals related to sustainable agricultural production. The literature suggests that delivering extension services through mixed public-private arrangements has potential for reaching these goals by drawing on the strengths of public and private sectors (Feder et al., 2011; Norton and Alwang, 2020). The challenge then is to develop systems that avoid falling into the pitfalls of both sectors by being demand driven while concurrently covering wider sustainability concerns. In that regard, this PhD thesis provides elements to consider when building mixed public-private arrangements.

In Chapter 5, the analysed farm management indicators were selected based on the guidelines and targets of Irish extension (Department of Agriculture Food and the Marine, 2020; Donnellan et al., 2015; Teagasc, 2016). However, no indication was provided in the data about farmers' opinions of programme content. One may wonder if limited extension effectiveness was due to the supply-driven nature of the programme (Feder et al., 2011; Ragasa and Mazunda, 2018). To counter such limitations, measures of service quality and farmers' satisfaction could be included into the assessment of extension programmes, as previously implemented in Buehren et al. (2019) and Ragasa and Mazunda (2018). In this way, the information in relation to farmers' private benefits could be better matched to their needs (Ragasa and

Mazunda, 2018). Extension systems can only be effective if they promote technologies that can give a relative advantage to farmers and are suitable to their farming conditions (Montes de Oca Munguia and Llewellyn, 2020; Norton and Alwang, 2020; Pannell et al., 2006). More attention should thus be paid to developing extension schedules that can, to some extent, match farmers' preferences and technologies with corresponding traits (Macours, 2019; Montes de Oca Munguia and Llewellyn, 2020).

By paying fees to participate, farmers express their service preferences through the market mechanism, even in mixed public-private arrangements (Feder et al., 2011; Norton and Alwang, 2020). With the predominant goal of improving agricultural sustainability, such a type of financing mechanism may not be suitable if farmers are only willing to pay for advice related to production or lifestyle objectives. To overcome such limitations, incentive structures must be implemented to attract farmers to participate in programmes that will not only cover their private benefits but also wider sustainability concerns. In the Irish context, the results in Chapter 6 indicated that paying farmers to participate based on their attendance record was not successful in leading to environmental enhancements (Department of Agriculture Food and the Marine, 2020). Following the example of results-based agri-environmental schemes (Bartolini et al., 2020; Cullen et al., 2018), it may be more (cost-)effective to implement results-based extension schemes, whereby farmers are paid based on concrete sustainability outcomes. Another option would be to provide free-of-charge extension (e.g., Nordin and Höjgård, 2017), thus ensuring that farmers who participate are truly interested by programme content. Finally, introducing a progressive fee scale based on years of extension participation could be a means to attract new participants, while decreasing the need for public support over time.

7.3. Limitations and future research

This PhD thesis uses unique, detailed farm-level data about farmers' adoption and extension behaviours, and sustainability performance. However, it is important to acknowledge that the conclusions drawn from the econometric analyses may be sensitive to the precision and choice of farm sustainability indicators (Latruffe et al., 2016). Two main limitations arise. First, data availability guided, to some extent, the choice of sustainability issues focused upon throughout the thesis. As previously highlighted by Lynch et al. (2019), while economic sustainability is generally well-covered by the Teagasc National Farm Survey (NFS) data, there are limited indicators of social sustainability available, notably encompassing issues of animal welfare, antibiotic resistance, or farmers' wellbeing. In the environmental dimension of farm sustainability, lack of data availability regarding biodiversity loss also restricts the possibilities of including it into empirical analyses. These issues are very relevant in the context of dairy expansion and intensification, and deserve more attention in data collection and future research (Chen and Holden, 2018; Holden and Butler, 2018; Kelly et al., 2017; Lynch et al., 2019; Martin et al., 2020; More et al., 2017). Additional survey data could be collected on Teagasc NFS farms to complement the current pool of variables. Moreover, merging the Teagasc NFS with data collected for regulatory purposes by the Department of Agriculture, Food and the Marine could be a means to access more information regarding certain sustainability aspects (e.g., animal welfare, antibiotic use) at a reduced cost.

Second, selected environmental sustainability indicators could also be improved in future work. Currently, environmental measures are built mostly on farm activity data and do not account for important factors such as manure and slurry transfers, and soil nutrient stocks. More detailed modelling of GHG emissions and nutrient losses to water bodies could be performed with additional information from geospatial datasets and farm soil test results (Lynch et al., 2019).

Despite efforts to reduce self-selection concerns throughout the PhD thesis, methodological options to estimate causal effects were limited by the absence of credible instrumental variables in the Teagasc NFS. It is important to plan a way to assess causal impacts before implementing new publicly funded extension systems. In this way, programme (cost-) effectiveness can be evaluated, and lessons can be learnt for future public investments. An interesting approach would be to pilot the new extension design on a small sample of farmers through randomised control trials. In cases of positive outcomes, the extension system could then be rolled out at a greater scale with higher chances of success. Alternatively, if randomised control trials are not a feasible option and extension schemes are implemented at national level straight away, data should be collected before, during, and after the programme on both participating and non-participating farms. This would allow the use of the difference-in-differences method to estimate causal effects (Imbens and Wooldridge, 2009).

While the Teagasc NFS records whether farmers participate or not in discussion groups, a more detailed examination of extension systems could be carried out if a distinction was made at data collection between State and private discussion groups. As the KTP ended in 2019 and private discussion groups are growing in popularity, it is a task for future research to assess the differences between State and private groups. The type of mixed public-private arrangement under which State discussion groups operate could be further analysed. In this way, more could be learnt about coordination mechanisms between public and private sectors.

This PhD thesis provided evidence that the link between Irish extension, recommended technologies, and farm environmental sustainability was weak. However, it cannot be determined from the data whether limited environmental effects are due to a problem of access to or engagement with information. Previous research has shown that farmers may have cognitive and behavioural biases regarding the extension message, which can lead to a lack of engagement with accessible information and new technologies (Hennessy et al., 2016; Maertens, 2017; Mills et al., 2017; Sutherland et al., 2013). Similarly, extension agents may also have their own cognitive and behavioural biases, which can make them filter certain information or affect their motivation to transfer knowledge (Faure et al., 2012; Feder et al., 2011; Klerkx, 2020; Shikuku et al., 2019). These issues should be considered to a greater extent when analysing the effectiveness of extension programmes, notably to identify ‘where things went wrong’. This is an important avenue for future research.

Finally, while participatory extension is considered as the preferred learning approach (Norton and Alwang, 2020), little is known about the effect of relational dynamics within participants on technology adoption and extension effectiveness, as well as potential knowledge spillovers to non-participants. Detailed analyses of social learning among farmers have been previously carried out (BenYishay and Mobarak, 2019; Genius et al., 2014; Maertens, 2017; Nakano et al., 2018b; Shikuku et al., 2019; Songsermsawas et al., 2016), but quantitative evidence in the context of participatory extension is lacking. In the frame of Irish discussion groups, qualitative research has shown that the degree to which group peers are willing to discuss and exchange information affects their learning experience (Macken-Walsh, 2019; Prager and Creaney, 2017). This PhD thesis attempted to delve deeper into the questions of participants' relational dynamics and knowledge spillovers to non-participants. Additional data about farmers' reliance on different advice sources and technology adoption was collected in 2018 through the Teagasc NFS (please find the survey questions in Appendix D). Despite having conducted a pilot survey with 12 farmers to ensure question clarity, 122 surveys were returned incomplete. The final sample included only 92 discussion group members and 82 non-members (i.e., about 53% of the original dairy Teagasc NFS sample). The observation count was not sufficient to analyse the data in a robust manner. Hence, more data could be collected in the future to explore these questions.

Despite these limitations, this PhD thesis made an important contribution to the literature by exploring the economic, environmental, and social sustainability benefits of technology adoption, and examining the effectiveness of extension systems for greater farm sustainability. It provided valuable and new insights into the suitability of several farming practices in helping Irish dairy farmers to achieve sustainable intensification. Finally, the thesis pointed out multiple avenues to improve Irish extension services.

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Appendices

Appendix A: Supplementary material for Chapter 4

Table A. 1: Estimation of adoption decision models (logit regressions)

Covariate	Odds ratio	
	Model 1	Model 2
Herd size	1.05*** (0.011)	1.06*** (0.012)
Herd size squared	1.00*** (0.000047)	1.00*** (0.000047)
Specialisation	10.51** (11.06)	7.42* (8.12)
Soil	1.02 (0.27)	1.08 (0.30)
Education	1.16 (1.86)	1.07 (1.78)
Age	1.00 (0.025)	1.00 (0.026)
Education * Age	1.01 (0.030)	1.01 (0.031)
Household	1.10 (0.098)	1.11 (0.10)
Stocking		0.48** (0.15)
Concentrates		1.00 (0.00032)
Fertiliser		1.01** (0.0030)
Extension		1.00 (0.0083)
Pseudo R^2	0.15	0.17
Log-likelihood	-174.83	-170.41
Observations	296	296
Overlap region	[0.064; 0.85]	NA

Note: ***, **, and * significant at the 1%, 5%, and 10% level, respectively. Results reported as odds ratios and standard errors in parentheses. Model 1 is the propensity score estimation model and Model 2 is used for comparison purposes in section 4.6.2. NA = Non-Applicable.

Table A. 2: Standardised differences between both groups before and after propensity score matching (in %)

	Original	Matched
Herd size	69.00	-0.94
Herd size squared	48.71	-2.07
Specialisation	27.74	-2.55
Soil	10.48	-6.46
Education	42.32	-6.18
Age	-17.24	10.01
Education * Age	35.44	0.44
Household	27.96	-2.75
Total reduction in bias	34.86	3.93
Number of observations	296	290
Treated observations	145	145
Control observations	151	145

Figure A. 1: Kernel density distribution of propensity score, by treatment status

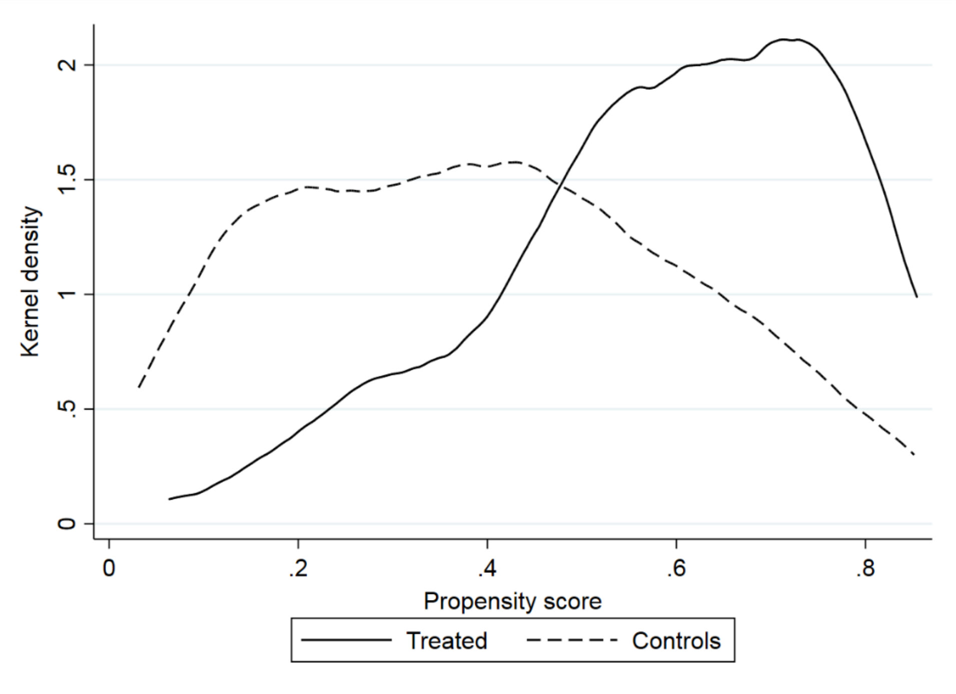

Figure A. 2: Propensity scores for treated and matched comparison units after matching (with 2 NN and replacement), lowest to highest

Appendix B: Supplementary material for Chapter 5

Table B. 1: Full estimation results for the cost control indicator

Variables	FE equation-by-equation (OLS)			FE SUR (FGLS)			FE SUR (GMM 3SLS)		
	Homegrown grass	Calving rate	Costs	Homegrown grass	Calving rate	Costs	Homegrown grass	Calving rate	Costs
Extension $_{t-1}$	0.0023 (0.077)	0.36*** (0.10)		0.0012 (0.078)	0.35*** (0.11)		0.0023 (0.077)	0.36*** (0.10)	
Homegrown grass			-0.15*** (0.013)			-0.15*** (0.013)			-0.15*** (0.013)
Calving rate			-0.021*** (0.0074)			-0.022*** (0.0076)			-0.021*** (0.0073)
Grazing $_{t-1}$	0.013 (0.0089)			0.013 (0.0093)			0.013 (0.0089)		
Leased land	0.044 (0.032)			0.044 (0.032)			0.044 (0.032)		
Household	0.22 (0.25)			0.21 (0.26)			0.22 (0.25)		

Variables	FE equation-by-equation (OLS) *(Continued from previous)*			FE SUR (FGLS) *(Continued from previous)*			FE SUR (GMM 3SLS) *(Continued from previous)*		
	Homegrown grass	Calving rate	Costs	Homegrown grass	Calving rate	Costs	Homegrown grass	Calving rate	Costs
Artificial insemination		-0.0077 (0.025)			-0.0092 (0.025)			-0.0077 (0.025)	
BTSCC		-0.0034 (0.0043)			-0.0034 (0.0044)			-0.0034 (0.0043)	
Milk recording		-0.091 (0.057)			-0.090 (0.056)			-0.091 (0.056)	
Farm area $_{t-1}$	-0.047* (0.027)	-0.065 (0.043)	0.018** (0.0092)	-0.048 (0.034)	-0.058 (0.048)	0.019* (0.011)	-0.047* (0.027)	-0.065 (0.042)	0.018** (0.0092)
Specialisation $_{t-1}$	0.038 (0.041)	-0.049 (0.058)	0.0023 (0.015)	0.036 (0.043)	-0.053 (0.059)	0.0024 (0.015)	0.038 (0.041)	-0.049 (0.058)	0.0023 (0.015)
Stocking rate $_{t-1}$	-2.88*** (1.04)	-2.92** (1.27)	0.51** (0.23)	-2.78*** (1.06)	-2.66** (1.25)	0.54** (0.22)	-2.88*** (1.04)	-2.92** (1.26)	0.51** (0.23)
Age	0.41*** (0.15)	0.84*** (0.24)	-0.015 (0.051)	0.40*** (0.15)	0.82*** (0.24)	-0.013 (0.051)	0.41*** (0.15)	0.84*** (0.24)	-0.015 (0.050)

Note: n = 1,945 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. For the FGLS estimator, clustered standard errors obtained through bootstrapping with 1,000 replications. Individual and time fixed effects controlled for.

Table B. 2: Full estimation results for the gross margin indicator

Variables	FE equation-by-equation (OLS)			FE SUR (FGLS)			FE SUR (GMM 3SLS)		
	Homegrown grass	Calving rate	Margin	Homegrown grass	Calving rate	Margin	Homegrown grass	Calving rate	Margin
Extension $_{t-1}$	0.0023 (0.077)	0.36*** (0.10)		0.0013 (0.078)	0.35*** (0.11)		0.0023 (0.077)	0.36*** (0.10)	
Homegrown grass			5.82*** (0.72)			5.79*** (0.73)			5.82*** (0.72)
Calving rate			4.80*** (0.52)			4.84*** (0.57)			4.80*** (0.52)
Grazing $_{t-1}$	0.013 (0.0089)			0.013 (0.0093)			0.013 (0.0089)		
Leased land	0.044 (0.032)			0.044 (0.032)			0.044 (0.032)		
Household	0.22 (0.25)			0.21 (0.26)			0.22 (0.25)		

Variables	FE equation-by-equation (OLS) *(Continued from previous)*			FE SUR (FGLS) *(Continued from previous)*			FE SUR (GMM 3SLS) *(Continued from previous)*		
	Homegrown grass	Calving rate	Margin	Homegrown grass	Calving rate	Margin	Homegrown grass	Calving rate	Margin
Artificial insemination		-0.0077 (0.025)			-0.0090 (0.025)			-0.0077 (0.025)	
BTSCC		-0.0034 (0.0043)			-0.0034 (0.0044)			-0.0034 (0.0043)	
Milk recording		-0.091 (0.057)			-0.090 (0.056)			-0.091 (0.056)	
Farm area $_{t-1}$	-0.047* (0.027)	-0.065 (0.043)	-0.90 (0.65)	-0.048 (0.034)	-0.058 (0.048)	-0.87 (0.78)	-0.047* (0.027)	-0.065 (0.042)	-0.90 (0.64)
Specialisation $_{t-1}$	0.038 (0.041)	-0.049 (0.058)	0.57 (1.04)	0.036 (0.043)	-0.053 (0.059)	0.56 (1.08)	0.038 (0.041)	-0.049 (0.058)	0.57 (1.03)
Stocking rate $_{t-1}$	-2.88*** (1.04)	-2.92** (1.27)	-24.29 (20.55)	-2.78*** (1.06)	-2.66** (1.25)	-23.14 (19.99)	-2.88*** (1.04)	-2.92** (1.26)	-24.29 (20.46)
Age	0.41*** (0.15)	0.84*** (0.24)	7.69* (3.96)	0.40*** (0.15)	0.82*** (0.24)	7.51* (3.93)	0.41*** (0.15)	0.84*** (0.24)	7.69* (3.94)

Note: n = 1,945 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. For the FGLS estimator, clustered standard errors obtained through bootstrapping with 1,000 replications. Individual and time fixed effects controlled for.

Table B. 3: Full estimation results for the nitrogen surplus indicator

Variables	FE equation-by-equation (OLS)			FE SUR (FGLS)			FE SUR (GMM 3SLS)		
	Homegrown grass	Calving rate	Nitrogen	Homegrown grass	Calving rate	Nitrogen	Homegrown grass	Calving rate	Nitrogen
Extension $_{t-1}$	0.0023 (0.077)	0.36*** (0.10)		0.000035 (0.078)	0.35*** (0.11)		0.0023 (0.077)	0.36*** (0.10)	
Homegrown grass			-1.34*** (0.23)			-1.37*** (0.24)			-1.34*** (0.22)
Calving rate			0.025 (0.10)			0.034 (0.10)			0.025 (0.10)
Grazing $_{t-1}$	0.013 (0.0089)			0.013 (0.0093)			0.013 (0.0089)		
Leased land	0.044 (0.032)			0.044 (0.033)			0.044 (0.032)		
Household	0.22 (0.25)			0.21 (0.26)			0.22 (0.25)		

Variables	FE equation-by-equation (OLS) *(Continued from previous)*			FE SUR (FGLS) *(Continued from previous)*			FE SUR (GMM 3SLS) *(Continued from previous)*		
	Homegrown grass	Calving rate	Nitrogen	Homegrown grass	Calving rate	Nitrogen	Homegrown grass	Calving rate	Nitrogen
Artificial insemination		-0.0077 (0.025)			-0.0089 (0.025)			-0.0077 (0.025)	
BTSCC		-0.0034 (0.0043)			-0.0034 (0.0044)			-0.0034 (0.0043)	
Milk recording		-0.091 (0.057)			-0.090 (0.056)			-0.091 (0.056)	
Farm area $_{t-1}$	-0.047* (0.027)	-0.065 (0.043)	0.59*** (0.19)	-0.048 (0.034)	-0.058 (0.048)	0.58** (0.10)	-0.047* (0.027)	-0.065 (0.042)	0.59*** (0.18)
Specialisation $_{t-1}$	0.038 (0.041)	-0.049 (0.058)	-0.49* (0.26)	0.037 (0.043)	-0.053 (0.059)	-0.49* (0.26)	0.038 (0.041)	-0.049 (0.058)	-0.49* (0.25)
Stocking rate $_{t-1}$	-2.88*** (1.04)	-2.92** (1.27)	23.48*** (5.82)	-2.78*** (1.06)	-2.66** (1.25)	23.15*** (5.74)	-2.88*** (1.04)	-2.92** (1.26)	23.48*** (5.79)
Age	0.41*** (0.15)	0.84*** (0.24)	2.28*** (0.88)	0.40*** (0.15)	0.82*** (0.24)	2.41*** (0.85)	0.41*** (0.15)	0.84*** (0.24)	2.28*** (0.87)

Note: n = 1,945 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. For the FGLS estimator, clustered standard errors obtained through bootstrapping with 1,000 replications. Individual and time fixed effects controlled for.

Table B. 4: Full estimation results for the GHG emission efficiency indicator

Variables	FE equation-by-equation (OLS)			FE SUR (FGLS)			FE SUR (GMM 3SLS)		
	Homegrown grass	Calving rate	GHG	Homegrown grass	Calving rate	GHG	Homegrown grass	Calving rate	GHG
Extension $_{t-1}$	-0.044	0.31***		-0.044	0.31***		-0.044	0.31***	
	(0.078)	(0.11)		(0.082)	(0.12)		(0.078)	(0.11)	
Homegrown grass			-0.0017**			-0.0016*			-0.0017**
			(0.00085)			(0.00085)			(0.00085)
Calving rate			0.0011*			0.0011*			0.0011**
			(0.00058)			(0.00055)			(0.00058)
Grazing $_{t-1}$	0.0079			0.0084			0.0079		
	(0.011)			(0.011)			(0.011)		
Leased land	0.081**			0.081**			0.081**		
	(0.040)			(0.040)			(0.040)		
Household	0.42			0.41			0.42		
	(0.32)			(0.32)			(0.31)		
Artificial insemination		-0.00036			-0.0014			-0.00036	
		(0.027)			(0.028)			(0.027)	

Variables	FE equation-by-equation (OLS) *(Continued from previous)*			FE SUR (FGLS) *(Continued from previous)*			FE SUR (GMM 3SLS) *(Continued from previous)*		
	Homegrown grass	Calving rate	GHG	Homegrown grass	Calving rate	GHG	Homegrown grass	Calving rate	GHG
BTSCC		-0.0059			-0.0059			-0.0059	
		(0.0067)			(0.0066)			(0.0067)	
Milk recording		-0.094			-0.094			-0.094	
		(0.073)			(0.073)			(0.073)	
Farm area $_{t-1}$	-0.072**	-0.050	0.00073	-0.072*	-0.050	0.00073	-0.072**	-0.050	0.00073
	(0.028)	(0.040)	(0.00063)	(0.041)	(0.057)	(0.00090)	(0.028)	(0.040)	(0.00063)
Specialisation $_{t-1}$	0.024	-0.027	-0.0034**	0.024	-0.027	-0.0034**	0.024	-0.027	-0.0034**
	(0.049)	(0.078)	(0.0013)	(0.051)	(0.077)	(0.0014)	(0.048)	(0.077)	(0.0013)
Stocking rate $_{t-1}$	-3.89***	-3.06**	-0.014	-3.89***	-3.06*	-0.014	-3.89***	-3.06**	-0.014
	(1.12)	(1.49)	(0.023)	(1.17)	(1.58)	(0.024)	(1.12)	(1.48)	(0.023)
Age	1.01***	0.58	-0.038***	1.01***	0.58	-0.038***	1.01***	0.58	-0.038***
	(0.32)	(0.43)	(0.0056)	(0.32)	(0.43)	(0.0056)	(0.31)	(0.43)	(0.0056)

Note: n = 1,371 observations (2013-2017 time period). ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. For the FGLS estimator, clustered standard errors obtained through bootstrapping with 1,000 replications. Individual and time fixed effects controlled for.

Table B. 5: FE SUR estimation results exploring management pathways between extension and farm economic sustainability (GMM 3SLS estimator) (balanced panel)

Variables	Direct production costs per unit of output			Gross margin per cow		
	Homegrown grass	Calving rate	Costs	Homegrown grass	Calving rate	Margin
Extension $_{t-1}$	0.0078 (0.095)	0.48*** (0.14)		0.0078 (0.095)	0.48*** (0.14)	
Homegrown grass			-0.15*** (0.017)			5.45*** (0.92)
Calving rate			-0.030*** (0.011)			5.00*** (0.74)

Note: n = 1,078 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. Individual and time fixed effects, and farm and farmers' characteristics controlled for.

Table B. 6: FE SUR estimation results exploring management pathways between extension and farm environmental sustainability (GMM 3SLS estimator) (balanced panel)

Variables	Nitrogen surplus per ha			GHG emitted per unit of output $_a$		
	Homegrown grass	Calving rate	Nitrogen	Homegrown grass	Calving rate	GHG
Extension $_{t-1}$	0.0078 (0.095)	0.48*** (0.14)		0.013 (0.11)	0.47*** (0.17)	
Homegrown grass			-1.35*** (0.27)			-0.00039 (0.0010)
Calving rate			0.16 (0.14)			0.0011* (0.00063)

Note: n = 1,078 observations. $_a$ for the GHG indicator, data available only from 2013-2017 and thus n = 762 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and clustered standard errors at the farm level in parentheses. Individual and time fixed effects, and farm and farmers' characteristics controlled for.

Table B. 7: Sensitivity analysis based on Oster (2019) (balanced data)

		FE SUR (GMM 3SLS) results		Oster procedure		
Equations	Sensitivity tested for	$\hat{\beta}$ (SE)	95% confidence interval	Bounds $\Delta = [\widetilde{\beta_1};\ \beta_1^*(1,1)]$	Includes 0?	% included in 95% confidence interval
Calving rate	Extension $_{t-1}$	0.48*** (0.14)	[0.20; 0.77]	[0.48; 1.71]	No	23.6
Cost control	Homegrown grass	-0.15*** (0.017)	[-0.18; -0.11]	[-0.15; 0.061]	Yes	19.0
Cost control	Calving rate	-0.030*** (0.011)	[-0.052; -0.0090]	[-0.030; 0.0065]	Yes	57.5
Profitability	Homegrown grass	5.45*** (0.92)	[3.64; 7.26]	[5.45; 5.92]	No	100
Profitability	Calving rate	5.00*** (0.74)	[3.54; 6.46]	[5.00; 5.50]	No	100
Nitrogen surplus	Homegrown grass	-1.35*** (0.27)	[-1.88; -0.82]	[-3.79; -1.35]	No	21.7
GHG emission efficiency $_a$	Calving rate	0.0011* (0.00063)	[-0.00017; 0.0023]	[0.0011; 0.0040]	No	41.4

Note: n = 1,078 observations ($_a$ except for the GHG equations that has 762 observations). ***, ** and * significant at the 1, 5 and 10% levels.

Appendix C: Supplementary material for Chapter 6

Table C. 1: Estimated relative-risk ratios for the multinomial logit model exploring the determinants of farmer cohorts

Base alternative	Non-members	
Farmer cohort	KTP group	Private group
Farm area	1.04*** (0.0098)	1.06*** (0.011)
Specialisation	1.03* (0.013)	1.04*** (0.016)
Household members	1.13 (0.13)	1.10 (0.14)
BTSCC	1.00** (0.0022)	0.99** (0.0035)
Homegrown grass	1.00 (0.012)	1.06*** (0.021)
Log-pseudolikelihood	-10865.44	
AIC	21754.88	
BIC	21797.28	

Note: n = 253 observations. ***, ** and * significant at the 1, 5 and 10% levels. Relative-risk ratios and standard errors reported in parentheses. AIC = Akaike Information Criterion and BIC = Bayesian Information Criterion.

Table C. 2: Results of additional linear regression models exploring the relationship between farmer cohorts and farm economic sustainability

Outcome	Gross margin		Milk yield	
KTP discussion group	120.78** (48.10)	95.57** (48.14)	366.05** (145.50)	287.45** (144.93)
Private discussion group	189.37*** (50.31)	115.46** (52.06)	460.87*** (154.26)	477.95*** (175.01)
Farm area	1.69* (0.95)	1.69* (0.94)	11.65*** (3.22)	7.05** (3.13)
Specialisation	3.07* (1.61)	1.85 (1.52)	10.51* (5.68)	7.46* (4.40)
Household members	20.36 (13.62)	15.25 (13.25)	8.58 (47.40)	5.38 (42.09)
BTSCC		-0.93*** (0.30)		-3.25*** (0.71)
Homegrown grass		3.81* (1.98)		-23.49*** (4.90)
Stocking rate		37.85 (38.80)		-157.58 (117.84)
South		61.89 (46.23)		-72.22 (125.97)
Age		0.60 (1.92)		1.23 (6.15)
Education		56.52 (61.81)		271.97* (146.10)
F statistic	5.85***	4.87***	7.67***	9.74***
R^2	0.14	0.23	0.16	0.31
AIC	3619.74	3604.56	4209.34	4172.90
BIC	3640.94	3646.96	4230.54	4215.30
Breusch-Pagan test	8.99***	12.28***	3.03*	1.02
Likelihood-ratio test	21.36***	5.82	42.50***	5.94
Nested model	Yes	In Table 6.4	Yes	In Table 6.4
Full model	In Table 6.4	Yes	In Table 6.4	Yes

Note: n = 253 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and robust standard errors reported in parentheses (regular standard errors in the second model of the milk yield indicator, when the Breusch-Pagan test is insignificant). Non-members as base dummy variable. Breusch-Pagan test used to test for heteroskedasticity, with significance indicating the need for robust standard errors (Breusch and Pagan, 1979; Wooldridge, 2012). Likelihood-ratio tests performed between nested models and full models (indicated in rows 'Nested model' and 'Full model' in the table), without controlling for heteroskedasticity.

Table C. 3: Results of additional linear regression models exploring the relationship between farmer cohorts and farm environmental sustainability

Outcome	Nitrogen surplus		GHG efficiency	
KTP discussion group	13.15 (14.22)	7.67 (11.85)	-0.024 (0.023)	-0.017 (0.022)
Private discussion group	8.26 (14.33)	10.71 (11.92)	-0.031 (0.025)	-0.0088 (0.027)
Farm area	0.48** (0.23)	0.54*** (0.17)	-0.0013** (0.00058)	-0.0013** (0.00060)
Specialisation	1.32*** (0.38)	0.76** (0.31)	-0.0087*** (0.0011)	-0.0085*** (0.00098)
Household members	8.14** (3.99)	5.65* (3.09)	-0.0022 (0.0082)	-0.00023 (0.0086)
BTSCC		-0.14*** (0.053)		0.00022 (0.00022)
Homegrown grass		-1.45*** (0.39)		-0.0020* (0.0012)
Stocking rate		72.88*** (12.25)		0.014 (0.028)
South		8.62 (9.56)		-0.0050 (0.028)
Age		0.046 (0.42)		0.00096 (0.00099)
Education		-18.38 (12.59)		-0.0032 (0.035)
F statistic	8.61***	15.26***	15.30***	9.97***
R^2	0.12	0.43	0.36	0.38
AIC	2929.88	2829.73	-159.92	-157.07
BIC	2951.08	2872.13	-138.72	-114.67

Outcome	Nitrogen surplus *(Continued from previous)*		GHG efficiency *(Continued from previous)*	
Breusch-Pagan test	7.53***	16.08***	36.57***	37.20***
Likelihood-ratio test	36.56***	75.58***	7.94**	1.21
Nested model	Yes	In Table 6.5	Yes	In Table 6.5
Full model	In Table 6.5	Yes	In Table 6.5	Yes

Note: n = 253 observations. ***, ** and * significant at the 1, 5 and 10% levels. Coefficients and robust standard errors reported in parentheses. Non-members as base dummy variable. Breusch-Pagan test used to test for heteroskedasticity, with significance indicating the need for robust standard errors (Breusch and Pagan, 1979; Wooldridge, 2012). Likelihood-ratio tests performed between nested models and full models (indicated in rows 'Nested model' and 'Full model' in the table), without controlling for heteroskedasticity.

Appendix D: Supplementary material for Chapter 7

2018 additional survey questions

Grassland management practices: Please answer the following (tick).

(a): Have you drawn up a map of your grazing paddocks?	☐ Yes ☐ No
(b): During the main grazing season (March to November), how often do you walk your farm?	☐ Never ☐ At least once per week ☐ Approximately twice per month ☐ Approximately once per month ☐ Less than once per month
(c): During the main grazing season (March to November), how often do you complete a farm grass cover?	☐ Never ☐ At least once per week ☐ Approximately twice per month ☐ Approximately once per month ☐ Less than once per month
(d): If you answered more than 'Never' to part (c) How do you primarily measure grass? Enter year started - "X" if pre 2015	☐ Visual observation ☐ Plate meter or Bluetooth ☐ Quadrant and scale ☐ Enabled plate meter Year: ……………….
(e): On average, how often do you soil test your farm?	☐ I never soil test my farm. ☐ Approximately every year ☐ Approximately every other year ☐ Approximately every 3 to 5 years ☐ Less than every 5 years

Source of advice: please consider the following questions.

(a): Are you **currently** in **any** of the following dairy discussion groups?	☐ **Only** in a KT discussion group ☐ In **both** a KT discussion group **and** another private discussion group ☐ **Only** in a private discussion group ☐ **Not** in any discussion group

(b): Imagine that you are facing an issue with your grassland. Before deciding how to manage it, you would like an outside perspective on the matter. In this situation, how likely would you be to seek the advice of the following?

Please express your opinion by ticking **one box per row** in the following table. If you are **a member of a dairy discussion group (both KT and/or private)**, complete **only the rows from part A and C**. If you are **not a member of a dairy discussion group**, complete **only the rows from part B and C.**

		Extremely likely	Very likely	Somewhat likely	Not so likely	Not likely at all
PART A *FOR DAIRY DISCUSSION GROUP MEMBERS*	A member of **your** dairy discussion group (excluding the facilitator)					
	Your dairy discussion group facilitator					
	An advisor or consultant (other than your discussion group facilitator)					
	A farmer from a **different** discussion group					
PART B	An advisor or a consultant					

FOR NON-DAIRY DISCUSSION GROUP MEMBERS	A farmer who is in a discussion group					
PART C *FOR ALL DAIRY FARMERS*	Another farmer who is **not** in a discussion group					
	A family member					
	A contractor					
	An input or output merchant (fertiliser, seed or machinery sales rep, co-op, etc.)					
	The media (Internet, Farmers' Journal, etc.)					
	Other (please specify): …………………………………………………….					