Labour input and economic efficiency of Irish dairy farms

A thesis submitted in application for the degree of
Doctor of Philosophy

To the J.E. Cairnes School of Business and Economics

At the University of Galway

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June 2023

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Declaration of work

I, Luis Garcia-Covarrubias, 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-June-2023

Date

Abstract

The EU milk quota abolition initiated considerable restructuring in the EU dairy sector. Ireland is one of the countries that experienced significant growth, which has led to changes in farm labour demand. This PhD thesis aims to assess the role of family and hired labour, and automation in enhancing the efficiency of farms in an evolving dairy sector. Based on farm-level panel data sets from 2000 to 2019, and a cross-section supplementary data in 2018, the thesis presents three analyses of farm labour and productivity on Irish dairy farms. The first analysis explores the effect of hired labour on farms' technical efficiency (TE). Using a state-of-the-art stochastic frontier model that controls for endogeneity between inputs and TE, the findings reveal that hired labour positively affects farms' TE, improving dairy production. The findings suggest that the positive effect of hired labour on TE is marginally higher for smaller farms. The second analysis examines the role of automation in the efficiency of Irish dairy farms. A latent class stochastic frontier model is used to jointly estimate TE scores and identify two latent classes of farms utilising different technologies in their production, i.e., smaller, less intensive, and larger, more intensive farms. The results show that automated technologies (i.e., automatic parlour feeders, cluster removers, and scrapers) have heterogeneous effects on farms TE. Specifically, automated cluster removers and scrapers are correlated with higher TE scores in the smaller, less-intensive farms. Automated parlour feeders positively correlate to the TE of the larger-more-intensive farms. The third analysis focuses on estimating the shadow wage of family labour and assesses its role in the demand for hired labour on the farm. A two-step structural production function approach is used to estimate unpaid family labour shadow wage, and a semi-parametric censored dependent variable data model is applied to explore the role of shadow wages on hired labour demand. The findings show that as the size of the farm increase, so does the family labour shadow wage. Moreover, the results indicate positive returns to farmers' formal agricultural education. Finally, findings suggest a substitution and income effect of shadow wages in demand for hired labour— the substitution effect is larger for the demand of casual hired labour. Overall, this thesis provides an improved understanding of farm labour and its link with automation and efficiency as crucial factors for the sustainable development of an evolving dairy sector.

Acknowledgements

Thanks to my supervisors, Dr Doris Läpple, Dr Emma Dillon, and Dr Fiona Thorne. I couldn't be more grateful for all your support and guidance. Doris, thank you for your guidance and encouragement to improve every detail of my work continuously. Your comments, research and advice are now one of my biggest influences on how I conduct my work and study. Emma, thank you for your guidance, advice, and support throughout my doctoral project. Your empathy and kindness only match your quality as a researcher. Fiona, thank you for coming on board at a time of need and for your useful feedback through my PhD project.

To Prof. Stephen Hynes and Dr Yiorgos Gadanakis, the examiners of this thesis, I'm thankful with you for reading this thesis and providing constructive and useful comments on it, I thoroughly enjoyed my *Viva*.

Thanks to the University of Galway, the College of Business, Public Policy and Law, its staff and lecturers, and the J.E. Cairnes School of Business and Economics. Special thanks for their guidance and support to Brendan Kennelly, Dr Ashley Piggins, Dr Jason Harold, Dr John Cullinan, Dr Raghav Srinivas, Dr Thomas Van Rensburg, Dr Tom McDermott, Prof. Kieran Walsh, Prof. Paddy Gillespie, Prof. Stephen Hynes, and Olvia McBride from the International Office.

I'm grateful to Teagasc's (the Agriculture and Food Development Authority in Ireland) programmes and staff. Thanks to the Teagasc Walsh Scholarship program that funded my doctoral project throughout these four years. Thanks also for granting me the Teagasc International Travel Award that allowed me to complete my research stay at the University of California Riverside. Special thanks to Hilary King for all her support.

I express my deepest gratitude to the Teagasc NFS team. Estimating all empirical models in this thesis is only possible with the continued support and help from Teagasc staff, recorders and farmers. Special thanks to John

Lennon and Brian Moran for their patience and kindness in sharing their knowledge of statistics and databases with me. I also want to thank the excellent economists and researchers at the Teagasc Rural Economy and Development Centre for our discussions and their comments on my work at seminars. Specifically, many thanks to Anne Kinsella, Cathal Buckley, Kevin Hanrahan, Kevin Kilcline, Michele McCormack, and Trevor Donnellan.

Thanks to the Department of Environmental Sciences (DES) of the University of California Riverside for receiving me as a visiting scholar in the Spring Semester of 2022. Special thanks to Dr Edgar Tellez-Foster for being my sponsor during this research stay; your support and guidance were beneficial for my research. Thanks to fellow PhD students and postdoctoral researchers at DES for your advice and friendship. Thanks to Alejandro McDonald, Aral, Hector, Juan Acero, Julio, Rebeca, and Sandra Armengol. Thanks to M.S., CCC-SLP. Christopher Fairleigh, for proofreading two chapters of this thesis.

Thanks to the sincere friends I have made in Ireland, especially those with whom we shared the process of doing a PhD. Thank you, Áine, Anastasios (Tasos), Anna, Dan Cassidy, Dinaly, Edgar Gomez, Felipe, Garreth, Giannis Margaritis, Giannis Titilas, Gloria, John Flynn, Mara, Mary Brennan, Rocio, Rosy, Ryan, and Stefano. Thanks to Andreas Tsakiridis and Lorraine Balaine, who helped me improve my thesis work with their comments, I am very grateful for being able to call two economists I deeply admire *mis amigos*. Thanks to the woman of my life and best friend, Deborah, words cannot describe the value of your role in this process. I cannot imagine going through this journey without you.

Thanks to my family for their love, understanding, and patience during this process. Special thanks to my lifelong friends: Alejandro, Mario, Pactli, Ricardo, Rodrigo, Saul, and Itzel.

Finally, thanks to my therapist MD Antonia Carbajal. Building a therapeutic space with you has given me the crucial support system to conclude my doctoral research and enjoy living. *Gracias*.

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List of abbreviations and acronyms

AI	Artificial Insemination
AWU	Average Working Unit
CAP	Common Agricultural Policy
CD	Cobb-Douglas
CME	Chicago Mercantile Exchange
CSO	Irish Central Statistics Office
D	Dummy variable
DAFM	Department of Agriculture, Food and the Marine
DEA	Data Envelopment Analysis
EU	European Union
ETUC	European Trade Union Confederation
FADN	Farm Accountancy Data Network
FRS	Farm Relief Services
GHG	Greenhouse Gas
GMM	Generalised Method of Moments
GTRE	Generalised True Random Effects
ha	Hectares
kg	Kilograms
LCSF	Latent Class Stochastic Frontier
MLMS	Macra Land Mobility Services
NFU	National Farmers Union
OLS	Ordinary Least Squares
RCM	Random Coefficients Model
SCC	Somatic Cell Count
SD	Standard Deviation
SE	Standard Error
SFA	Stochastic Frontier Analysis
TE	Technical Efficiency
TFP	Total Factor Productivity
Teagasc NFS	Teagasc National Farm Survey
US	United States of America
USD	United States Dollar
€	Euro

Chapter 1 – Introduction

1.1 Context of the thesis

The economic development of the 20th century led to significant adjustments in the agricultural labour market, mainly related to technological improvements (Alvarez-Cuadrado and Poschke, 2011; Acemoglu and Restrepo, 2019). Specifically, these improvements in technology, both in agriculture and other industries, led to an outflow of labour from agriculture to other sectors in the late 19th and early 20th centuries that resulted in a significant decrease in the share of agricultural employment (Alvarez-Cuadrado and Poschke, 2011; Ros, 2013; Acemoglu and Restrepo, 2017). For instance, data from 12 developed economies shows that the share of agricultural employment declined from 71% in 1800 to only 5% in 2000 (Alvarez-Cuadrado and Poschke, 2011; Alvarez-Cuadrado et al., 2017).[1] These significant labour outflows from rural households to other economic sectors have ended in most developed economies (Tocco et al., 2012a; Ros, 2013; Alvarez-Cuadrado et al., 2017).

The labour market in agriculture faces particular challenges for several reasons. The agricultural labour market is continuously changing regarding quantity, skills, and innovative technologies (Rizov and Swinnen, 2004; Tocco et al., 2012b). Moreover, most agricultural labour markets face structural constraints that often become market imperfections (Lopez, 1984; Skoufias, 1994; Rizov and Swinnen, 2004; Tocco et al., 2012b). For instance, these constraints often include lower levels of human capital and an aged population, imperfect and asymmetric information, higher uncertainty in food production, underemployment of farm labour, less off-farm opportunities, less commuting infrastructure and services provision due to a rural location (Tocco et al., 2012b; Loughrey and Hennessy, 2014; Almeida and Bravo-Ureta, 2019). Although issues relating to market imperfections are more prevalent in developing countries (e.g., Skoufias, 1994; Almeida and Bravo-

[1] The list of the 12 developed economies is: Belgium, Canada, Finland, France, Germany, Japan, the Netherlands, South Korea, Spain, Sweden, the UK, and the US.

Ureta, 2019), they are also often present in the agricultural labour markets of developed economies (Benjamin and Kimhi, 2006; Loughrey and Hennessy, 2014; Bousmah and Grenier, 2020). Consequently, a well-functioning agricultural labour market is still vital for the income and development of rural households (Tocco et al., 2012a; Tocco et al., 2012b).

Along with such constraints, labour shortages in agriculture have become an additional challenge for the sector (Hou and Lu, 2017; Bousmah and Grenier, 2020; FAO, 2021; Castellano-Canales, 2022), particularly in the context of the current tight labour market (McGrath, 2021; Castellano-Canales, 2022). For instance, in the US, the agricultural labour shortages reached record-high levels in 2021, in which 66% of agricultural employers experienced *some or a lot of difficulties* hiring adequate labour in 2021, compared to 30% in 2020 (Purdue University and CME Group, 2021; Castellano-Canales, 2022). In the same year, labour shortages were quite pressing in the UK since about 500,000 vacancies could not be filled in the agricultural sector, with an average labour shortage ratio of 13% to the agri-labour force (NFU, 2021; Environment Food and Rural Affairs Committee, 2022). Moreover, in the EU in 2021, 3% of available jobs were vacant, the highest percentage since 2006 (Allenbach-Ammann, 2022), and, in agriculture, in some EU Member States (i.e., Czech Republic, Germany, Italy), this percentage is higher (up to 13%) and has required policy strategies to tackle down the labour shortages (ETUC, 2020; Weber et al., 2021).

The policy strategies to address labour shortages in agriculture vary by country and region. For example, the US and Canada heavily rely on a policy that facilitates the immigration of agricultural labour as a key strategy to mitigate the effects of labour shortages (Bousmah and Grenier, 2020, Haan et al., 2021).[2] In the EU, some Member States (i.e., France, Germany, Italy, Spain, Poland) also rely on this type of policy (i.e., Article 45 of The EU) to

[2] In the 2023 North American Leaders' Summit, the issuance of temporary work permits for foreign agricultural workers through the H-2A Visa scheme was reaffirmed (White House, 2023). Also, President Lopez-Obrador of Mexico acknowledged the efforts made by the government of Prime Minister Justin Trudeau of Canada to expand the Temporary Foreign Worker Program that now benefits 25,000 Mexican agricultural workers.

aim in reducing the labour shortages (Augère-Granier, 2021).[3] Moreover, in some EU Member States (e.g., Spain, Portugal) recent initiatives, based on Directive 2014/36/EU (EU Parliament, 2014), open the possibility for hiring agricultural workers form a third country (Augère-Granier, 2021; Allenbach-Ammann, 2022). On the other hand, developing countries tend to rely more on a policy that increases the agricultural market wage and the minimum wage to ensure the permanence of workers in the sector (Aguirre et al., 2013).

Labour shortages are also present in some EU Member States' dairy sectors, particularly in Ireland (Kelly et al., 2020; Weber et al., 2021). Among other factors, the increased labour demand is driven by the abolition of the EU milk quota in 2015 which set in motion the expansion (e.g., the Netherlands, Ireland) and contraction (e.g., Bulgaria, Romania) of milk production across some EU Member States (Läpple and Sirr, 2019; Osawe et al., 2021).[4] The Irish dairy sector experienced the most considerable growth of all EU Member States, with milk production increasing by 67% between 2010 and 2021 (Eurostat, 2022).

More specifically, milk production growth was achieved through significant dairy herd expansion on the vast majority of Irish dairy farms (i.e., 80%) (Dillon et al., 2022). From 2010 to 2021, dairy herd size increased, on average, by 34% (Dillon et al., 2022). Also, the percentage of farms with a herd size of more than 100 cows increased from 10% to 33% in the same period, accounting for 60% of total milk production in 2021 (Dillon et al., 2022). In addition, milk yield per cow increased from an average of 5,099 litres in 2010 to 5,800 in 2021 (Eurostat, 2022; Dillon et al., 2022). In 2021, Irish dairy output represented 6.2% of EU dairy production, an increase of 52% since 2010 (Eurostat, 2022). However, from 2010 to 2021, the total labour hours on the farm, on average, increased only by 9% (Hennessy et al., 2012; Dillon et al., 2022). Therefore, the mismatch between increasing herd

[3] Article 45 of the Treaty on the Functioning of the European Union guarantees the freedom of movement for EU workers within the Union (Augère-Granier, 2021).
[4] The EU milk quota was introduced in 1984 and constrained milk production for over 30 years. The European Common Agricultural Policy (CAP) Mid-Term Review discussed abolishing EU milk quotas in 2003 and then officially announced in the CAP Health Check in 2008 plans towards its complete abolition by 2015. The EU milk quota abolition reached full implementation in 2015.

size and labour is recognised as a particular challenge for the dairy sector (Kelly et al., 2020; Brennan et al., 2022).

Against the backdrop of such significant structural change, the subsequent increase in labour demand in the Irish dairy sector is particularly challenging for two additional reasons. First, Irish dairy production is based on a spring calving system that gives the Irish dairy sector a competitive advantage by reducing herd feeding costs (Thorne et al., 2017; O'Brien, 2018). However, such a production system's downside is the resulting uneven labour demand. Specifically, in calving-milking-related tasks, labour demand peaks in the first 3-4 months of the year (Deming et al., 2017; 2018; NFS, 2020).[5] These initial months represent more than half of the yearly workload on dairy farms (Deming et al., 2018; O'Brien et al., 2018). Second, the predominance of family farming in the Irish dairy sector is a further aggravating factor, with 93% of the available workforce either farm holders or other family members (CSO, 2020).[6] Consequently, relying on family labour with significantly larger dairy herds is not sustainable, with the increasing workload and labour shortages being a significant concern to dairy farmers (Brennan et al., 2021; Brennan et al., 2022).

In addition to these challenges, sourcing additional hired labour has become an extra hurdle for dairy farmers. For instance, data from a 2018 labour survey indicates that 73% of farmers reported problems hiring labour, with 14% unable to hire additional labour despite requiring it (O'Brien et al., 2019). Moreover, anecdotal evidence suggests that farmers might be reluctant to delegate part of the workload to non-family labour due to productivity concerns. Therefore, even though hired labour is promoted as a practical resource to relieve farmer stress related to the increasing workload (Brennan et al., 2022), hired labour still needs to be more utilised and facilitated on Irish dairy farms (Garcia-Covarrubias et al., 2022).

[5] In Chapter 6, this thesis provides further detail on a pilot time-use study that confirms the increased need for farm labour in calving, milking and breeding (NFS, 2020).
[6] Family farming remains the mainstay of agriculture in the EU. In 2020, there were 9.1 million agricultural holdings in the EU, with 94.8% per cent of them as family farms, i.e., farms on which 50 % or more of the regular agricultural labour force is provided by family members (Eurostat, 2022).

The farm labour challenges also relate to technology improvements (Kimhi, 2009; Kelly et al., 2020). Due to the increased labour requirement, automated technologies have been put forward as a potential solution and are becoming more prevalent in the dairy sector (Kelly et al., 2020). For instance, in 2021, compared to 2020, the specific investment in machinery increased by 57%, a similar percentage increase year-on-year since 2015 (Dillon et al., 2022). Some of this investment is made to reduce labour-intensive tasks related to the milking and calving process with automated technologies on dairy farms (Conlon, 2021; Prendergast et al., 2022). More specifically, on farms with less than 150 cows (86% of dairy farms in 2018), improvements in facilities related to the milking process showed a reduction of approx. 20% in labour hours per cow (Deming et al., 2017; Deming et al., 2018).

This PhD thesis provides an improved understanding of the labour input utilised on Irish dairy farms using nationally representative data. Since efficiency is a situation where the inputs of production are assigned to their most beneficial uses (Kumbhakar et al., 2015; Pindyck and Rubinfeld, 2017), this thesis explores the role of labour and labour-saving technologies on farm efficiency. Moreover, it investigates the role of the economic value of unpaid family labour and how it influences the demand for hired labour on the farm. Finally, this thesis informs the debate on why and how farm labour and efficiency are crucial factors in facing the challenges of agri-food production in the 21st century.

1.2 Research objectives and thesis structure

The overall objective of this PhD thesis is to analyse the role of labour as a factor of production in the economic performance of Irish dairy farms. More precisely, the thesis is divided into three empirical chapters, which address the following research objectives:

1. Explore the effect of hired labour on farm efficiency in a family farming context (Chapter 3).
2. Explore the role of automation in farm efficiency in an expanding dairy sector (Chapter 4).
3. Estimate the economic value of family labour and explore its role in the demand for hired labour. (Chapter 5).

As mentioned, the main body of the thesis consists of three empirical chapters (Chapter 3, Chapter 4, and Chapter 5). However, these empirical chapters are preceded by two other chapters, i.e., the present introductory chapter and a literature review chapter.

Chapter 2 contains a literature review to identify some of the knowledge gaps addressed in the thesis. Firstly, the chapter provides an overview of labour in agricultural economics. Secondly, more detail is provided on the role of labour in farm efficiency. Thirdly, the issues of farm labour and automation in the productivity literature are explored. Finally, the chapter examines the literature on the economic value of unpaid labour and the demand for hired labour on family farms. The chapter concludes by highlighting the direction of the PhD research, its overall objectives and its contributions to the literature.

Chapter 3 explores the *win-win* potential of hiring labour to reduce the increasing workload on dairy farms, while improving efficiency. Relevant literature on the role of hired labour in improving the productivity and efficiency of family farms is first reviewed. The background section provides a detailed description of the Irish dairy sector's spring-calving system. The methodology outlines how the endogeneity problem (between inputs and efficiency) is resolved by estimating a heteroscedastic Generalised True Random Effects Model (GTRE). There follows a presentation of the panel data set used along with descriptive statistics on farm labour input and farm characteristics. Estimation results and a discussion of same are then reported, followed by resulting conclusions and policy implications.

Chapter 4 examines the role of automation in farm efficiency. Since automation, which is usually labour-saving, has always played a significant role in the productivity and efficiency of agriculture, the chapter provides a detailed background on labour and automation in the Irish dairy sector. The third section of this chapter provides a detailed literature review on automation, labour and efficiency. The latent class stochastic frontier (LCSF) model applied to a cross-sectional data set in this chapter is explained in the methodology section. The empirical model and the descriptive statistics of the variables analysed in this chapter are provided in a following section. Then, the empirical results and the discussion are reported, followed by a section including conclusions and policy implications.

Chapter 5 estimates the economic value (shadow wage) of family labour and explores its role in the demand for hired labour on family farms. The chapter provides a detailed conceptual framework on the assumptions needed to estimate the shadow wage of family labour. Then, the chapter presents a concise literature review of previous studies analysing the value of unpaid labour and the demand for hired labour on family farms. A data section describes the panel data set, and the variables analysed in the chapter. The methodology section outlines the production function approach used to estimate the shadow wage of family labour, and the censored dependent variable panel model applied to estimate the demand for hired labour on Irish dairy farms. In a following section, the results and discussion are presented. The chapter ends with conclusions and policy implications.

The final chapter (6) contains an overall conclusion, which incorporates the main findings of this PhD thesis, recommendations for policy-making and future research, and identifies some limitations of the work.

1.3 Thesis outputs

There have been a number of outputs to date from the research undertaken for this PhD thesis. The analysis presented in Chapter 3 has been resubmitted for peer review after a second round of paper revisions. The study presented in Chapter 4 has been submitted and is currently under peer-review. Chapter 5 will shortly be submitted to an agricultural economics journal. The PhD research was also presented at various conferences and seminars (both internationally and domestically). More detail on the associated outputs is provided below.

Journal article re-submitted following revisions on 1st July 2022. R&R 15th April 2023.

Garcia-Covarrubias, L., Läpple, D., Dillon E., Thorne, F. (2023). The role of hired labour on technical efficiency in an expanding dairy sector: the case of Ireland. *Australian Journal of Agricultural and Resource Economics*.

Journal article Published in the QOpen Journal of Agriculture and Environmental Economics Oxford University Press. 5th May 2023.

Garcia-Covarrubias, L., Läpple, D., Dillon E., Thorne, F. (2023). Automation and efficiency: a latent class analysis of Irish dairy farms. *Q-Open Journal of Agricultural, Climate, Environmental, Resource and Food Development Economics*. https://doi.org/10.1093/qopen/qoad015

Working paper

Garcia-Covarrubias, L., Läpple, D., Dillon E., Thorne, F. (2023). Shadow wage of family labour and its role in hired labour demand: evidence from Irish dairy farms. Target Journal: *World Development Journal.*

Conference and seminar presentations

Garcia-Covarrubias, L., Läpple, D., Dillon E. (2020). The role of hired labour on transient and persistent efficiency on Irish dairy farms – presented at:

- AAEA (Agricultural and Applied Economics Association) conference Annual Meeting, NY, USA. Online. (June, 2020).
- Accepted to AES (Agricultural Economic Society, UK) conference Annual Meeting, Warkwick, UK. Which was cancelled due to the CODIV-19 Pandemic. (March, 2020).
- Agricultural Economics and Farm Surveys Online Seminar Series, Teagasc, Athenry, Ireland (March, 2020).

Garcia-Covarrubias, L., Läpple, D., Dillon E., Thorne, F., (2021). The role of automated technologies on the technical efficiency of Irish dairy farms, 2021/2022 – presented at:

- Brownbag Seminar Centre for Economic Research on Inclusivity and Sustainability (CERIS) at the National University of Ireland Galway (May, 2021).

- Irish Postgraduate and Early Career Economics Online workshop (June 2021).

- Brownbag seminar at the Permanent seminar series in the College of Agriculture and Natural Sciences at the University of California Riverside (May, 2022). Updated title: Automation, labour and technical efficiency on Irish dairy farms.

Garcia-Covarrubias, L., Läpple, D., Dillon E., Thorne, F., 2021. Shadow wages and hired labour demand on Irish dairy farms – presented at:

- AAEA (Agricultural and Applied Economics Association) conference Annual Meeting, Boston, USA. Online. (June, 2021).

- This working paper is part of a sponsored Track Session of the Food and Agricultural Marketing (FAMPS) and International Section titled Demand and Supply Distortions, Environmental Challenges and Adaptation of New Technologies in the Dairy Sector in the July 2023 AAEA annual conference in Washington D.C., USA.

- Awarded the Bob O'Connor Prize at the Agricultural Economic Society of Ireland Early Career Conference Best PhD Scholar Presentation Teagasc, Ashtown.

Garcia-Covarrubias, L., Dillon E., Läpple, D. 2020. The use of a tablet and a booklet to analyse labour input on the farm: a pilot time-use study on Irish dairy farms.

- Economics and Farm Surveys Seminar Series, Teagasc, Athenry, Ireland. Overall PhD Thesis *Labour Input and Economic Efficiency of Irish Dairy Farms* (December, 2023).

Outreach article

Garcia-Covarrubias, L., Läpple, D., Dillon E., Thorne, F., 2022. For hire: the benefits of hired labour for family farms. TResearch Summer 2022 17 (2), 28-31. Online Available at: https://www.teagasc.ie/about/research--innovation/research-publications/tresearch-summer-2022/hired-labour-for-family-farms/

Chapter 2 - Literature review

2.1 Introduction to labour in agricultural economics

Labour has been a long-standing topic in the agricultural economics and rural development literature. During the late 19th century and the first half of the 20th century, economic development was commonly associated with a decreasing contribution of agriculture to total employment (Ros, 2013). More specifically, there was a considerable movement of people out of agriculture to other sectors with a decline in the absolute level of agriculture in the national accounts and the relative importance of agricultural employment, especially in Europe (Lewis, 1954; Breustedt and Glauben, 2007; Acemoglu and Restrepo, 2018). Most of these movements that relocated human resources from the farm labour market to other labour markets were mainly motivated, amongst other factors, by the 20th century economic growth, technological change, and improved commuting systems (Tocco et al., 2013; Ros, 2013; Acemoglu and Restrepo, 2019).

The literature's focus on farm labour has changed from analysing the implications of labour flows out of agriculture towards studying the economic, technology and productivity implications of labour in the agricultural sector. The reason for this focus change in the literature is due to the fact that the macro-level labour flow adjustments facilitated by economic growth and technical change have ended in most developed countries (Ros, 2013). Yet in the late 20th century and in the 21st century, agriculture remains an important source of income and employment for many rural households in Europe (Eurostat, 2022). Consequently, analysing labour markets in agriculture is important to understand the rural economy and the national, regional and global economy as a whole.

Although it is worth noting that agriculture is not the only sector engaged in the rural economy, it often dominates employment in rural areas (Le, 2009; Tocco et al., 2012a). Hence, the focus on labour is in analysing the functioning of agricultural labour markets as the main driver of the rural economy and employment. It is highlighted in the literature that many economies are characterised by imperfect agricultural labour markets. These imperfections are due to transaction costs and structural impediments, which can result in a sub-optimal allocation of labour, lower income of workers, unequal productivity of family and hired labour, and thus constrained rural development (Kancs et al., 2009; Tocco et al., 2012a). Therefore, understanding the functioning of the agricultural labour markets becomes a crucial factor in improving the development and living conditions of rural households/areas (Kancs et al., 2009).

This thesis heavily relies on the empirical literature that analyses the functioning of agricultural labour markets. The majority of this literature is based on microeconomic premises that strongly depend on the framework of the *farm-household model*. The farm-household model is based on neoclassical assumptions and integrates agricultural production and labour supply decisions into a single framework (Jacoby 1993; Tocco et al., 2012a). This model assumes that the farm household acts as a single decision maker[7]. The farm household is assumed to derive utility from total consumption (C) and leisure (L), which varies due to exogenous individual characteristics (i.e., age, education, farming experience), household characteristics (H), and location characteristics (Z). Therefore, the utility equation of the farm household can be written as:

$$U = U(C, L, H, Z) \tag{1.1}$$

The household maximising utility levels of consumption and leisure are subject to the constraints of time, income, and farm production. In the farm household model, leisure includes home production time (e.g., cleaning, cooking, family time) (Apps and Rees, 1997; Tocco et al., 2012a). Therefore, total time available (T) is allocated between off-farm work (O), on farm work (F), and leisure (L), so that:

[7] The farm household model can be extended to a multi-person household model where farmers and spouses make decisions as a result of a bargaining process including other household members. These extended farm household model can be specified as a bargained one decision maker (farmer and spouse) (e.g., Kancs et al., 2009; Tocco et al., 2012a) or two separate models, one for farmer and other for spouses, can be estimated (e.g., Rosenzweig, 1980; Corsi and Findeis, 2000; Goodwin and Holt, 2002; Fall and Magnac, 2004).

$$T = O + F + L \tag{1.2}$$

Total consumption in value terms CP_c (i.e., consumption of goods and services multiplied by the vector of prices P_c) is determined by the budget constraint (B_c). The budget constraint is determined by off-farm income (i.e., off-farm work (O) multiplied by the market wage W), net farm income (i.e., the value of farm output $P_f Y_f$ minus the production costs $I_f X_f$) and exogenous household wealth (V) (i.e., family inheritance, savings, transferences, subsidies. Then, we can write CP_c as follows:

$$CP_c = B_c \tag{1.3}$$

$$B_c = WO + (P_f Y_f - I_f X_f) + V \tag{1.4}$$

Thus, in (1.4) it is implicitly assumed that the farm household has no savings. The off-farm wage (W) is assumed to reflect individual human capital[8] characteristics (H) as well as labour market conditions (Z):

$$W = W(H, Z) \tag{1.5}$$

The final constraint on the farm household utility maximisation is on farm labour (F); which is dependent on the production function with decreasing marginal returns as follows:

$$Q = f\left(F, X_f; H, Z_f\right) \tag{1.6}$$

where total production (Q) is a function of farm labour (F) and the quantity of purchased inputs (X_f), including farm-land services and hired labour. Then, the efficiency of farm production depends on human capital and household characteristics (H) as well as other exogenous farm characteristics (Z_f).

This model has been extensively explored empirically in the literature to bestow a better understanding on the functioning of agricultural labour markets. This thesis identifies three leading research topics in the

[8] In the farm household model, human capital includes age, educational level, agricultural education, and experience in farming. In some studies, gender is included in the human capital characteristics (e.g., Skoufias, 1994; Le, 2010; Almeida and Bravo-Ureta, 2019). However, in most empirical studies analysing labour in agricultural economics, gender is considered another exogenous variable.

contributions of recent empirical literature about the functioning of agricultural labour markets i.e., productivity, automation, and supply and demand. This literature review clusters these three main research questions and organises them as subheadings as follows: (2.2) labour and productivity, (2.3) labour and automation, and (2.4) labour supply and demand. Finally, this chapter presents a figure on labour in agricultural economics to provide an indication of the research direction of this thesis.

2.2 Labour and productivity

The main research questions in the literature that studies farm labour productivity do so based on farms' output and profitability. These empirical studies commonly estimate a production or profit function to estimate the productivity of the labour input on the farm. Moreover, the literature highlights the importance of acknowledging the labour force's possible heterogeneous nature when estimating labour productivity in production (Tocco et al., 2012a; Kostov et al., 2019). More specifically, the productivity of labour might be heterogeneous based on the labour force characteristics (gender, human capital i.e., skilled/unskilled, education/experience), the seasonality feature of farm tasks, and the type of labour input (family/hired).

2.2.1 Labour force characteristics and productivity

2.2.1.1. Labour productivity by gender and level of education

The empirical studies that focus on heterogeneous labour productivity by gender frequently use data from developing countries (e.g., Skoufias, 1994; Mathenge and Tschirley, 2015; Almeida and Bravo-Ureta, 2019). The results of differences in productivity by gender are ambiguous. For instance, Corral and Reardon (2001) and Almeida and Bravo-Ureta (2019) find that female labour is more productive. In contrast, Jacoby (1993) finds that male labour is more productive. In turn, Skoufias (1994), Barrett et al. (2008), and Le (2009) do not find significant productivity differentials by gender. The implications of these studies point to labour market imperfections, i.e., the distance between rural areas and cities and accessibility to off-farm markets.

Also, the agricultural education of farmers, household characteristics, and the tasks performed on the farm by gender are the main reasons for finding heterogeneous productivity by gender (Corral and Reardon, 2001; Almeida and Bravo-Ureta, 2019).

The level of human capital, measured by education (general or agriculture-related) and working experience (on-farm and off-farm), is one of the most recurrent variables in the literature on heterogeneous farm labour productivity. A greater skill level of labour is associated with a higher marginal product of labour, ceteris paribus (Benjamin and Kimhi, 2006; Blanc et al., 2008; Kimhi, 2009; Heanue and O'Donoghue, 2014). Moreover, Blanc et al., (2008) and Heanue and O'Donoghue (2014) find that farm productivity is higher if farmers possess formal agricultural education. In turn, other studies find that years of experience in farming are associated with greater productivity for the farmer and farm labour (Feder, 1985; Benjamin and Kimhi, 2006). Finally, the educational level of the farmer and permanence in agricultural production are strongly correlated. In other words, the educational level of the farmer is not only associated with higher levels of labour productivity but also decreases the farm's risk of exiting agricultural production (Bojnec and Dries, 2005; Breustedt, and Glauben, 2007; Tocco et al., 2012a).

2.2.1.2. Seasonal tasks and productivity

Since the seminal work from Nath (1974), the literature underlines the importance of accounting for seasonal production to assess farm labour's heterogeneous productivity. This body of literature divides labour input into separate inputs into the production/profit functions in terms of the seasonality of labour. Most of this literature focuses on developing countries (Nath, 1994; Deolalikar and Vijverberg, 1987; Chowdhury, 2016). Most empirical studies dividing labour input by its seasonal feature find productivity differences given the seasonal feature of labour. More specifically, the marginal product of permanent labour (family and hired labour) and casual hired labour is positive in the case of the seasonal period of production (Tocco et al., 2012a).

In contrast, during the slack production season, the marginal product of (permanent) labour is zero (Benjamin and Kimhi, 2006; Tocco et al., 2012a).

2.2.1.3. Family and hired labour productivity

The differences in farm labour productivity imply distinguishing between family and hired labour. Before the seminal work of Benjamin and Kimhi (2006), most studies considered family and hired labour as perfect substitutes. Therefore, most studies about labour productivity specify it as a single input (family plus hired labour) (Findeis et al., 1991; Tocco et al., 2012b; Bradfield et al., 2021). Nonetheless, several studies acknowledge that there might be different productivity between family and hired labour due to several factors. Such as differing incentives and preferences for farm work, the type of tasks performed on the farm, and supervisory and management costs. Therefore, these factors might motivate different marginal products for family and hired labour.

To discover whether the productivity of the type of labour is identical or not, a body of literature has tested the perfect substitutability between family and hired labour hypothesis (Deolikar and Vijverberg, 1987). The seminal results from Deolikar and Vijverberg (1987) suggest a low elasticity of substitution in family farms, which indicates labour productivity heterogeneity between family and hired labour. The primary justification for this heterogeneity in productivity is that family labour is used permanently, and hired labour is often used seasonally/causally.

Furthermore, another explanation for the productivity differential by type of labour widely explored in family farms concerns the management and supervisory feature of labour tasks. Specifically, some studies argue that family labour is usually more involved than hired labour in the management of the farm (Benjamin and Kimhi, 2006; Blanc et al., 2008; Tocco et al., 2012a; Brennan et al., 2021). Therefore, the productivity findings would often show the best estimate in productivity terms for the family when compared to hired labour (Blanc et al., 2008; Tocco et al., 2012a; Kostov et al., 2019). However, although there is consensus in the literature regarding the heterogeneity of productivity by type of labour, family labour is not always more productive than hired labour (Kloss and Petrick, 2014; Kostov et al., 2018; Kostov et al., 2019).

For instance, Kloss and Petrick (2014) reject the notion that hired labour is generally less productive than family labour. Farms with a higher share of hired workers are more productive than pure family farms in countries traditionally characterised by family labour (Kloss and Petrick, 2014). Moreover, Kostov et al. (2018) findings suggest limited support for the claimed positive productivity effects of family labour, which only materialise after considerable family involvement is committed (Kostov et al., 2018).

An essential part of the literature on farm labour productivity focuses on its role in farms' technical efficiency (TE).[9] TE is a key component of total factor productivity and economic efficiency (Kumbhakar, 1990; Varian, 1992; Kumbhakar et al., 2015). Theoretically, TE indicates how well things are done regarding farm production. Therefore, exploring the role of labour input in the TE of farms is crucial for understanding the productivity of family and hired labour.

2.2.2 Labour and TE

2.2.2.1. Labour efficiency, economic efficiency, and technical efficiency

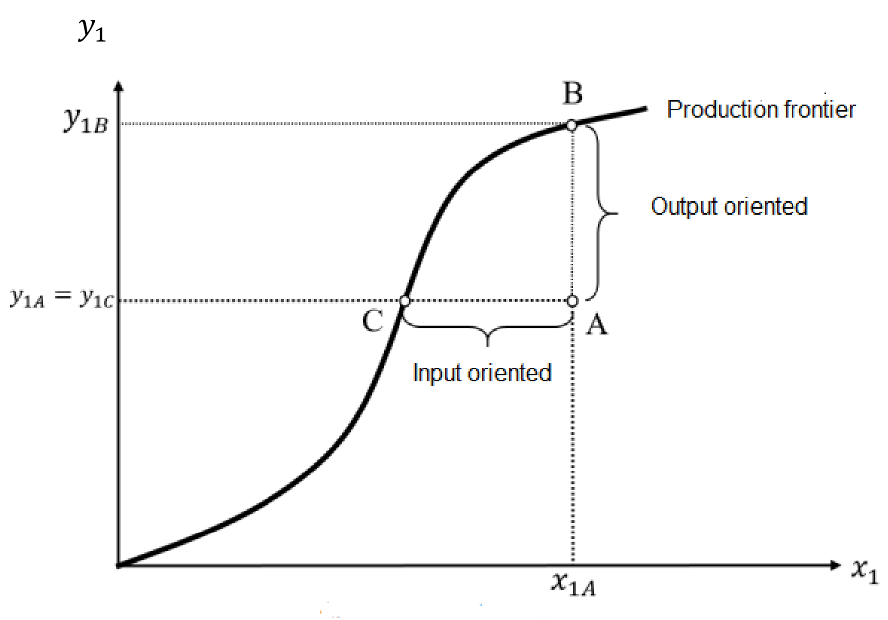
Labour efficiency is the productive ability of a worker to do more or better work, or both, during a given period (Ros, 2013). In the case of agriculture, labour efficiency is defined as the labour hours per unit of production or input. For instance, for cattle and dairy farms, labour efficiency is the annual, quarterly, or monthly hours of labour per cow or livestock unit (Deming et al., 2017; Deming et al., 2018; Martinez-Cillero et al., 2019). In this thesis, we define labour efficiency as the hours of labour per cow/livestock unit annually.

[9] The other components of TFP are allocative efficiency, and technical change (in SFA scale efficiency is also calculated as part of TFP) (Kumbhakar, 1990; Kumbhakar et al., 2015; Gadanakis and Areal, 2018).

Economic efficiency comprises allocative, dynamic, and TE (Varian, 1992). Allocative efficiency is the ability of firms/farms to fulfil consumer demand by distributing goods and services proficiently, given the price level. Therefore, a fully allocative efficient firm/farm would be one whose consumer demand is entirely met by supply (Varian, 1992). Dynamic efficiency refers to the changes in time in allocative and TE, and it is closely related to technological change (Abel et al., 1989; Varian, 1992).

As mentioned, TE is one of the main concepts analysed in Chapter 3 and Chapter 4 of this thesis. Therefore, it is carefully defined here. TE is closely related to production economics because the output is obtained through input utilisation. TE is then estimated through a production, profit or cost function to a set of inputs (i.e., capital, labour, land, and other inputs). The maximum potential any set of inputs can produce is the production frontier. The distance between the production frontier and any farm's actual output is its TE level. Figure 2.1 shows a graphical representation of the production frontier with a single input.

Figure 2.1 Production frontier with a single input



Note: Adapted from Kumbhakar et al., (2015, p. 12).

In Figure 2.1, y_1 represents the output axis, and y_{1A}, y_{1B}, and y_{1C} are different output levels. x_1 is an input used for production; the curve on the graph represents the production frontier. Points A, B and C indicate output levels (y_1) given an input level (x_1). More specifically, point A represents the actual production level of a firm/farm, so the distance from Point A to Point B represents its TE level. The farm would produce with complete TE (i.e., 100% TE score) by reducing this distance from Point A to Point B or C. As this distance is reduced, the TE increases. Two approaches to increase TE are the input-oriented (IO) and output-oriented (OI) approaches.

The IO approach refers to moving from point A to point B with higher TE to produce the same level of output (y_{1A}=y_{1C}) using less input (x_1). The OO approach refers to moving from point A to point C, producing a higher output (y_{1B}) with the same level of input (x_{1A}). This thesis focuses on the OO approach.

In the literature, TE can be estimated non-parametrically through Data Envelopment Analysis (DEA) and parametrically using Stochastic Frontier Analysis (SFA).

2.2.2.2.The DEA approach

Based on the work of Farrell (1957), Charnes et al. (1978) introduce the DEA approach and defines it as a mathematical programming model that identifies economic relations such as production functions and efficient production possibilities using empirical data. Although there are various DEA models in the linear programming literature, the Charnes et al. (1978) DEA model is the most applied in the agricultural economics literature (e.g., Basurto, 2019; Gadanakis and Areal, 2018; Gadanakis and Areal, 2020).

In the non-parametric DEA method, after computing the farm-specific efficiency scores, this approach examines the determinants of inefficiency in a second stage, which is a separate regression (Chavas et al., 2005; Cooper et al., 2011). Truncated regressions or censored Tobit models are often used in this second DEA stage.[10] These studies use labour as an input of the

[10] Simar and Wilson (2007) developed a single and double bootstrap procedure in the DEA framework to estimate TE. The double bootstrap procedure allows valid statistical inference for TE score estimation in the second-stage regression. Moreover, a non-discretionary DEA model can be specified to explain changes in farms TE from inputs that are outside the control of the farmer, e.g., rainfall, length of the growing season, periods of price instability (Gadanakis and Areal, 2020; Gadanakis et al., 2020).

production function. Therefore, they do not define labour as a determinant of TE. However, some studies that apply DEA use labour shares (share of family or hired labour) to analyse its influence on TE of farms (e.g., Olson and Vu, 2009; Maenvska-Tasevska et al., 2011). Only a few studies focus on the role of labour in TE applying DEA; however, precedents exist.

For instance, Manevska-Tasevska et al. (2011) find that a better share of hired labour is associated with higher levels of TE in their sample of farms from Kansas, US. Therefore, smaller farms with more family labour involvement have higher levels of TE. These results are consistent with the DEA applied by Olson and Vu (2009), where a higher proportion of hired labour has a negative effect implying family labour is more crucial than hired labour in improving productivity. However, Kostov et al. (2019) findings suggest that family labour involvement does not significantly affect the efficiency derived from management capabilities on family farms compared to corporate farms. Therefore, Kostov et al. (2019) do not find evidence that can claim that the efficiency of family labour is greater than the efficiency of hired labour. In conclusion, the superiority of family labour over hired labour in terms of efficiency is non-conclusive in the non-parametric TE literature.

2.2.2.3.The SFA approach

Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) introduced the parametric SFA approach into the economic literature. Among others, Kumbhakar and Lovell (2003), Coelli et al. (2005), and Filippini and Greene (2016) define the SFA as a mixed econometric method that accommodates technical inefficiencies and random shocks in the production of agricultural outputs. The SFA models fit a production frontier using either the Cobb-Douglas (CD), the generalised, the *transcendental* or the *translog* specifications (Kumbhakar, 1990; Battese and Coelli, 1995; Kumbhakar et al., 2015). Using the parameter estimates of the frontier, the SFA then computes observation-specific TE scores (Kumbhakar, 1990; Battese and Coelli, 1995; Kumbhakar et al., 2015).

The SFA approach hypotheses the non-negative error term as a function of variables linked to efficiency. Thus, this method estimates a separate equation to identify TE's main determinants (Kumbhakar et al., 2015). Recently, empirical studies have used a single-step maximum likelihood (ML) estimator to simultaneously obtain parameter estimates for both the frontier and the inefficiency equation since this estimator outperforms the two-step DEA procedure (Wang and Schmidt, 2002; Basurto, 2019).

There are two main advantages of the SFA approach compared to DEA. Firstly, deviations from the frontier are not only attributable to TE since it accommodates random shocks. Secondly, the single-step ML method is more consistent and efficient than the two-step DEA procedure (Wang and Schmidt, 2002; Bojnec and Latruffe, 2009; Basurto, 2019).

Previous studies estimating TE applying SFA use the wage rate, number of workers, or working hours per annum to account for labour in the frontier (Basurto, 2019). Although the wage rate measure may capture different levels of workers' skills, it does not consider unpaid family labour. The second measure (number of workers) may misrepresent labour since some farmers hire labour casually and this figure is not always reported (Tocco et al., 2012a; Basurto, 2019). Working hours have the advantage of including and aggregating all sources of labour, including family labour, into a single variable. However, as mentioned, this measure does not distinguish between different types of labour. Some studies introduce education indices to differentiate the type of labour, e.g. high, skilled versus low-skilled workers (Dinar et al., 2007; Basurto, 2019).

Furthermore, regarding managerial practices, the share of family labour to total labour positively affects TE if family members are better skilled (education level) than hired labour or are sufficiently involved in farming activities (Zhu and Lansink, 2010; Basurto, 2019). Conversely, Karagiannis and Sarris (2005) argue that a large share of hired labour to total labour incentivises farmers to be more efficient. They explain this result by assuming farmers aim for higher revenues to clear higher labour costs of hiring additional labour. Also, they suggest that hired labour can be asked and trained to perform tasks more efficiently, which is only sometimes possible with family labour. Their results are consistent with the findings of Bradfield et al. (2021), who find that a higher labour share is associated with higher TE scores. In conclusion, in previous studies of TE applying SFA, hired and family labour roles on TE are positive; however, the specific effect of hired labour on farms TE remains unexplored. Chapter 3 *The role of hired labour on technical efficiency (TE) in an expanding dairy sector: the case of Ireland* in this thesis fills this knowledge gap.

2.2.2.4. Endogeneity in SFA

Previous studies analysing the efficiency of family and hired labour in TE do so by neglecting endogeneity problem when applying SFA. SFA models have endogeneity problems due to (1) a correlation between the inputs and the random error term at the frontier, (2) a correlation between the efficiency effects and the random error term, or (3) a correlation between the use of inputs and TE (Lattrufe et al., 2017; Lai and Kumbhakar, 2018; Lien et al., 2018; Balezenthis and Sun, 2020).

For instance, Latruffe et al. (2017) address the first source of endogeneity by using a 4-step estimation procedure. This issue arises if farmers adjust intermediate inputs (e.g. fertilisers, irrigation or pesticides) as a response to stochastic events (e.g. weather shocks or plagues), which are usually part of the error term. Lai and Kumbhakar (2018) and Balezenthis and Sun (2020) address the endogeneity between the efficiency effects and the random error term by specifying a 4-component stochastic frontier model. Lai and Kumbhakar (2018) address this endogeneity by developing a two-step estimation procedure with a non-generalised least squares feasible estimator.[11] While Balezenthis and Sun (2020) apply an input distance function to the frontier to address the endogeneity between efficiency and the random shocks. This endogeneity problem can arise because the response to stochastic events can be adjusted by the determinants of efficiency specified in the models (subsidies, credit) and the characteristics of the individuals (age). Finally, Lien et al. (2018) address the third type of endogeneity (between inputs and efficiency effects) by specifying a two-step semi-

[11] An essential drawback of the methodology developed by Lai and Kumbhakar (2018) is that their model only converges with balanced panel data sets.

parametric procedure. This endogeneity arises since any input from the production function can also be an efficiency driver and vice-versa (e.g., capital, labour, subsidies, grants) (Basurto, 2019; Musuau et al., 2021). To the best of our knowledge, none of the studies addressing the endogeneity issue in the SFA models explicitly study the effect of labour on TE.

This thesis considers it essential to isolate the causal effect of hired labour in TE of family farms. In this way, it contributes to the discussion of the productive heterogeneity of the type of farm labour in the context of family farming. Obtaining a positive causal effect of hired labour on family farms' TE would answer whether hired labour is skilled and up to the challenge of helping farm efficiency. To the best of our knowledge, the effect of hired labour on the TE of farms addressing the endogeneity issue in SFA has yet to be explicitly studied. Chapter 3 of this thesis contributes to the literature by exploring the specific effect of hired labour on farms TE.

2.3 Farm labour and automation

Automation and labour are the key factors in explaining the economic growth and development of the 20th century. Specifically, *labour's push* and *pull* channels are identified as the main drivers of economic growth and development (Álvarez-Cuadrado et al., 2011; Bustos et al., 2016). The *labour push* channel refers to the new technologies in agriculture that caused an increase in the total productivity of the sector. Then, the *labour push* channel caused the large-scale movement of workers from agriculture to industry (Lewis, 1954; Bustos et al., 2016). For instance, the mechanisation of agriculture in the 19th century (e.g., horse-powered reapers, harvesters, and ploughs) and in the 20th century (e.g., tractors and combined harvesters) majorly displaced agricultural workers to the industry (Alvarez-Cuadrado et al., 2011). The *labour pull* channel refers to technological progress in the industry that increased the demand for labour from agriculture (Bustos et al., 2016). The *labour pull* channel dominated until 1920, and the *labour push* channel dominated from 1960 (Álvarez-Cuadrado et al., 2011). Since these labour flow movements from agriculture to other sectors have ended for most countries (Ros, 2013), the focus of the literature on automation has shifted towards its implications on productivity and efficiency (Acemoglu and Restrepo, 2017; 2018; 2019).

Automation and labour should always be analysed hand in hand. Automation has two main labour-related effects, i.e., labour-saving and labour-productivity. The labour-saving effect refers to automated technologies replacing labour in production (Acemoglu and Restrepo, 2017). This labour-saving effect is not the only effect of automation in labour; if so, robots would have already replaced the entire labour force (Acemoglu and Restrepo, 2011; 2018). Therefore, the labour-productivity effect refers to the reallocation of labour in new tasks (due to automation) with higher labour productivity (Acemoglu and Restrepo, 2018; 2019).

For instance, automation changes the labour demand over time, affecting other spheres of labour input and the labour market. More specifically, when a technological change is motivated by automation, the first effect it has on labour is the labour-saving effect (Acemoglu and Restrepo, 2018). However, these laid-off workers can find a way out of unemployment and find new employment by dedicating time to training and labour development to further increase their skills and human capital (Acemoglu and Restrepo, 2017; 2018). This change in the demand for labour is known as the labour-productivity effect. The literature review section in Chapter 4 Automation and efficiency: a latent class analysis of Irish dairy farms, provides a more detailed review of automation's labour-saving and labour-productivity effects.[12]

Previous empirical studies that analyse the role of automation in productivity focus on macro-level or intersectoral data (D'Antoni, 2011; Acemoglu and Restrepo, 2017; 2019), and very few analyse the agricultural sector (Lin, 2011; Acemoglu and Restrepo, 2018). Therefore, few studies focus on analysing the role of automation in productivity at the micro-level. For instance, Sheng et al. (2015) and Sheng et al. (2016) explore the role of

[12] Automation has other impacts on labour. For example, the labour-saving effect of automation can have mental health impacts on people. It has been found that being replaced by a robot, or an automated technology is a growing stress and anxiety-related concern for workers in all sectors of the economy (McLure, 2018). However, this topic exceeds the analytical limits of this PhD thesis, and it is not further discussed in the document.

automation and farm size in the productivity of farms. Their findings suggest that adopting automated technologies is crucial in increasing productivity rather than increasing farm size alone.

An important limitation of the literature regarding automation on farms is that it mainly focuses only on one automated technology, e.g., robotic milking parlours in dairy farms. For instance, previous studies focus on comparing the productivity and efficiency between adopters and non-adopters of robotic milking parlours (Kompas and Che, 2006; Steeneveld et al., 2012; Salfer et al., 2017; Alem et al., 2019). The findings from these previous studies suggest that adopting robotic milking parlours is generally associated with increased productivity and efficiency (Kompas et al., 2006; Salfer et al., 2017; Alem et al., 2019). However, Steeneveld et al. (2012) and Steeneveld et al. (2015) do not find an explicit substitution of capital for labour or significant differences in efficiency between adopters and non-adopters of robotic milking systems. Moreover, the role of other milking management technologies (i.e., automated feeders, cluster-removers, scrapers, washers) on farm productivity and efficiency is, unexplored. Consequently, the role of automation in productivity and efficiency at the farm level remains unclear. Chapter 4, *Automation and efficiency: a latent class analysis of Irish dairy farms*, fills this knowledge gap.

Finally, focusing only on farm and farmer characteristics and neglecting the performance and aim of the automated technologies is another area for improvement in the literature (Oca-Munguia and Llewelyn, 2020). Therefore, it is crucial to understand automated technologies' performance and specific aims while exploring their role in farm productivity and efficiency (Macours, 2019). This way, the role of automated technologies in the productivity and efficiency of farms can result in more specific policy recommendations. For instance, automation can increase the farmer's overall workload if the automated technology requires increased management hours. Chapter 4 of this thesis also focuses on understanding the aim and performance of several automated technologies that aim to reduce labour-intensive tasks in the milking process.

2.4 Labour supply and demand

2.4.1 Farm labour supply

One of the leading research questions in the literature is how farmers and family labour allocate their time to on- and off-farm work. Most empirical studies that analyse on- and off-farm labour allocation do so by estimating labour supply functions (Jacoby, 1993; Ahituv and Kimhi, 2002; Almeida and Bravo-Ureta, 2019). The labour supply functions heavily rely on the farm household framework. Hence, they are conditional on the farm production function (Skoufias, 1994; Benjamin and Kimhi, 2006; Almeida and Bravo-Ureta, 2019).

There are two main methods in the literature to estimate labour supply functions. The first method uses a production function's estimated values as determinants of the labour supply function (Findies et al., 1991; Tocco et al., 2012a). The second method, more widely used, estimates equations in reduced form. Therefore, this method incorporates exogenous variables that also follow the agricultural production function as determinants of the labour supply function (Goodwin and Holt, 2002; Benjamin and Kimhi, 2006). The main exogenous determinants studied are non-agricultural wages, farmer and family characteristics, and financial characteristics (Lass et al., 1991; Goodwin and Holt, 2002; Tocco et al., 2012a).

Findings in the off-farm supply functions literature indicate that off-farm wages increase days/hours supplied off-farm (Lass et al., 1991; Goodwin and Holt, 2002; Tocco et al., 2012a). Farmer education level has a mixed effect on off-farm labour supply. On the one hand, it increases the possibility of off-farm work but also could reduce off-farm labour supply since education increases on-farm productivity (Jensen and Salant, 1985; Goodwin and Holt, 2002; Hennessy and Rehman, 2007). Moreover, the positive effects of education on off-farm labour supply increase when farm spouses also work off-farm (Huffman and Lange, 1989; Corsi and Findeis, 2000; Goodwin and Holt, 2002) [13].

Regarding the household size and the number of children, it is generally found that the number of children decreases the hours of work supplied off-farm (Huffman and Lange, 1989; Mishra and Goodwin, 1997; Goodwin and Hold, 2002). However, increased household members are commonly associated with increased off-farm labour (Goodwin and Holt, 2002). Other income and social benefit payments tend to be associated with fewer hours supplied off-farm (Hennessy and Rehman, 2007; 2008). Finally, decoupled subsidies are positively associated with off-farm labour supply (Jensent and Salant, 1985; Hennessy and Rehman, 2008).

For on-farm supply functions, studies use similar determinants for off-farm supply functions (Fall and Magnac, 2004; Rizov and Swinnen, 2004). The main variables that increase on-farm supply are the agricultural education of the farmer, the age of the farmer, on-farm labour returns, output prices, land ownership, farmer gender (male), livestock units, and investment in machinery and buildings (Tocco et al., 2012a). Conversely, the variables that decrease on-farm labour supply are off-farm market wages and other income sources (Rizov and Swinnen, 2004; Tocco et al., 2012a). Finally, farm household size positively (e.g., Blanc et al., 2008; Almeida and Bravo-Ureta, 2019) and negatively (e.g., Fall and Magnac, 2004; Rizov and Swinnen, 2004) affects on-farm labour supply.

Furthermore, most empirical studies in the farm labour supply literature have relied on the assumption of perfect competition (Lopez, 1984; Jacoby, 1993; Almeida and Bravo-Ureta, 2019). This perfect market assumption indicates that farm production decisions are separable from household consumption decisions (Skoufias, 1994; Tocco et al., 2012b). Therefore, as shown above, most studies have treated the farm production variables as exogenous factors in the labour supply functions. As argued by Lopez (1984), Jacoby (1993)

[13] However, a simultaneous estimation of farm households' labour supply and production decisions suggests that education increases both off- and on-farm labour supply. The impact of education is larger on the off-farm labour supply (Lopez, 1984; Skoufias, 1994; Almeida and Bravo-Ureta, 2019).

and Skoufias (1994), farm households' utility and profit maximisation decisions are not likely to be independent. Thus labour supply and production decisions should be analysed simultaneously to avoid biased results and implications (Tocco et al., 2012a).

2.4.1.1. Shadow wages of family labour and labour supply

The studies that simultaneously estimate labour on - and off-farm supply functions on family farms also estimate the shadow price (i.e., wage) of unpaid family labour (e.g., Barrett et al., 2008; Le, 2009; Karimov, 2013; Almeida and Bravo-Ureta, 2019). A shadow price is an estimated price for something that is not regularly priced or sold in the market (Riley, 2012). Therefore, the shadow wage of family labour provides an economic market value to unpaid farm labour (Le, 2009). The method applied in studies that simultaneously estimate labour supply functions and shadow wages, consist of also specifying a farm production function from which the marginal products of labour are used to derive the shadow wages (Jacoby, 1993; Skoufias, 1994; Le, 2009; Almeida and Bravo-Ureta, 2019).

Following this method, the literature focuses on the role of shadow wages in the labour supply functions on different types of farms, e.g., rice producers (Barrett et al., 2008), crop farmers (Le, 2009), vegetable farms (Karimov, 2013), and crops and livestock farmers (Almeida and Bravo-Ureta, 2019). These studies also calculate the shadow income of the farm (i.e., the farm's income if family labour gets paid their shadow wage) to analyse its role in off-farm labour supply. The results suggest a shadow wage gap by gender, and female workers tend to work more hours off-farm than male workers. Increases in the shadow income of the farm are commonly associated with more hours supplied off-farm by farmers and spouses. Finally, as for dairy farms, Bezlepkina et al. (2005) analysed a sample of specialised dairy farms in Russia. They focus on the role of subsidies in short-term profits and estimate the specific shadow prices of all inputs. Their results suggest that labour, land, and livestock hold lower shadow prices than capital input. However, to the best of our knowledge, there are no previous studies available that focus on the shadow wage of farm family labour on dairy farms. Chapter

5 in this thesis contributes to the literature by estimating the shadow wage of family labour on Irish dairy farms.

2.4.2 Farm labour demand

The literature focuses on analysing the determinants of the demand for on-farm labour. A farms' technology and structure are essential determinants of the demand for farm labour. Specifically, farm size, specialisation level, and productivity are determinants of changes in the demand for on-farm labour (Kimhi, 2009; Tocco et al., 2012a). Moreover, larger farms usually require more labour, increasing the total demand for farm labour (Kimhi, 2009; Anderson, 2020). However, larger farms often require less labour input per unit of output (Kimhi, 2009; Anderson, 2020; Kelly et al., 2020). This latter result suggests that economies of scale increase labour efficiency by livestock, herd size units (Glauben et al., 2003). Also, the type of farm structure (i.e., family farm, co-ownership/cooperative, corporate) influences the demand for on-farm labour (Kancs et al., 2009).

Several previous studies explore the demand for hired labour on family farms (e.g., Bardhan, 1984; Allen and Lueck, 1998; Benjamin and Kimhi, 2006). Farm production characteristics and human capital of the farmer strongly correlate with hired labour demand on family farms (Blanc et al., 2008; Benjamin and Kimhi, 2006; Kimhi, 2009). The level of education of the farmer is positively associated with the decisions to hire labour (Benjamin and Kimhi, 2006; Kimhi, 2009). This result implies that educated individuals might be more inclined to seek off-farm employment, reducing their on-farm work, and thus requiring hired labour for their farm (Blanc et al., 2008). Formal agricultural education is also associated with increased hired labour demand.[14] This result may suggest that educated farmers are more efficient, which allows them to hire more labour and dedicate themselves to managerial tasks or leisure (Benjamin and Kimhi, 2006; Kimhi, 2009; Tocco et al., 2012a). Moreover, the scale of the farm is also an important factor to increase

[14] Agricultural training and farm experience similarly affect hired labour demand (Tocco et al., 2012a).

hired labour demand (Benjamin and Kimhi, 2006; Blanc et al., 2008; Kimhi, 2009).

Furthermore, more family farm members are commonly associated with lower demand for hired labour (Kimhi, 2009). However, additional household members are sometimes associated with increased hired labour demand in a context where larger farms are equal to larger farm households (Darpeix et al., 2014). Farm subsidies correlate with decreased hired labour demand by incentivising family participation (Benjamin and Kimhi, 2006). Finally, a structural improvement on the farm that often implies higher farm productivity is associated with a higher demand for hired labour on family farms (Blanc et al., 2008; Kimhi, 2009). To the best of our knowledge, no previous study explicitly analyses the role of shadow wage and shadow income of family labour on demand for hired labour on family farms. Chapter 5 in this thesis, *Shadow wage of family labour and its role in hired labour demand: evidence from Irish dairy farms*, fills this knowledge gap.

Finally, Figure 2.2 summarises the main issues raised in this chapter and addressed in this PhD thesis.

Figure 2.2 Conceptual framework and research direction of this thesis

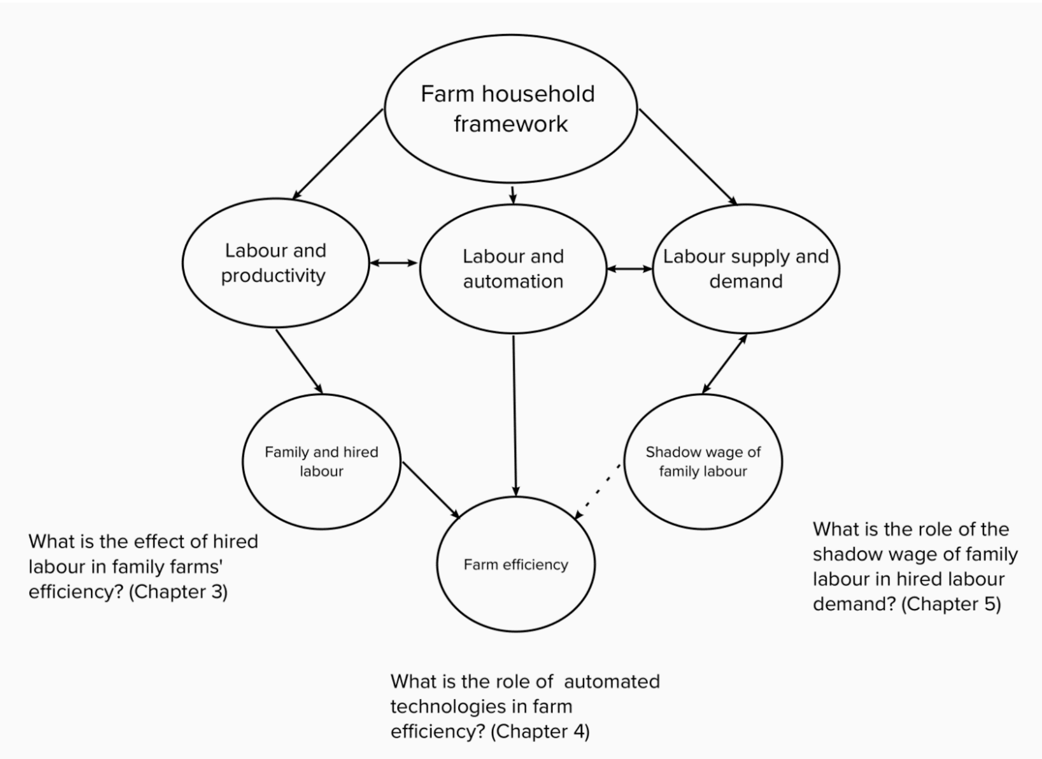


Figure 2.2 shows how, within the conceptual framework of the farm household model, the leading research questions in the literature are closely interrelated. As mentioned, labour is always linked to the automation process, thus, to farm productivity. These farm labour phenomena are related to farm labour's supply and demand. This thesis identifies three main knowledge gaps that are the research direction of the thesis.

First, this thesis explores farm efficiency (Chapter 3 and Chapter 4). More specifically, it explores the effect of hired labour on the efficiency of family farms, thus answering whether hired labour is up to the recent challenges related to increased workload faced by farms in an expanding dairy sector (Chapter 3).

Furthermore, the thesis explores the role of automation of the milking process in farm efficiency and describes in detail the interrelation between automation and farm labour (Chapter 4). Finally, this thesis estimates the economic value i.e., shadow wage of family labour to explore its role in the demand for hired labour (Chapter 5). In this way, it discusses the implications of changes in the shadow wage of family labour and its relationship with the demand for both casual and permanent hired labour in a family farming dairy sector. As Figure 2.2 shows with a dot arrow, this thesis does not explore the role of shadow wage of family labour on farm efficiency. Overall, the thesis contributes to the ongoing debate on how farm labour (i.e., availability, efficiency, economic value, and demand) and its relationship to technology are critical to maintaining the productivity and efficiency of the dairy sector in the 21st century.

Chapter 3 - The role of hired labour on technical efficiency in an expanding dairy sector: the case of Ireland

3.1 Introduction

The European dairy sector has experienced significant structural change initiated by the abolition of milk quotas in 2015. Some countries have contracted their dairy sector (e.g., Bulgaria and Romania), while others have significantly expanded their milk production (e.g., the Netherlands and Ireland) (EU-FADN, 2018; Augère-Granier, 2018). These adjustments in dairy production have led to changes in labour demand on farms (Kimhi, 2009; Kelly et al., 2020).

Ireland is one of the countries that has experienced significant growth in its dairy sector due to milk quota abolition. Between 2008 and 2018, the volume of milk produced has increased by over 50% (CSO, 2020). As the majority of dairy farms in Europe and Ireland are family farms (96% and 99%, respectively) (Augère-Granier, 2018; EuroStat, 2018), a significant concern arises from the mismatch of increasing herd size and labour availability (Deming et al., 2018; Kelly et al., 2020). Indeed, the increase in herd size and labour on dairy farms has been quite uneven (Dillon et al., 2019; Kelly et al., 2020). This is reflected in the fact that the average herd size increased by 47% but total labour hours only by 16% between 2008 and 2018 (Donnellan et al., 2019) which suggests that more labour is required to achieve sustainable growth. Although family labour may be a temporary relief to labour shortages, the structural change leading to significant growth in average herd size requires additional non-family labour (Thorne et al., 2017; Kelly et al., 2020). In other words, when farms grow, family labour is used more intensively first, but for continued expansion, farms need additional hired labour to meet the increasing workload (Blanc et al., 2008).

Irish dairy farms are primarily pasture-based with a spring calving system. The Irish dairy sector relies on a mild and rainy climate suitable for growing grass for most of the year. While this gives the Irish dairy sector a comparative advantage in producing milk (Thorne et al., 2017; Läpple et al., 2020), the downside of such a production system is an uneven demand for labour throughout the year, which makes sourcing additional labour more challenging. More specifically, demand for labour peaks in February to June due to calving and breeding which occur during this period of the year (Dillon et al., 2019). These months represent half of the annual workload on Irish dairy farms (Deming et al., 2018; Dillon et al., 2019).

Therefore, the role of hired labour (i.e., permanent and seasonal) has become crucial. However, an additional challenge relates to sourcing workers that have adequate skills to conduct the required tasks on the farm. Anecdotal evidence suggests that it is not easy to source such labour, but some programmes exist to facilitate access (Kelly et al., 2017). This challenge also relates to technology improvements (Kimhi, 2009; Kelly et al., 2020). For instance, investment in machinery, livestock and buildings on dairy farms increased on average by 36% from 2008 to 2018 (Dillon et al., 2019). Thus, on top of the general challenge of labour availability, the need for skilled labour has become an extra hurdle for dairy farmers.

In addition, farmers can be hesitant to hire labour. For instance, in 2018, only 11% of dairy farmers stated that they plan to hire extra labour within the next five years (Dillon et al., 2019). However, 34% of farmers plan to expand their production in the same period, and only 7% of those who plan to expand their production also plan to hire more labour. Exploring this data in more detail reveals that most farmers (i.e., 71%) also have no plans to invest in labour-saving technologies. This data suggests that farmers are reluctant to hire additional labour. This decision may be driven by the belief that family labour is more suitable for their farm. This belief goes hand in hand with anecdotal evidence suggesting a reluctance to delegate the workload to non-family labour on the farm. All of this is surprising, given that the increased workload associated with larger herds has become a significant source of stress for Irish farmers (Kelly et al., 2020, Brennan et al., 2021).

The literature highlights the importance of hired labour in estimating farms' technical efficiency (TE) (Devadoss and Luckstead, 2018; Kostov et al., 2019). However, very few studies focus on the direct role of hired labour on TE, but rather focus on other determinants of TE, e.g., off-farm work, farm size, subsidies, or direct costs (e.g., Carroll et al., 2011; Wollni and Brümmer, 2012; Martinez-Cillero et al., 2019). This chapter explores the role of hired labour on farms' TE in a family farming context. We consider it important to address the role of hired labour on TE.[15] Since TE is *doing things right*, a positive role of hired labour on farms TE may suggest that such labour is suitably skilled and equipped to improve farm efficiency (Kostov et al., 2019). This result would indicate that hired labour can assist in meeting some of the challenges posed by production expansion in the aftermath of milk quota abolition and assist in reducing farmers' hesitancy towards hiring labour.

In our analysis, we use a representative panel data sample of Irish dairy farms from 2000 to 2018. The period under investigation includes a significant agricultural policy change, i.e., milk quota abolition, which led to increased production, larger farms, and higher demand for additional labour. Therefore, it is essential to acknowledge the relevance of time when estimating the role of hired labour on TE.

Since TE may have short (i.e., transient) and long-run (i.e., persistent) components over a long period, splitting the efficiency term according to a farms' transient and persistent TE may also have important policy implications. For example, consideration could be given to when TE is associated with (unobserved) management, which is assumed to be time-invariant. Consequently, TE will also be time-invariant, at least in part. Now, more realistically, if we assume management changes over time, it will have a time-invariant and a time-varying component. If TE is associated with management, we have a situation in which TE has a time-invariant and a time-varying component (Tsionas and Kumbhakar, 2014). This brief example illustrates time-invariant and varying determinants that influence farms' TE

[15] The pronouns *we/us/our* are used in Chapters 3, 4, and 5, to comply with the guidelines of journals. These guidelines require to use the first person to indicate the researcher's or research team's actions.

(Tsionas and Kumbhakar, 2014; Lai and Kumbhakar, 2018). Recognising this difference, we estimate transient and persistent TE for Irish dairy farms considering the importance of time and the time-varying property of hired labour in TE estimation. Finally, we analyse dairy farms' TE during three distinct stages of EU milk quota abolition since the difference in TE scores can result in varying policy implications over a long period. These relate to the quota (2000-2007), soft landing (2008-2014), and post-quota periods (2015-2018).

This chapter offers two explicit contributions to the existing literature. First, we explore the effect of hired labour on TE in a predominantly family farming context, which has —to the best of our knowledge— not been explicitly studied before. As outlined above, the significant structural change initiated by EU milk quota abolition led to increased demand for hired labour. However, due to uncertainty about sourcing and quality of hired labour, the effect on farm economic efficiency is unknown at present. This study aims to fill this knowledge gap. Second, on the methodological side, following Lien et al. (2018), we apply a state-of-the-art stochastic frontier (SF) model that accounts for endogeneity, a problem frequently disregarded in the SF literature (Badunenko and Kumbhakar, 2017; Lai and Kumbhakar, 2018). Thus, we get consistent estimates of all parameters that we report.

The chapter proceeds as follows. The following section provides background information about the Irish dairy sector—section 3.3 reviews relevant literature on labour and TE in agricultural economics and transient and persistent TE literature. Section 3.4 describes the methodology, while section 3.5 explains the data and the empirical specification. Section 3.6 presents and discusses the results, while section 3.7 offers concluding remarks.

3.2 Background

Due to the temperate climate in Ireland, the Irish dairy sector is a pasture-based production system, which allows for the outdoor grazing of cows for most of the year (Läpple et al., 2020). This competitive advantage makes Irish dairy farms the second-lowest cash-cost production system in the EU, surpassed only by Belgium (Thorne et al., 2017; Kelly et al., 2020). Against this backdrop, the Irish dairy sector experienced significant change initiated by EU milk quota abolition.

The EU milk quota system was introduced in 1984 and constrained milk production growth for over 30 years. The European Common Agricultural Policy (CAP) Mid-Term Review discussed abolishing EU milk quotas in 2003. However, it took until the 2008 CAP Health Check to confirm its abolition in 2015. Thus, the elimination of milk quotas was a gradual process. For instance, the EU implemented increases in milk quota of 1 to 1.5% annually between 2008 and 2014 (known as the soft landing period). Moreover, in 2008, the Irish government set a target to increase milk production volume by 50% by 2020 compared to the 2007 to 2009 base (Läpple and Hennessy, 2012; Kelly et al., 2020). The Irish dairy sector exceeded this target two years ahead of time in 2018 (Kelly et al., 2020).

Needless to say, this major growth in milk production initiated significant changes at the individual farm level that posed challenges to farmers. Due to these recent adjustments in the dairy industry, one of the main challenges for the predominantly family farm dairy sector is the availability of skilled labour (Kelly et al., 2020). To overcome this problem, some programmes have been implemented to facilitate farmers' access to hired labour (Kelly et al., 2017). For instance, Farm Relief Services (FRS) is a farmer-owned cooperative that provides skilled labour to meet farmers' labour requirements (FRS, 2020). In addition, the Macra Land Mobility Service (MLMS), a farmer collaborative enterprise, aims to ease increased workload on dairy farms (MLMS, 2021). In addition, labour shortages are seen as a major stress factor (Kelly et al., 2017) and, despite these programmes, in 2018, around 36% of dairy farms did not employ hired labour (Donnellan et al., 2019).

3.3 Literature

3.3.1 Labour and TE in agricultural economics

While TE in agriculture has received significant attention in the literature (e.g., Aigner et al., 1977; Battese and Coelli, 1992; Sabasi et al., 2019; Martinez-Cillero et al., 2021), few studies examine the role of hired labour on TE. However, one aspect of the literature focuses on contrasting farms' TE between family and corporate farms, i.e., those managed by hired labour (Kostov et al., 2018). Thus, empirical studies often neglect the direct role of hired labour in family farms' TE. For instance, Kloss and Petrick (2018) analyse hired and family labour productivity in panel data across eight EU countries. Their results suggest that hired labour is more productive than family labour in countries characterised by family farms, i.e., France, West Germany, and Poland (Kloss and Petrick, 2018). They find the opposite result in the UK sample. This conflicting result may be due to the prevalence in the UK of smaller farms where farmers supervise paid and unpaid labour (Kloss and Petrick, 2018). In a cross-sectional sample, Kostov et al. (2019) analyse the comparative TE of family and corporate farms in four EU countries, i.e., the Czech Republic, Hungary, Romania and Spain. Their findings suggest that family farms have higher TE due to better motivation and lower management costs. However, if family labour involvement is low, family farms do not compare favourably to corporate farms' TE. Also, their results suggest that insufficient managerial capabilities limit family farms' output potential (Kostov et al., 2018; 2019). Hence, from these studies, the specific role of hired labour on farms' TE remains ambiguous.

In a slightly different context, several studies explore the role of labour allocation decisions on farms' TE. For instance, on US dairy farms, studies find a negative and significant correlation between off-farm work and TE (Fernandez-Cornejo et al., 2007; Sabasi et al., 2019). However, in a sample of Slovenian dairy farms, the results of Bojnec and Ferto (2013) suggest the opposite correlation. In addition, using a sample of Spanish dairy farms, Alvarez et al. (2008) conclude that farms with labour-saving technologies are closer to their stochastic frontier.

Several studies explored TE on Irish dairy farms. For example, Kelly et al. (2012) and Kelly et al. (2013) used a representative sample of farms to calculate TE and achieve TE scores between 76%-83%. Factors such as breeding season length, milk quality, discussion group membership, and soil quality are associated with TE. Moreover, high labour intensity correlates with optimal scale. Carroll et al. (2011) apply SFA to a panel of a representative sample of Irish dairy farms and show that efficiency levels correlate with extension use, soil quality, farm size, and the level of dairy specialisation. Bradfield et al. (2021) estimate an SFA for a cross-section of Irish dairy farms from 2014 to explore the correlation of land fragmentation with TE. Their results yielded an average TE score of 91% for dairy farms in their sample. Furthermore, higher levels of TE are correlated with increased parcel area, reduced travel distances, contact with advisory services, and intensive practices (Bradfield et al., 2021). Similarly, in a large panel (1975-2012), Gillespie (2015) applies SFA and finds that Irish dairy farms are efficient over the observed forty years period.

3.3.2 Transient and persistent TE

Transient and persistent TE was first introduced by Kumbhakar and Heshmati (1995). However, the authors neglected firm effects and assumed that the time-invariant component is due to persistent TE (Agasisti and Gralka, 2019). This drawback was solved by Colombi et al. (2014), Kumbhakar et al. (2014), and Tsionas and Kumbhakar (2014). They developed a novel approach that resulted in a four-way error component model, i.e., latent heterogeneity of firms, transient and persistent TE, and random shocks. The model is known as the homoscedastic Generalised True Random Effects (GTRE) (Tsionas and Kumbhakar, 2014).

Since the development of the persistent and transient TE model, only a few empirical applications are available in the agricultural economics literature. For example, Kumbhakar et al. (2014) apply the model to a panel data set of Norwegian grain farms. They benchmark the model to previous panel SFA approaches, finding that efficiency results are sensitive to model specifications. The variability of the results demonstrates the difficulty in 'correctly' measuring efficiencies (Kumbhakar et al., 2014: p.335). Thus, they suggest that the model selection for the empirical estimation of TE scores should rely on a comprehensive understanding of the data's institutional and production environment (Kumbhakar et al., 2014; Badunenko and Kumbhakar, 2016).

Following transient and persistent TE, Badunenko and Kumbhakar (2016) use, among other panel sets, the Spanish dairy farm data from Alvarez et al. (2008). They find that not accounting for transient and persistent TE leads to an underestimate of overall TE. Additionally, they show that persistent and transient TE are more accurate in data sets where the time series is small and the number of firms is large. Another example is Pisulewski and Marzec (2019) who analyse a panel of Polish crop farms. They conclude that agricultural policy should focus on factors assumed to influence transient inefficiencies, e.g., adopting new technologies, managerial skills, grants and subsidies, or seasonal hired labour. These applications, along with the GTRE model's estimation through a one-step maximum likelihood approach in Filippini and Greene (2016), have the drawback that only unobservable factors determine transient and persistent TE.

3.3.2.1. Endogeneity in transient and persistent TE models

SFA endogeneity is a common problem when determining TE terms (Battese and Coelli, 1995; Lai and Kumbhakar, 2018; Baležentis and Sun, 2020). However, in the standard GTRE model, endogeneity of TE components is not considered due to the assumptions of homoscedasticity in the error term. Not addressing endogeneity in the GTRE model leads to biased output elasticities in the production function and an underestimation of TE scores (Lai and Kumbhakar, 2018; Lien et al., 2018). This shortcoming was solved by Badunenko and Kumbhakar (2017), Lai and Kumbhakar (2018); Lien et al. (2018), and Baležentis and Sun (2020).

Badunenko and Kumbhakar (2017) apply a heteroscedastic GTRE to a sample of Indian financial banks. Their model is a one-step maximum likelihood approach to allow TE's determinants. Lai and Kumbhakar (2018) propose a one-step approach to specify inefficiency determinants to a dataset of U.S.

power plants. Within the agricultural economics literature, Lien et al. (2018) propose a multi-step approach to specify a heteroscedastic GTRE model that allows for determinants of transient TE. They apply the model to a sample of Norwegian crop-producing farms. The main advantage of the multi-step approach of Lien et al. (2018) is that the production parameter estimates are not biased by distributional assumptions which are central to a one-step procedure. Finally, another method to address endogeneity in the GTRE model is the approach taken by Baležentis and Sun (2020). They apply an input distance function method, which represents the frontier (Levinsohn and Petri, 2003; Shee and Stefanou, 2015), for a Lithuanian dairy farms sample.

In the empirical analysis below, we focus on the role of hired labour on farms' transient TE. That is, we address the endogeneity between inputs and the GTRE's error term to estimate the marginal effects of hired labour in transient TE (Lien et al., 2018). In this way, we explore the relationship between hired labour and dairy farms' TE in a predominantly family farming context.

3.4 Methodology

SFA is a widely implemented frontier estimation method to obtain TE measures. However, in SFA endogeneity arises when inputs are also determinants of TE (Kumbhakar et al., 2003; Kumbhakar et al., 2015), but this problem is often ignored in TE analyses (Lai and Kumbhakar, 2018; Lien et al., 2018). We address this problem by estimating a GTRE model (Kumbhakar et al. 2014) that controls for endogeneity between inputs and TE components following a method outlined by Lien et al. (2018). This way, we estimate the latent heterogeneity of Irish dairy farms, as well as transient, persistent, and overall TE scores. Finally, we estimate the corresponding marginal effects of transient TE's determinants following Wang (2002; 2005).

3.4.1 GTRE addressing endogeneity

As mentioned in Chapter 2, addressing the endogeneity issue that arises in TE when identifying the efficiency drivers in an SFA model is essential to obtain consistent and unbiased marginal effects. SFA models have endogeneity problems due to (1) a correlation between the inputs and the random error term at the frontier, (2) a correlation between the efficiency effects and the random error term, or (3) a correlation between the use of inputs and TE drivers (Lattrufe et al., 2017; Lai and Kumbhakar, 2018; Lien et al., 2018; Balezenthis and Sun, 2020). This Chapter addresses the endogeneity between the use of inputs and TE drivers.

Lien's et al. (2018) method is an updated version of Kumbhakar's et al. (2014) homoscedastic GTRE model. In the approach of Lien et al. (2018) the transient technical inefficiency (i.e., the flip side of TE) component is not homoscedastic. Its mean and variance are a function of inefficiency determinants that are time-variant (Musau et al., 2021). Thus, the transient inefficiency component is heteroscedastic. We keep the distributional assumptions of the persistent inefficiency term and random shocks as homoscedastic.

Step 1. Estimates of the production function and the composed error term

Following Kumbhakar et al. (2014), we define a Cobb-Douglas (CD) production function as follows:

$$y_{it} = \beta_0 + f(x_{it};\beta) + A_{it} \tag{3.1}$$

where y_{it} is output for farm i in time t. x_{it} are the inputs for farm i in time t for the CD production function ($i.e., f(x_{it};\beta)$). The composed error term (A_{it}) includes the latent heterogeneity of farms, persistent and transient inefficiency, and random shocks. The GTRE model by Kumbhakar et al. (2014) is homoscedastic; that is, all the $\hat{A}_{it}$ components are assumed to be random, independent, and identically distributed (i.e., *iid*) (Colombi et al., 2014; Filippini and Greene, 2016). To allow for determinants of technical inefficiency, Lien et al. (2018) propose a multi-step approach where the transient technical inefficiency term is a function of time variant observable determinants. Thus, we rewrite Eq. (3.1) as follows:

$$\hat{Y}_{it} = \hat{\beta}_0 + \sum_{j=2}^{J} \beta_j \hat{X}_{jit} + \hat{A}_{it} \tag{3.2}$$

where $\hat{Y}_{it} = \ln(\hat{y}_{it}/X_{1it})$ is the natural logarithm of the ratio of the dependent variable for the *ith* farm in time t and input X_1. $\hat{X}_{jit} = \ln(X_{jit}/X_{1it})$, $j = 2, \ldots, J$ is the natural logarithm for the ratio of each input in the production function to input X_1. And $\hat{A}_{it}$ is the estimated error term that includes four components (i.e., latent heterogeneity of farms, transient and persistent inefficiency, and random shocks).

A fundamental assumption of the Lien et al. (2018) model is that the producers' objective maximizes the return to outlay (i.e., total revenue divided by total cost). Thus, the model allows both inputs and output to be correlated with inefficiency and random shocks. In this way, the production function in Eq. (3.2) is homogeneous of degree 1 in inputs at the equilibrium (Lien et al., 2018). This degree 1 homogeneity means that the estimated returns to scale are constant by model construction (Lien et al., 2018). To test the validity of this assumption, we estimated constant returns to scale following Kumbhakar's et al. (2014) model (not reported here) and achieved almost constant returns to scale (i.e., 1.03). Moreover, our estimate is consistent with previous empirical analyses in the sector, obtaining constant returns to scale that span between 1.00 and 1.07 (Carroll et al., 2011; Kelly et al., 2013; Bradfield, 2021). Consequently, we assume that the assumption of maximizing return to outlay is valid for our data from the Irish dairy sector.

The standardization carried out to $f(x_{it}; \beta)$ in Eq. (3.1) by input X_1 allows the regressors ($\hat{X}_{jit}$) in Eq. (3.2) to be independent from the composed error term ($\hat{A}_{it}$). In other words, any random element of $\hat{A}_{it}$ that is correlated with some element from $f(x_{it}; \beta)$ affects output and input ratios in Eq. (3.2) $(i.e., \hat{Y}_{it}; \hat{X}_{jit})$ in the same magnitude; therefore, the input ratios ($\hat{X}_{jit}$) are now independent from $\hat{A}_{it}$.

Then, we use equation (3.2) to obtain the parameters from the GTRE model as follows:

$$\hat{Y}_{it} = \hat{\beta}_0 + \sum_{j=2}^{J} \beta_j \hat{X}_{jit} + \beta_t t + b_i - \eta_i + v_{it} - u_{it} \tag{3.3}$$

where the error term $\hat{A}_{it}$ in Eq. (3.1) is disentangled in four components in Eq. (3.3). The component b_i is the latent heterogeneity of farms assumed to be and $E(b_i) = 0$ with constant variance σ_b^2. η_i represents persistent inefficiency assumed to be $iid\ N^{+}(0, \sigma_\eta^2)$. v_{it} captures the random shocks (i.e., $iid\ N(0, \sigma_v^2)$), u_{it} is the transient inefficiency component, and $\beta_t t$ is a time trend to observe technical change. Then, we follow the distributional assumptions by Lien et al. (2018) on the transient inefficiency term:

$$\hat{Y}_{it} = \hat{\beta}_0 + \sum_{j=2}^{J} \beta_j \hat{X}_{jit} + \beta_t t + b_i - \eta_i + v_{it} - u_{it}\,(Z_{it}) \tag{3.4}$$

where Z_{it} are the determinants of transient inefficiency. In this way, the transient inefficiency term is no longer assumed to be a random *iid* term, as it is now expressed as a function of a vector Z_{it} of *K* observable determinants. To resolve the endogeneity between the transient inefficiency term $u_{it}\,(Z_{it})$ and inputs $\hat{X}_{jit}$, we reformulate Eq. (3.4) into a partial linear model for random effects panel data where the random shocks v_{it} are assumed to have zero-mean and constant variance (Lien et al. 2018) as follows:

$$\hat{Y}_{it} = [\hat{\beta}_0 - \alpha - g(Z_{it})] + \beta' \hat{X}_{jit} + [b_i - (\eta_i - \alpha)] + [v_{it} - (u_{it}\,(Z_{it}) - g(Z_{it}))] \tag{3.5}$$

The term $\alpha = E(\eta_i)$ is assumed to be *iid*, while $g(Z_{it}) = E\big(u_{it}\,(Z_{it})\big) \geq 0$ is the expected mean of the transient inefficiency term, and $\beta' \hat{X}_{jit}$ includes $\sum_{j=2}^{J} \beta_j \hat{X}_{jit}$ and $\beta_t t$ from Eq. (3.4). For simplicity, we rewrite Eq. (3.5) as:

$$\hat{Y}_{it} = h(Z_{it}) + \beta' \hat{X}_{jit} + \alpha_i + \varepsilon_{it} \tag{3.6}$$

where $h(Z_{it}) = [\beta_0 - \alpha - g(Z_{it})]$, $\alpha_i = b_i - (\eta_i - \alpha)$ and $\varepsilon_{it} = v_{it} - [u_{it}\,(Z_{it})$ - $g(Z_{it})]$. Therefore, $E(\alpha_i) = 0\ and\ E(\varepsilon_{it}) = 0$. We estimate the parametric component $\beta' \hat{X}_{jit}$ as in Robinson (1988) and Lien et al (2018) taking the conditional expectation on each side of Eq. (3.6) subject to Z_{it}:

$$E(Y_{it}|Z_{it}) = E\left(\left(h(Z_{it}) + \beta' \hat{X}_{jit} + \alpha_i + \varepsilon_{it}\right)\middle|Z_{it}\right)$$

Since $E(\alpha_i|Z_{it}) = 0$, and $E(\varepsilon_{it}|Z_{it}) = 0$, then:

$$E\left(\hat{Y}_{it}\middle|Z_{it}\right) = h(Z_{it}) + \beta' E(\hat{X}_{jit}|Z_{it}) \tag{3.7}$$

Consequently, we subtract (3.7) from (3.5) to obtain:

$$Y_{it}^* = \beta' X_{jit}^* + \beta_t t + \alpha_i + \varepsilon_{it} \tag{3.8}$$

where $Y_{it}^* = \hat{Y}_{it} - E(\hat{y}_{it}|Z_{it})$ and $X_{jit}^* = \hat{X}_{jit} - E\left(\hat{X}_{jit}\middle|Z_{it}\right)$. To obtain the conditional means (i.e., $E\left(\hat{Y}_{it}\middle|Z_{it}\right)$ and $E(\hat{X}_{jit}|Z_{it})$) as a function of vector Z_{it}, we estimate Eq. (3.8) by means of a nonparametric local kernel regression using the *npregress* command included in Stata®16. Therefore, Eq. (3.8) allows for determinants of transient inefficiency while dealing with the problem of endogeneity in inputs (Lien et al. 2018). Furthermore, Lien's et al. (2018) approach provides consistent estimates of β' regardless of the distribution of error components α_i and ε_{it} which we use in the following steps to estimate persistent and transient inefficiency (Baltagi, 2008; Lien et al. 2018).

Step 2. Estimates of persistent inefficiency and persistent TE

Due to data limitations regarding time invariant observable determinants in our panel data set, we keep the homoscedastic distributional assumptions of the persistent technical inefficiency term. Thus, we use the predicted values of α_i assuming that the latent heterogeneity of farms (b_i) is $iid\ N(0, \sigma_b^2)$ and the persistent inefficiency term (η_i) is $iid\ N^+(0, \sigma_\eta^2)$ (Colombi et al. 2014; Kumbhakar et al. 2014 and Filippini and Greene, 2016). Then, we estimate:

$$\alpha_i = \alpha + b_i - \eta_i \tag{3.9}$$

Using the standard SF model for pooled data and the maximum likelihood procedure proposed by Jondrow et al. (1982), we obtain the predicted values of persistent technical inefficiency. Therefore, we can estimate persistent TE (PTE) as $PTE = \exp(-\eta_i)$.

Step 3. Estimates of transient technical inefficiency, transient TE, overall TE and marginal effects.

To estimate the transient technical inefficiency ($u_{it}\,(Z_{it})$) in Eq. (3.4) we use the predicted values of ε_{it} obtained from (3.8). Therefore:

$$\varepsilon_{it} = g(Z_{it}) + v_{it} - u_{it}\,(Z_{it}) \tag{3.10}$$

As mentioned, we assume v_{it} is *iid* $N(0, \sigma_v^2)$, and $u_{it}\,(Z_{it}) \sim N^+(0, \sigma_u^2(Z_{it}))$ which means $E\big(u_{it}\,(Z_{it})\big) = \sqrt{\frac{2}{\pi\sigma_u}}(Z_{it}) \equiv g(Z_{it})$. Thus, we estimate Eq. (3.10) by the SFA technique (Jondrow et al., 1982; Kumbhakar, 1990; Kumbhakar et al., 2014) treating ε_{it} as the dependent variable and $g(Z_{it})$ as regressors. Since $g(Z_{it})$ has no new parameters other than those in the variance of u_{it}, we need to make sure that the exact relationship between $g(Z_{it})$ and the variance of $u_{it}\,(Z_{it})$ is maintained in estimating the model (Lien et al., 2018). To do so, and to make it non-negative, $\sigma_u^2(Z_{it})$ is parameterized as $\exp(w_{uit}{}'\mathrm{Z_{it}})$. The term w' is a vector parameter to be estimated (Lien et al., 2018). Therefore, we obtain the estimates for transient technical inefficiency and we compute the transient TE (TTE) as $TTE = \exp(-u_{it}(Z_{it}))$. Finally, we obtain the overall TE (OTE) from the product of PTE and TTE, i.e., $OTE = PTE * TTE$.

Additionally, given the half-normal distribution of the transient inefficiency term $(i.e., u_{it}\,(Z_{it}) \sim N^+(0, \sigma_u^2(Z_{it})))$ and the parametrisation of its variance $(i.e., \sigma_u^2(Z_{it}) = \exp(w_u Z_{it}{}'))$, we compute the marginal effect of the *kth* variable of Z_{it} on $E\big(u_{it}\,(Z_{it})\big)$ as:

$$\frac{\partial E(u_{it}(Z_{it}))}{\partial Z[k]} = w_u[k]\,\frac{\sigma_u(Z_{it})}{2}\left[\frac{\phi(0)}{\Phi(0)}\right] = w_u[k]\,\sigma_u(Z_{it})\phi(0) \tag{3.11}$$

Where ϕ and Φ are the probability density and cumulative distribution functions of a standard normal variable, respectively. The term $\phi(0)$ is approximately 0.3989 (Kumbhakar et al., 2015; p. 72), and $w_u[k]$ is the estimated coefficient of the *kth* variable of Z_{it}. Therefore, the assumptions of Lien et al. (2018) for the transient technical inefficiency term create similar marginal effects to the Caudill and Ford (1993); Caudill, Ford, and Gropper (1995); Hadri (1999) (i.e., CFCFGH) model. Consequently, Lien et al. (2018) and the CFCFGH model assume monotonic marginal effects of the variables determining the inefficiency term (Kumbhakar et al., 2015).[16] Finally, we use the *sfpredict* command included in Wang (2005) for Stata®16 to estimate the marginal effects of Z_{it} in the transient technical inefficiency term.

3.5 Data and empirical models

We use an unbalanced panel data set from a representative sample of Irish dairy farms (939 farms and 7,420 observations). The data spans from 2000 to 2018 and comes from the Teagasc National Farm Survey (NFS), collected as part of the EU Farm Accountancy Data Network (FADN).

The NFS is published on an annual basis since 1972. Approximately 900 farms are surveyed by a professional data collection team annually, representing a farming population of about 92,000 farms. This analysis restricts the data to specialised dairy farms, which results in approximately 390 observations per year. Beyond standard farm accountancy measures, the Teagasc NFS also captures farm labour through self-reported hours and work units, calculated on an annual basis. Farm labour is divided into paid, i.e., any hired labour and unpaid, i.e., family labour.

3.5.1 Hired labour hours

As mentioned, the role of hired labour on farms' TE is of main interest in this analysis. Data on labour refers to both seasonal and permanent hired labour reported on an annual basis by the farmer. Table 3.1 illustrates the development of hired labour on Irish dairy farms from 2000 to 2018.[17]

[16] Monotonicity of marginal effects means that the sign (i.e., positive or negative) of the marginal effect remains the same for all the observations in the dataset (Wang, 2002).
[17] For ease of presentation and consistency across Tables included in this thesis, we report two decimal points in Tables including descriptive statistics. We report three decimal points in Tables presenting estimated results.

Table 3.1 Hired labour hours on Irish dairy farms 2000-2018

(1) Year	(2) Farms	(3) Hired labour hours (farms that hire labour).	(4) Hired labour in AWU	(5) % Of farms with no hired labour	(6) Hired labour share
2000	486	512 (806.96)	0.42	35.18%	10.96%
2001	535	475.57 (786.22)	0.39	37.94%	9.92%
2002	490	457.94 (758.95)	0.38	36.53%	10.25%
2003	501	474.76 (778.01)	0.39	36.92%	10.41%
2004	465	499.84 (837.9)	0.42	41.29%	9.91%
2005	440	467.49 (787.12)	0.42	43.41%	9.99%
2006	408	459.65 (730.1)	0.40	41.42%	10.44%
2007	377	501.47 (739.06)	0.42	38.72%	11.16%
2008	362	534.85 (794.3)	0.44	38.39%	11.44%
2009	345	457.66 (746.34)	0.42	42.02%	10.16%
2010	335	518.16 (829.93)	0.44	39.71%	10.87%
2011	347	579.65 (783.54)	0.48	39.48%	12.3%
2012	342	506.21 (710.24)	0.45	39.18%	11.82%
2013	342	548.57 (806.73)	0.45	37.42%	11.67%
2014	342	503.81 (728.47)	0.41	32.74%	11.78%
2015	335	511.09 (756.42)	0.41	34.62%	11.47%
2016	328	572.55 (810.82)	0.46	34.75%	12.27%
2017	315	666.15 (912.68)	0.51	33.01%	13.23%
2018	325	738.91 (979.52)	0.55	36.00%	14.10%
All years	390	520.5 (796.21)	0.43	37.93%	11.13%

Source: Teagasc NFS data. (3) Mean and standard deviations in parentheses. (4) An AWU represents 1,800 hours a year, and one AWU is capped at 1,800 hours even if a person works more than 1,800 hours. People under 18 years of age are allocated the following labour-unit equivalents: 16 to 18 years = 0.75 AWU and 14 to 16 years = 0.50 AWU. Labour variables weighted by a dairy specialisation factor.

The data indicates that Irish dairy farms utilise a yearly average of 520 hours of hired labour across the time period examined (i.e., Column 3). Additionally, the average figure has increased during the post-quota period (2015-2018), particularly during 2017 and 2018. During the quota years and soft-landing phase, hired labour hours remained stable, with few exceptions: 2002, 2005, 2006 and 2009 where the proportion of hired labour was low. This is a likely consequence of the milk quota, and, in 2009, low milk prices caused a drop in milk supply (Dillon et al., 2019). Across all years examined, farms that hire labour have an average of just 0.43 AWU (i.e., Column 4). All of the above indicates that despite a significant increase, the proportion of farms utilising hired labour remains relatively low. Column (4) also demonstrates the increase in labour required i.e., hired labour expressed in AWUs have increased to 55% AWU in 2018 compared to the 41% figure in 2015. This increase is understandable given the strong growth in milk production experienced post-quota (CSO, 2020). However, Column (5) shows that a non-trivial percentage of farms do not hire labour in the period (i.e., 38% on an annual average). Also, 2005, 2006 (i.e., milk quota) and 2009 (i.e., soft-landing and economic recession) showed the highest percentage of farms with no hired labour (*see* Column 5). In Column (6), we can see that hired labour represents 11% of the total labour hours over the period, emphasising the prevalence of family farming (reflected in the unpaid family labour component) in an Irish context. However, we observe an increase in the ratio of hired labour to 13% and 14% in 2017 and 2018.

Table 3.2 presents descriptive statistics for several variables relevant to Irish dairy production from 2000 to 2018.

Table 3.2 Relevant descriptive statistics Irish dairy farms 2000-2018

Variable	Description	Mean	Min	Max
Milk output	Total milk output in hundreds of euros	1,576.28	6.70	6,963.77
		(836.42)		
Capital	Machinery, buildings, and livestock in hundreds of euros	1650.82	21.06	12,214
		(1,281.98)		
Labour	Paid and unpaid self-reported annual hours on the farm	1,956.19	13.98	8,685.18
		(950.11)		
Miscellaneous inputs	Direct costs incurred in dairy production in euros	522.93	1.96	4,272.25
		(398.11)		
Land	Dairy forage area in hectares	61.24	3.70	281.40
		(34.26)		
Herd size	Average annual herd size by farm	61.15	1	318.42
		(38.15)		
Herd expansion	Average annual growth rate of herd size in the period	2.11%	-97%	154%
		(12.8%)		
Farms in herd expansion	Percentage of farms with herd growth rate above zero	65.16%	55.48%	80.3%

Source: Teagasc NFS data from 2000 to 2018. All monetary variables deflated by agricultural price indices (CSO, 2020; base year 2015). Standard deviations in parentheses.

In Table 3.2, milk output describes total milk produced by the average dairy farm in hundreds of euros. Capital comprises machinery, buildings, and livestock as follows: the aggregated value of machinery and buildings and the value of the dairy herd, calculated according to the end of year valuation based on a replacement cost methodology. This approach acknowledges the capital input as both a flow of income and a stock (Ros, 2013). In this way, we obtain unbiased output elasticities for the capital input (Martinez-Cillero et al., 2019). Labour accounts for total labour input on the entire farm, including unpaid and paid labour. Miscellaneous inputs are direct costs incurred in dairy production, such as concentrates, fertiliser, purchased seeds, building repairs, livestock expenses, veterinary and artificial insemination expenses, farm insurance, advisory fees, among others. Land is based on dairy forage area in hectares.

Herd size is the average number of cows in the dairy herd over a twelve-month period. Herd expansion is the average annual growth rate of herd size in the period. Farms with herd expansion is the average percentage of farms with a positive herd growth rate annually. Detailed yearly statistics of the variables in Table 2 are included in Table A.1 in the Appendix A. Finally, all monetary values are deflated using Irish national price indices (with the base year 2015) taken from the Irish Central Statistics Office (CSO, 2020). In addition, we weight farms' inputs (i.e., capital and labour) by a specialisation factor (i.e., gross dairy output as a proportion of gross farm output) (Kelly et al., 2013), as dairy farms can use inputs to produce other outputs (e.g., crops, sheep, livestock, calves) and the data does not provide enterprise specific breakdowns for capital and labour.

3.1.1. Empirical specification

We apply the heteroscedastic GTRE model by Lien et al. (2018) described in section 3.4. For the dependent variable specified in equations (3.2) to (3.8) of section 4 (i.e.,$\hat{Y}_{it}$, Y_{it}^*), we use the natural logarithm of milk output measured in constant euros. The vector of inputs (i.e., $\hat{X}_{jit}$; X_{jit}^*) used in these equations includes capital, labour, miscellaneous inputs, and land. The GTRE model by Lien et al. (2018) allows to any input in the production function to be used as the numeraire. As specified in equation (3.2) in section 3.4, we use land as the numeraire input (X_1) and applied natural logarithms to all the inputs included in vectors $\hat{X}_{jit}$ and X_{jit}^*.

Using the estimated parameters in equation (3.8) we compute the following output elasticities (eq. 3.12), and technical change (i.e., eq. 3.13) as follows:

$$\frac{\partial Y_{it}^*}{\partial X_{it}^*} = \beta_j{}' X_{jit}^*, \quad j = 2, \dots, J \tag{3.12}$$

$$\frac{\partial Y_{it}^*}{\partial t} = \beta_t \tag{3.13}$$

3.5.2 Determinants of transient technical inefficiency

For the empirical specification of technical inefficiency determinants (Z_{it}) in equations (3.4) to (3.8), we use the annual hired labour hours. We applied the log-transformation suggested by Cameron and Trivedi (2010) to Z_{it} to avoid losing information due to the number of farms that do not hire labour annually. The log-transformation consists in approximating a gamma constant to the zero values in the sample to keep the logistic distribution of the variables. Finally, to obtain the marginal inefficiency effects by Wang (2002) described in section 3.4.1, we use the Stata® code introduced by Wang (2005).

3.6 Results and discussion

3.6.1 Production function

We begin our results with the output elasticities, technical change and returns to scale reported in Table 3.3.

Table 3.3 Output elasticities, technical change and returns to scale

Milk output	(1) Coefficients
Capital	0.199*** (0.009)
Labour	0.106*** (0.008)
Miscellaneous inputs	0.701*** (0.009)
Land (*calc.)*	0.014
Technical change	0.012*** (0.001)
Region[a]	0.063
Returns to scale	1.00
Constant	-0.119*** (0.007)
Observations	7,420
Number of farms	939

Note: [a]None of the regional dummies are statistically significant. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

First, all the output elasticities are positively and significantly correlated with output. Due to the transformation of the variables to control for endogeneity between inputs and the composed error term (*see* Section 3.4), we can interpret the output elasticities of capital, labour, and miscellaneous inputs in terms of percentage changes per hectare per farm. Also, the modelling approach specified in equations (3.3) to (3.9) that included hired labour as a determinant of transient inefficiency implies that the output elasticity for labour is a proxy for unpaid labour, i.e., family labour. Finally, at 1.18% per year on average, the estimate of technical change is also statistically significant and positive. These findings are similar to previous output elasticities for Irish dairy farms and technical change estimates reported by Gillespie (2015) and Bradfield et al. (2021). Therefore, we can confirm that technical change is an important element for productivity improvements on Irish dairy farms.

3.6.2 Overall, Transient and Persistent TE scores

Table 3.4 includes the estimates of average overall, transient, and persistent TE scores for the years 2000 to 2018. We also report the TE scores from the homoscedastic GTRE (Kumbhakar et al. 2014) as a robustness analysis.

Table 3.4 Average overall, transient and persistent TE scores

	(1)	**(2)**
Efficiency	**Homoscedastic GTRE**	**Heteroscedastic GTRE**
Overall TE	0.755	0.791
	(0.091)	(0.072)
Transient TE	0.876	0.884
	(0.065)	(0.059)
Persistent TE	0.861	0.88
	(0.077)	(0.061)

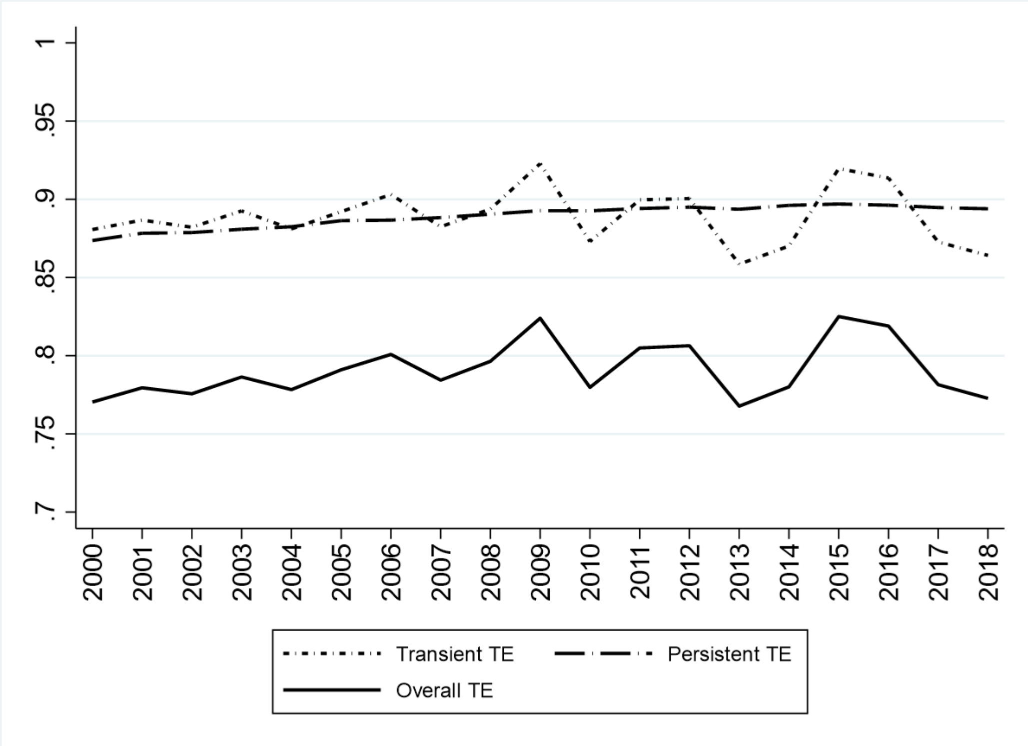
Observations	7,420	7,420
Number of farms	939	939

Note: Standard deviations in parentheses

The results confirm that not addressing endogeneity in a GTRE model may lead to an underestimation of TE scores, which is in line with findings by Lai and Kumbhakar (2018) and Lien et al. (2018). Table 3.4 shows that in our analysis, this underestimation is around 3.5% of farms' overall TE from 2000 to 2018 (*see* Columns 1 and 2). In Column 2, overall TE is 0.79, which suggests that Irish dairy farms are highly efficient. As such, our results are consistent with the findings of Geary et al. (2012), Kelly et al. (2013), Gillespie (2015) and Bradfield et al. (2021) who all report average TE of Irish dairy farms above 70%. Additionally, average transient and persistent TE scores are very similar for Irish dairy farms (i.e., 88.4% and 88%, respectively). This result suggests that, on average, Irish dairy farm production is highly efficient in the short (i.e., transient) and long run (i.e., persistent).

In Figure 3.1, we show the development of transient, persistent, and overall TE over the observation period.

Figure 3.1 Development of transient, persistent and overall TE on Irish dairy farms (2000-2018).



Note: Estimates from SF model by Lien et al. (2018) applied to Teagasc NFS panel data 2000-2018.

During the milk quota period (2000-2008), we observe an increasing trend of transient TE that remains close to its persistent trend (i.e., persistent TE). In 2008, the EU initiated the soft-landing period (2008-2014) in preparation for a deregulated market in 2015 (Läpple and Hennessy, 2012). Figure 3.1 displays that transient TE shows greater variation in the soft-landing period. The above may be caused by the high volatility in dairy markets due to the international recession during this time (i.e., 2008-2011), and dairy farmers' adaptation processes towards the milk quota abolition. There is a considerable dip in transient TE in 2013 that recovers in the following year. This may partly be due to the uptake of new technologies by farmers since, in 2013 and 2014, significant investments have been made in the Irish dairy sector initiated by private sector and government grants (Promar-International, 2018; Donnellan et al., 2019; Kelly et al. 2020).

Lastly, during the post-quota period (2015-2018), we observe a growing trend of transient TE from 2015 to 2017, which reverses in 2018. This dip in TE can be related to adverse weather that affected agricultural production (and costs) in 2018, with a significantly negative impact on Irish farm incomes (Dillon et al., 2019).

It is important to note that observed variation in persistent TE scores' is due to the unbalanced panel dataset.[18] In other words, for each farm, persistent TE is constant and the small variation on persistent TE in Figure 3.1 over time is due to a different set of observations each year.

3.6.3 Marginal effect of hired labour on transient technical inefficiency

In the last part of our analysis, we focus on the marginal effect of hired labour on transient technical inefficiency, presented in Table 3.5.

Table 3.5 Marginal effects of hired labour on technical inefficiency

(1) Variable	(2) Coefficient	(3) Marginal effect of hired labour
Hired labour	-0.064 (0.01)	-0.0042%***
Wald Chi2	2,323.95***	

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

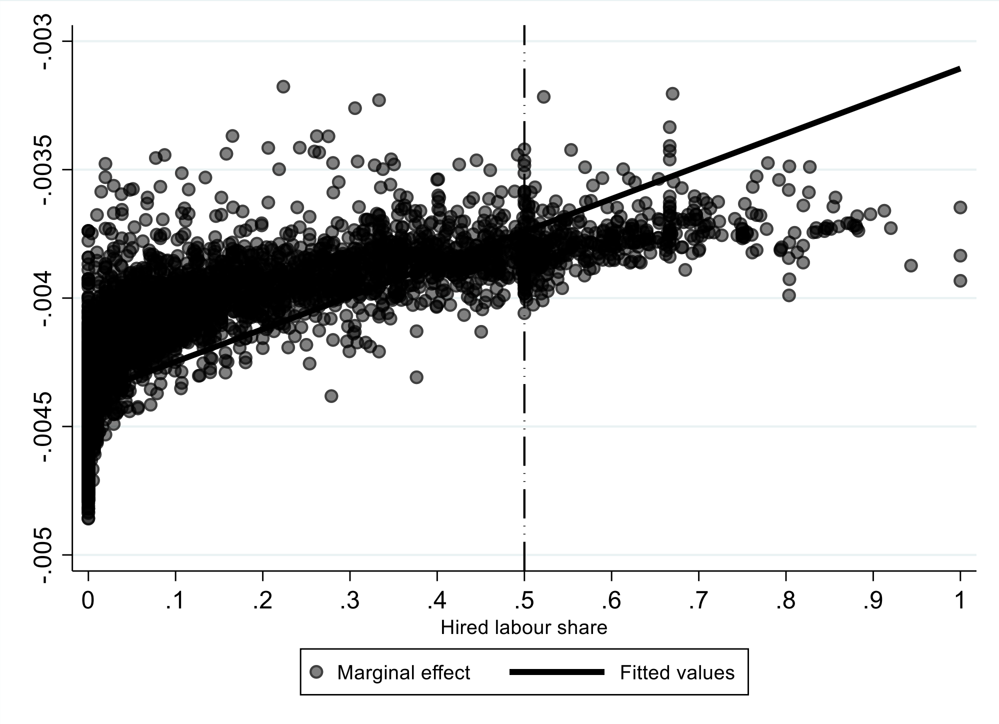
Since the coefficients in Column 2 in Table 3.5 have no direct interpretation, we report the marginal effects of hired labour on TE in Column 3. This result shows that, on average, a 1% increase in hired labour has a decreasing marginal effect of -0.0042% on transient technical inefficiency. To set this in context, a 1% increase in hired labour is only 5.2 hours per year, which explains the small economic significance of our coefficient estimate. Note

[18] A *balanced panel* is a dataset in which each panel member (i.e., farm) is observed every year. Consequently, if a balanced panel contains N farms and T periods, the dataset's number of observations (n) is n = N×T. In contrast, an unbalanced panel is a dataset where farms are observed a different number of times. A balanced panel is ideal, but this is not always true because of missing values and attrition (Cameron and Trivedi, 2010). However, most panel data regression models, including the heteroscedastic GTRE model applied here, can be used for unbalanced datasets.

that the coefficients in Table 3.5 present the effect of hired labour on technical inefficiency; therefore, the effect on TE is the opposite. Consequently, our findings suggest that hired labour has a significant yet small effect on increasing TE of Irish dairy farms.

In the following figures, we explore this effect in more detail. In Fig. 3.2, we show the marginal effects of hired labour on TE (i.e., *y-axis*) by hired labour share (i.e., *x-axis*).

Figure 3.2 Marginal effects of hired labour on technical inefficiency

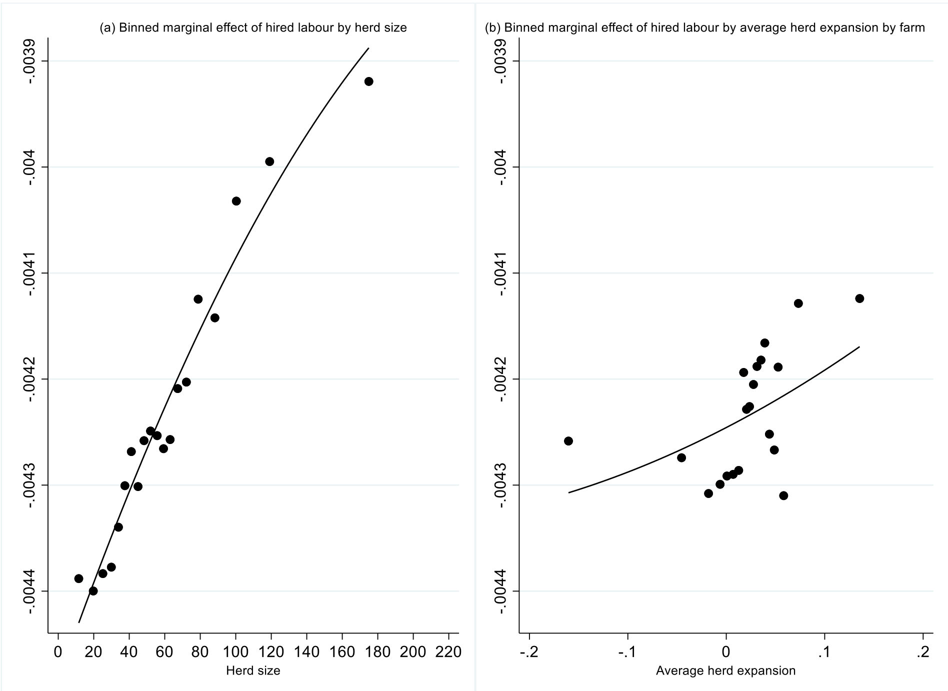


Note: Results from Lien et al. (2018) marginal effects. The dash-dot line represents 50% of hired labour share.

For ease of interpretation, we place a linear fit over the marginal effect of hired labour and the variable included in Fig. 3.2 to show the marginal effects. We also tried a quadratic and cubic relationship, but it does not fit the data well (not reported here). Our results suggest that the effect of hired labour on transient technical inefficiency is negative regardless of hired labour share's level. However, when the hired labour share increases, the marginal effect of hired labour declines. For instance, if a farm's hired labour share is below 50%, the effect on technical inefficiency will be more extensive than at higher levels of hired labour share (see Fig. 3.2). Since 95% of farms in the sample report less than 50% of hired labour share, most dairy farms will reduce their technical inefficiency by a larger magnitude by hiring extra labour.

Next, we explore how the effect of hired labour varies with herd size and expansion, measured as the average growth rate in herd size per farm. The findings are shown in Fig. 3.3.

Figure 3.3 Binned scatter plots of marginal effects of hired labour on TE by herd size and herd expansion



Note: Results from Lien et al. (2018) marginal effects. (b) Average herd expansion is annual and weighted by the number of years each farm is in the sample.

The results from Fig. 3.3 indicate the following. First, most farms cluster at a herd size of less than 80 cows. This is the case since herd size distribution is positively skewed. For most years in the sample, the average herd size is below 80 cows (see Table A.1 in Appendix A). As small and medium-sized farms tend to have a lower hired labour share working on the farm, the marginal effect of hired labour on technical inefficiency is larger than the average figure (i.e., >-0.0042). In other words, marginally increasing hired labour has a more extensive effect on TE when compared to larger farms with a higher hired labour share. Moreover, our results from Fig. 3.3 (b) suggest that the effect of hired labour on TE slightly declines as herd expansion grows. This result, combined with Figure 3.3 (a), implies that the acquisition of additional hired labour on larger farms (>80 cows) and in farms in expansion mode has a moderate lower impact in terms of reducing technical inefficiency. Therefore, the effect of hired labour on technical inefficiency is marginally more extensive on small and medium-sized farms and on farms that are not significantly expanding production.

3.7 Conclusions

EU milk quota abolition created significant opportunities and challenges for the European dairy sector. One such challenge relates to increased labour demand on farms expanding production.

This chapter examines the role of hired labour on Irish dairy farms' TE. The study uses representative farm-level panel data for the years 2000 to 2018. We apply a GTRE model that accounts for endogeneity in inputs and decomposes TE into transient and persistent TE scores. We also estimate the marginal effects of hired labour on transient TE, and our findings show that hired labour has a positive effect on Irish dairy farms' TE.

Consistent with the literature, we find that Irish farms are efficient in TE scores over time. The technical change estimation confirms its importance for Irish dairy productivity (Gillespie, 2015). In addition, we report that the average TE of Irish dairy farms is 79%, 88% and 88% for overall, transient and persistent TE, respectively. If we do not control for endogeneity, the efficiency scores are biased by approximately 3%. This result is consistent with Lai and Kumbhakar (2018) and Lien et al. (2018).

This research suggests that hired labour assists in increasing dairy farms' TE. However, the analysis indicates that relatively smaller farms (i.e., less than 80 cows) benefit more from hiring labour. We conclude that there are two main reasons for this. First, farms of smaller size have a lower hired labour share to begin with (i.e., 6% compared to 27% for smaller and larger farms, respectively), and small farms tend to be generally less efficient (Carroll et al., 2011; Bradfield et al., 2021). Therefore, it is easier to increase TE on these farms.

Besides, most dairy farms have little hired labour (i.e., 95% of farms have less than a 50% share of hired labour). Furthermore, in 2018, the average herd size in the sample was 88 cows, and the TE scores for smaller and larger farms are, on average, 74% and 79% (see Table A.1 in Appendix A). Then, the marginal effect of hired labour on TE is at its highest point for most Irish dairy farms. Therefore, there is considerable potential for farm TE improvement based on expanding hired labour.

Moreover, our findings suggest that the marginal effect of hired labour decreases to a small degree as herd size expands. Intuitively, as herd size expands, so too does the total labour input, increasing the reliance on hired labour and thus total labour costs (Kimhi, 2009; Kelly et al., 2020). Therefore, it is generally accepted that to manage the increasing workload on expanding farms, additional hired labour will be required as it is not sustainable in the long term for farmer/family labour to absorb it. Thus, in relation to the recommendation by Anderson (2020) and Kelly et al. (2020) that larger and expanding farms should utilise hired labour where available, our findings do not contradict this suggestion—although, the analysis suggests that the positive effects of hired labour on TE are more evident on smaller farms and non-expanding farms.

These findings have important practical and policy implications. The suggestion that small and medium-sized farms should increase their share of hired labour may be surprising as farmers generally aim to minimise labour costs, especially those involved in a smaller, family run operation. Besides, hired labour costs may also vary due to the location of the farm since it may be more challenging to source such labour in some regions (Loughrey and Hennessy, 2016). However, as Anderson (2020) and Kelly et al. (2020), we consider it a good general practice to treat labour costs as a standard running cost for the farm, similar to fertiliser or feed. Therefore, our findings suggest that policy should expand programmes that ease access to hired labour for all farms.

This suggestion is important as many dairy farmers may still be reluctant to hire additional labour due to concerns that it may reduce farm productivity. This reluctance may be mitigated by circulating factual information regarding the relationship between hired labour and farm productivity through extension agents such as Teagasc, the Farm Relief Services (FRS) and the Macra Land Mobility Service (MLMS) programmes. At the same time, Teagasc's social media has been proven to be an effective way to disseminate information to farmers regarding research outputs relevant to their farm operations (Moran, 2018). In this way, our findings should give farmers the confidence that hired labour is suitable for increasing the TE on their farm while allowing them to delegate labour-intensive tasks to hired labour, thus, easing the workload.

Finally, this chapter is one of the first that directly assesses the effect of hired labour on farms TE. We find a positive and significant effect of hired labour on farms' TE—yet the effect is small in economic terms. However, whether or not this TE increase will be enough to offset the increase in labour cost requires an input-oriented analysis, which is worth further investigation. Consequently, to further increase the efficiency of farms, it is not enough to delegate part of the workload to hired labour. Instead, it is necessary to continue adopting new technology and techniques (Deming et al., 2017). There may also be scope to contract out some work to external providers. Our finding of the positive impact of hired labour on TE is likely to also apply to other farms in developed countries, as many farms also heavily rely on family labour. However, it is important to keep in mind that our study is based on spring calving dairy production with a very seasonal labour demand. The implications of our study likely do not apply as directly to farms which do not have this seasonal labour condition. Moreover, our analysis does not distinguish between the specific work tasks executed by hired labour. Therefore, the allocation of hired labour on specific farm activities and how these influence farms' TE would be another clear direction for future research.

Chapter 4 - Automation and efficiency: a latent class analysis of Irish dairy farms

4.1 Introduction

Automated technologies play an important role in agriculture. Automation in agriculture means adopting new technologies that enable capital to be substituted for labour in various tasks (Acemoglu and Restrepo, 2019). Historically, the mechanisation of agriculture in the late 19th and early 20th century displaced agricultural workers in large numbers (Olmstead and Rhode, 2001; Acemoglu and Restrepo, 2019). As agriculture is susceptible to the cost and scarcity of labour, automation continues to play a significant role. A contemporary challenge for agriculture relates to the use of automation for further productivity increases in food production and in reducing its environmental impact.

Globally agriculture faces significant challenges such as population growth, climate change, resource shortages, and increasing demand for energy (Shakhramanyan et al., 2013; Zouabi, 2021). Such challenges accelerate the need to improve the efficiency of the sector (Steeneveld and Hogeveen, 2015; Schrijver et al., 2016). As such, continued automation has a critical role to play (Choudhury et al., 2021), not least in the context of increasing labour shortages (Van Evert et al., 2017). For instance, recent policy efforts and initiatives in the EU and USreflect the continued use of automation to face the agricultural challenges of the 21st century.[19]

Labour shortages in agriculture are a matter of concern in many EU countries (McGrath, 2021), particularly in the dairy sector (Weber et al., 2021). The increased labour demand, amongst other factors, is motivated by the significant restructuring of the EU dairy sector due to the abolition of milk

[19] In 2021, Robs4Crops in the EU was an 8 million euros four-year project aiming to increase the adoption of automated technologies in agriculture. Moreover, from 2010 to 2018, The United States Department of Agriculture (USDA) funded $3.4 billion toward 280 digital infrastructure projects that facilitated automation or mechanisation in food production and processing.

quotas in 2015. This structural change has caused significant production increases in some EU countries (Osawe et al., 2021). Regions with a comparative advantage, such as Ireland (with its spring calving pasture-based system), expanded production significantly (Läpple et al., 2022). For instance, Irish milk production increased by more than 70% from 2008 to 2021, and Ireland now produces 8,754 million litres of milk. Over 80% of Irish dairy farms expanded production through increased milk yield per cow and growth in average herd size. As a result, more than 35% of Irish farms have a herd size above 100 cows which accounted for 60% of total milk production in 2021 (Dillon et al., 2022).

Expansion of the Irish dairy sector poses particular challenges regarding farm-level labour requirements. While adding more cows to the herd increases total labour hours (Kimhi, 2009), herd expansion also tends to reduce hours worked per cow (Anderson, 2020). However, there can be significant variations in hours worked per cow across similar-sized herds (Deming et al., 2017) caused by differences in farm facilities, the adoption of automated technologies and labour efficiency (Kelly et al., 2020). Moreover, since the Irish dairy sector relies on a spring calving system, most of the workload (around 50%) arises between February to May due to calving and breeding (Deming et al., 2018; Dillon et al., 2019). Although family labour may temporarily relieve labour shortages, the structural change leading to significant growth in average herd sizes results in farmers needing other resources to meet the increased demand for labour.

The use of automated technologies in the dairy sector are becoming more prevalent (Kelly et al., 2020). For instance, dairy farms' investment in machinery, livestock, and buildings increased by 36% between 2008 and 2018 (Dillon et al., 2019). Some of this investment is made to reduce labour-intensive tasks with automated technologies on dairy farms (Conlon, 2021). In Ireland, milking, calving, feeding and cleaning are the most time-consuming labour activities on the farm (Deming et al., 2017; 2018). More specifically, on farms with less than 150 cows, according to Deming et al., (2018) improvements in facilities related to the milking process may result in an approx. 20% reduction in labour hours per cow. On larger farms (>150 cows), facilities are generally not an issue, but the availability of skilled labour to operate them is an issue (Deming et al., 2017; Kelly et al., 2020). Since the majority of Irish dairy farms have a herd size smaller than 150 cows (i.e., 86 % in 2018), exploring the productivity and efficiency implications of automation is crucial for the future of the Irish dairy sector.

This chapter explores the adoption of automated technologies in an expanding dairy sector and their role in farms' technical efficiency (TE) by using stochastic frontier analysis (SFA). TE is measured on a scale from 0 to 100%; therefore, it is an index of *doing things right* regarding farm production. SFA estimation has been a popular approach for assessing farm TE since the seminal work by Aigner et al. (1977). When SFA is used to estimate farm TE, it is based on the assumption that farms share the same underlying technology represented by the frontier (Kumbhakar et al., 1990; Battese and Coelli, 1995; Kumbhakar et al., 2015). However, the assumption that farms operate under a homogenous technology is widespread and can be too strong in specific contexts. If empirical research does not address technology heterogeneity, it will likely be subsumed into the producer-specific inefficiency measure, leading to its biased estimation (Orea and Kumbhakar, 2004; Martinez-Cillero et al., 2021; Dakpo et al., 2021a). Therefore, we consider the possibility of heterogeneous technology estimating TE of Irish dairy farms.

This chapter uses a representative sample of Irish dairy farms in 2018 to estimate TE scores. Beyond standard farm and household measures, we use data from a unique additional survey on automated technologies. These include automated parlour feeders, cluster removers, scrapers, and washers. Then, following Orea and Kumbhakar (2004) and Dakpo et al. (2021b), we apply a latent class stochastic frontier (LCSF) model that accounts for technology heterogeneity, a problem frequently disregarded in the SFA literature (Martinez-Cillero et al., 2019). Thus, we get unbiased estimates of all parameters we report.

We offer two explicit contributions to the existing literature. First, we explore the role of automation on farms TE while assessing technology heterogeneity, the latter in the context of significant structural change in the three years after the EU milk quota abolition. To the best of our knowledge, neither the LCSF model nor an exploration of the role of several automated technologies on dairy farms TE has been explicitly studied before. Second, previous literature has identified that automation is always and inexorably related to labour input (e.g., Alvarez-Cuadrado et al., 2011; D'Antoni, 2011; Acemoglu and Restrepo, 2011; 2018; 2019). However, the practical implications of adopting automated technologies on farm labour at the farm level still need to be clarified. This chapter aims to fill this knowledge gap. Thus, we provide detailed descriptive evidence of the implications of adopting automated technologies on farm labour.

The chapter proceeds as follows. The following section provides a background on automation and labour in the Irish dairy sector. Section 4.3 discusses relevant literature on automation, labour and TE. Section 4.4 describes the methodology, while section 4.5 explains the empirical approach and the data used. Section 4.6 presents the results, while section 4.7 offers concluding remarks.

4.2 Background on labour and automation in the Irish dairy sector

Irish dairy farms are primarily pasture-based with a spring calving system which provides a comparative advantage in producing milk at a low cost (Thorne et al., 2017; Dillon et al., 2022). However, a drawback of such a production system is the uneven demand for labour throughout the year. Specifically, from February to May, demand for labour peaks due to calving and breeding (Dillon et al., 2022). This uneven distribution of yearly workload generates seasonal labour shortages, aggravated in recent years by the significant production growth driven by the abolition of the EU milk quota in 2015.

Additionally, factors such as the farm's location and demographics make it more challenging to secure additional labour, despite programmes to facilitate access (Kelly et al., 2017; Loughrey et al., 2022). [20] Moreover, the mismatch between increasing herd size and limited (hired) labour availability poses an additional challenge for dairy farms in Ireland (Kelly et al., 2020).[21] For all of these reasons, labour shortages are seen as a major stress factor (Brennan et al., 2021), and, despite the available programmes, around 36% of dairy farms did not employ any hired labour in 2018 (Dillon et al., 2019). The majority of Irish farms are family farms (97%) (CSO, 2020), and although family labour can provide temporary relief to labour shortages, it is not sustainable in the long run (Thorne et al., 2017; Kelly et al., 2020).[22]

Automation can provide a solution to labour shortages. Automatic/robotic milking parlours can be an alternative to the increasing workload related to the milking process (Upton and O'Brien, 2013). However, replacing a milking parlour with a robotic milking parlour is a complex decision in the Irish dairy sector context. For instance, Upton and O'Brien (2013) contend that adopting robotic milking parlours to Ireland's seasonal grass-based calf milk production system is a critical issue to consider. Moreover, given the significant capital investment and operating costs required, gains made regarding reduced overall labour input must be larger (O'Brien and Upton, 2013; Upton and O'Brien, 2013). Data from the Teagasc National Farm Survey (NFS) in 2018 reveals a very low incidence of robotic/automatic milking systems on Irish farms.[23]

Moreover, data on the uptake of a range of relevant automated technologies was collected through the NFS in 2018. For instance, the survey indicated that automated parlour feeders used to increase labour efficiency were adopted on 57% of dairy farms. Such technology allows for the tailored feeding of cows taking account of milk yield, body weight, and stage of lactation. Similarly, automated cluster removers (to ensure efficient removal

[20] Farm Relief Services in Ireland is a farmer-owned co-operative organisation established in 1980 to provide skilled labour to meet Irish farmers' labour requirements.
[21] For instance, in 2018, 58% of farmers stated that it was complex or challenging to source hired labour, and 14% stated that they could not hire labour although they needed it (O'Brien et al., 2019).
[22] The United Nations Food and Agriculture Organisation (FAO) defines a family farm as *an agricultural holding managed and operated by a household that predominantly supplies farm labour*. Family farms are the most common type of farms in the EU (Eurostat, 2016).
[23] The data indicates that only 1.3% of farms in the survey have adopted a fully robotic milking system. Therefore, unfortunately, the data on robotic milking systems is insufficient for econometric analysis and we don’t include these farms in our sample.

after cows are milked) were used on 31% of farms, with the aim of reducing the labour required during the milking process. In addition, 63% of farms report the use of automated scrapers (to clean slurry from the cow shed). Another technology are automated washers, a mechanic system that washes the milking machine after the milking is complete and ensures the safe and accurate addition of cleaning chemicals to the water used for cleansing. The NFS indicates that these were utilised on 30% of farms in 2018.

4.3 Literature review

4.3.1 Automation and labour demand

Automation reduces the requirement for labour in production due to its substitution for capital (Graetz and Michaels, 2018). However, this labour-saving feature may be complemented by the productivity effect whereby labour productivity may increase by a more flexible allocation of tasks to labour (Acemoglu and Restrepo, 2017; 2018; 2019). Therefore, the net impact of automation on labour demand depends on how the labour-saving and productivity effects weigh against each other (Acemoglu and Restrepo, 2019). In other words, first, automation decreases labour demand, hence driving a positive increase in overall efficiency. Second, automation means labour productivity increases due to better use of labour resources.[24] Acemoglu and Restrepo (2018) use data from Lin (2011) and the Bureau of Labour Statistics in the US to empirically estimate the labour-saving and productivity effects from 1987 to 2015. Their findings suggest that about half of the new employment took place in occupations where job titles or tasks performed by workers changed due to automation (Acemoglu and Restrepo, 2018). In conclusion, the productivity effect of automation was as important as the labour-saving effect for economic development.

[24] Tim Burton's film Charlie and the Chocolate Factory (2005) presents an excellent anecdotal example of automation's labour-saving and labour-productivity effects. First, Charlie's father loses his job at the toothpaste factory and is replaced by an automated technology. After frictional unemployment, Charlie's father is re-employed at the factory as the technician who repairs the automated technology.

4.3.2 Automation and productivity

In most of the empirical analyses of automation, the agricultural sector is either not included (e.g., Alvarez-Cuadrado et al., 2011; Alvarez-Cuadrado et al., 2017), or the observation unit is at the task or type of work level for all sectors (e.g., Acemoglu and Restrepo, 2018). Only a handful of studies focus on agriculture's automation and productivity at the farm level. For example, Sheng et al. (2015) explore the productivity of Australian agriculture related to automation and farm size. Using a sample of *broadacre* farms (i.e., farms that produce grains, oilseeds and other crops), they found that smaller farms have limited capability to improve productivity by increasing their size without adopting different technologies (Sheng et al., 2015). Also, their findings suggest that larger farms achieve higher productivity by changing production technology rather than increasing scale alone (Sheng et al., 2015). Moreover, Sheng et al. (2016) confirm the benefits of automation with productivity increases. However, their results also suggest that increasing farm scale correlates with more efficient use of inputs.

Furthermore, Kompas and Che (2006) explored the role of technology choice (i.e., traditional or robotic milking parlour) and efficiency in a sample of Australian dairy farms. Their results suggest that eliminating price subsidies puts additional pressure on farms to become more efficient. Then, this agricultural policy change motivated higher efficient farms to increase their scale and make significant investments to improve their milking parlour (Kompas et al., 2006). Another body of literature focuses on the role of automation on profitability (e.g., Bijl et al., 2007; Salfer et al., 2017; Hansen et al., 2019) and milk quality (e.g., Koning, 2003; De Koning, 2010) of dairy farms in Germany, Netherlands and Denmark. There is a consensus that adopting automatic milking systems is associated with higher levels of profitability (Bijl et al., 2007; Salfer et al., 2017) and higher milk quality (Koning, 2003). Although there is consensus that automation aids in enhancing farm productivity and profitability, these implications are based solely on automatic milking parlours and not on other automated technologies.

4.3.3 Automation and TE

While TE in agriculture has received significant attention in the literature (e.g., Aigner et al., 1977; Battese and Coelli, 1995; Sauer and Morrison, 2013; Bradfield, 2021), very few studies focus on the role of automation on TE. Some studies (e.g., Alvarez et al., 2008; Cabrera et al., 2010; Alvarez et al., 2015) have found a positive association between farm intensification (i.e., highly stocked use of inputs) and higher levels of farms TE.[25] Moreover, Alem et al. (2019) explore TE differences by region in a study of dairy farms in Norway. Their findings suggest that training farmers on using automated technology is required to reduce regional differences in TE (Alem et al., 2019). The suggestion to train labour for the use of automated technology is consistent with the results of Kostov et al. (2018) and Kostov et al. (2019), who measured farm TE in a sample of four EU countries (i.e., the Czech Republic, Hungary, Romania and Spain). Hence, skilled labour and investment in automated technology are standard practical recommendations that may assist in increasing a farm's TE.

Although not many studies directly analyse the role of automated technologies in the TE of farms, precedents exist. For instance, for a sample of corn farms in the US, Delay et al. (2022) explore TE differences between adopters and non-adopters of precision agriculture (PA) technology. Their adopters of PA technology have higher TE scores. However, these differences in TE are due to inefficiencies in input usage rather than adopting the PA technology (DeLay et al., 2022). Moreover, Steeneveld et al. (2012) explore differences in TE in Dutch dairy farms that use automatic milking systems against farms that use conventional milking systems. Their results suggest that an explicit substitution of capital for labour is not observable. They also do not find significant differences in TE scores between both groups of farms. Also, the TE scores of early adopters of automatic milking systems are not different from those that adopted this technology in more recent years (Steeneveld et al., 2012; 2015). A significant limitation of these analyses is

[25] Alvarez et al. (2008) conclude that farm intensification has higher TE scores using a sample of Spanish dairy farms. This result is consistent with the findings of Cabrera et al. (2010) for a sample of dairy farms in Wisconsin and Alvarez et al. (2012) for a New York dairy farms sample.

that they focus on exploring TE based only on one automated technology (i.e., an automatic milking system).

4.3.4 Automation and TE on Irish dairy farms

To the best of our knowledge, the role of automation on TE has not been directly analysed on Irish dairy farms. However, several studies have analysed TE in the Irish dairy sector. For instance, Carroll et al. (2011) use a panel of a representative sample of Irish dairy farms and show that efficiency levels correlate with extension use, soil quality, farm size, and the level of dairy specialisation. Kelly et al. (2012) and Kelly et al. (2013) used a representative sample of farms to calculate TE and report TE scores between 76%-83%. They also found factors such as breeding season length, milk quality, discussion group membership, and soil quality to be associated with TE and that high labour intensity was correlated with optimal scale. Bradfield et al. (2021) estimate the correlation between land fragmentation and TE on a sample of Irish dairy farms in 2014. Their results yield an average TE score of 91% for dairy farms. Furthermore, higher levels of TE are correlated with increased land parcel area, reduced distances between parcels, contact with advisory services, and amongst more intensive farms and those with a higher hired labour share (Bradfield et al., 2021). Grovermann et al. (2021) analyse and estimate TE scores in a subsample of Irish dairy farms alongside 24 other EU countries. Their findings confirm high TE scores (i.e., 87%) in Irish dairy farming. Gillespie (2015) uses a large panel of Irish dairy farms (1975-2012) and finds that Irish dairy farms are highly efficient and improved TE over the observed forty years period.

Finally, previous case studies on the role of automation in the Irish dairy sector has focused on robotic milking parlours (e.g., O’Brien and Upton, 2013; Upton and O’Brien, 2013; Deming et al., 2018). However, the role of other automated technologies (i.e., automated parlour feeders, cluster removers, scrapers, and washers) related to labour-intensive tasks on the farm in improving farm efficiency and economic performance remains unexplored.

4.3.5 Technology heterogeneity and TE on dairy farms

As outlined above, the assumption that farms operate under a homogenous technology is widespread when estimating TE. The LCSF model has been increasingly acknowledged as the optimal way to estimate TE, accounting for technology heterogeneity (Orea and Kumbhakar, 2004; Dakpo et al., 2022). Recent studies implemented an LCSF model for different agricultural production systems. Baráth and Fertő (2015) implement an LCSF model for Hungarian crop farms and Sauer et al. (2012) for crop farms in Kosovo; while Martinez-Cillero et al. (2019) and Martinez-Cillero et al. (2021) use LCSF models for Irish beef farms. All these studies conclude that neglecting latent technology heterogeneity while estimating TE results in biased estimations and unreliable policy recommendations.

In relation to dairy farms, Alvarez and del Corral (2010) and Alvarez and Arias (2015) apply the LCSF model to a sample of Spanish dairy farms. Their results suggest that intensive farms with higher TE scores are more productive than extensive farms. Alvarez del Corral and Tauer (2012) implement the LCSF model in a sample of dairy farms in New York obtaining similar results regarding intensive farming being associated with higher technically efficient farms. Sauer and Morrison (2013) apply this approach to a sample of Danish dairy farms. Their findings also suggest that larger farms are more capital intensive, more productive and are more likely to experience scale economies. Kellermann and Salhofer (2014) apply an LCSF model for a sample of southern German dairy farms. Their findings suggest that extensively operating farms significantly lag in productivity compared to intensive farms.

Furthermore, Grovermann et al. (2021) estimate an LCSF model by using data from a panel of dairy farms from 25 EU countries. Interestingly, their findings show that the country of origin of the farm is not a significant determinant of the differences in the underlying technology. Instead, the type of climate conditions (e.g. cool, warm, and temperate conditions) and intensive and extensive production systems are significant determinants of farm classification. Alvarez del Corral and Tauer, (2012), Alvarez and Arias (2015), Kellermann and Salhofer (2014), and Grovermann et al. (2021) also confirm that more intensive farms tend to be classified in the group of higher TE scores.

4.4 Methodology

SFA is a widely implemented estimation method for obtaining TE measures (Kumbhakar et al., 2015). However, with the methodology described in this section, we try to overcome neglecting an underlying technology heterogeneity, a frequent limitation in previous SFA applications. Two main general approaches exist in the TE literature that attempt to account for technology heterogeneity, i.e., prior data partitioning and latent class models.

In prior data partitioning, the researcher takes one or more exogenous features from the data set to split the sample and then estimates separate frontiers for each subsample (e.g., Iraizos et al., 2007; Alvarez et al., 2008; Klopčič et al., 2019). The main problem with this subsampling is that it neglects farmers' self-selection of the variables chosen to partition the data. Therefore, the TE estimates will be biased (Martinez-Cillero et al., 2019). Another limitation of data partitioning is that it ignores the information contained in each subsample to estimate the technology of farms that belong to other groups (Martinez-Cillero et al., 2019). This limitation is essential since farms assigned to different groups often share standard features (Martinez-Cillero et al., 2019).

The other general approach that seeks to address technology heterogeneity when estimating TE is the LCSF model. The LCSF model allows the disentangling of technology heterogeneity from farm TE in a single step, thereby overcoming the limitations noted in the prior data partition approach. The self-selection issue on technology adoption is controlled since the information from the estimated classes is considered to determine each farm's probability of latent class technology (Sauer and Morrison, 2013). This feature is an advantage of the LCSF model over prior data partition (e.g., cluster analysis, principal component, and factor analysis).

In addition to the LCSF model, a random coefficients model (RCM) can be used to control for technology heterogeneity. Specifically, the RCM accounts for farms' technology differences in a continuous parameter variation (Greene 2005; Skevas 2020). However, the RCM requires larger data sets and strong distributional assumptions regarding the structure of random coefficients across farms/firms (Tsionas 2002; Martinez-Cillero et al. 2019). Therefore, we relax the assumption of a homogeneous technology for all farms by estimating an LCSF model developed by Dakpo et al. (2021b).[26]

4.4.1 The LCSF model framework

In the LCSF model, technology heterogeneity means the researcher does not know how many different underlying technologies there are in the sample nor what farms utilise each underlying technology (Martinez-Cillero et al., 2019). Therefore, the LCSF model implies that we can split the sample into a finite number of different latent classes underlying the technology in which the farms operate. We denote class membership by using the subscript j in equation (4.1) as follows:

$$Y_i = f(X'_i)_j + v_{i|j} - Su_{i|j} \tag{4.1}$$

where Y_i is the total output for the i^{th} farm, X'_i is the vector of inputs used in farm production, $v_{i|j}$ is the two-sided error term (i.e., random shocks), and $u_{i|j}$ is the one-sided error term (i.e., inefficiency term). S is equal to 1 if a frontier function is specified as a (profit) production frontier function, whereas$S$ is equal to -1 in the case of a cost frontier function. The LCSFM model classifies the sample into several classes, and each farm can be assigned to a particular class using the estimated class membership probabilities (Dakpo et al., 2021b).

[26] This LCSF model has several advantages over other LCSF model specifications. First, this model (code available in R®) is the best option for cross-sectional or pooled cross-section data as it includes nine optimization ML algorithms. This way, in contrast to other LCSF models, the orthogonality condition in the hessian of second partial-derivatives of the model is guaranteed and the convergence of the model is more likely in each of its components (i.e., cost/production function, class membership, efficiency drivers). Second, the model can estimate up to five classes where other LCSF models estimate up to four classes (e.g., Martinez-Cillero et al. 2019). Finally, as in Reifschneider and Stevenson (1991), Caudill and Ford (1993), Caudill et al. (1995) and Hadri (1999), the LCSF model applied in this paper can also account for heteroscedasticity in both one-sided and two-sided error terms (Dapko et al. 2021b; p.13).

By assuming a functional form for the generic function *f(.)* in equation (4.1) and imposing distributional assumptions on both elements of the compound error term, it is possible to estimate the LCSF model parametrically using Maximum Likelihood. We estimate the model in equation (4.1) using the Berndt-Hall-Hall-Hausman optimization algorithm with a robust Hessian matrix (Dakpo et al., 2021b). Then, we assume a half-normal distribution for the inefficiency term and variance σ_{uj}^2, and a normal distribution with zero mean and constant variance σ_{vj}^2 for the random shocks $v_{i|j}$.

The contribution of farm i to the likelihood conditional function on class j is defined as:

$$P(i|j) = \frac{2}{\sqrt{\sigma_{u|j}^2 + \sigma_{v|j}^2}} \phi \left(\frac{S\varepsilon_{i|j}}{\sqrt{\sigma_{u|j}^2 + \sigma_{v|j}^2}} \right) \Phi \left(\frac{\mu_{i*|j}}{\sigma_{*|j}} \right) \tag{4.2}$$

where $\varepsilon_{i|j} = v_{i|j} - Su_{i|j}$, $\mu_{i*|j} = \frac{-S\varepsilon_{i|j}\sigma_{u|j}^2}{\sigma_{u|j}^2 + \sigma_{v|j}^2}$, and $\sigma_*^2 = \frac{\sigma_{u|j}^2\sigma_{v|j}^2}{\sigma_{u|j}^2 + \sigma_{v|j}^2}$. The prior probabilities can be made dependent on a vector of separating variables defined as farm-specific to reflect differences in technologies or production systems used by dairy farms (Sauer and Morrison, 2013). We use a logit model specification to define the prior class membership probabilities as follows:

$$\pi(i,j) = \frac{\exp(\theta_j' Z_h)}{\sum_{m=1}^{J} \exp(\theta_m' Z_h)} \tag{4.3}$$

where Z_h are the covariates used as separating variables for class membership. θ_j' and θ_m' are coefficients to be estimated from the separating variables, and $\exp\left(\theta_j' Z_h\right) = 1$. The unconditional likelihood of observation i is the average over the j classes:

$$P(i) = \sum_{m=1}^{J} \pi\,(i,m) P(i|m) \tag{4.4}$$

The number of classes can be defined based on a statistical information criterion. We base our decision on the number of classes based on the Akaike information criteria (AIC) and the Hannan-Quinn information criterion (HQIC) as suggested by Orea and Kumbhakar (2004) and Dakpo et al., (2021a). Therefore, the log-likelihood of the LCSF model ($logLF$) can be written as:

$$logLF = \sum_{i=1}^{N} \log(\sum_{j=1}^{J} \pi(i,j) \times P(i|j)) \tag{4.5}$$

Each farm i can be assigned to a specific class by considering the largest posterior probability (Martinez Cillero et al., 2019; Dakpo et al., 2021a). We obtain the posterior probability using Bayes' rule for class j as follows:

$$w(j|i) = \frac{P(i|j)\pi(i,j)}{\sum_{m=1}^{J} P(i|m)\,\pi(i,m)} \tag{4.6}$$

Once the j production frontiers are identified, the distance from each farm observation to the frontier needs to be measured which provides an estimate of the farm's TE, recovered from the estimated compound error:

$$TE_{i|j} = \exp(-u_{i|j}) \tag{4.7}$$

As mentioned, TE refers to the ability of the farm to produce an output using minimum inputs or to obtain the maximum level of output given a set of inputs. We compute TE for the frontier with the higher posterior probability for each farm in the sample. In other words, we measure the TE of each farm for the specific frontier that most closely represents that farm's production technology. Finally, we modify the TE term to make it heteroskedastic (Martinez-Cillero et al., 2019) and specify a vector of efficiency drivers (Z_i) as follows:

$$u_{i|j} = [\exp(\eta|_j Z_i)] * U_{i|j} \tag{4.8}$$

where $U_{i|j} \geq 0$. As in equations (4.1)-(4.6), the subscript j refers to the different technologies underlying the data. Z_i is a vector of efficiency drivers, and $\eta|_j$ is a vector of parameters to be estimated.

4.5 Empirical model and data

We estimate a production frontier since it exploits input and output quantity data (Martinez-Cillero et al., 2019). An advantage of a production frontier over a cost or profit function is that it does not need data on prices or behavioural assumptions on producers (Kumbhakar et al., 2015). In this chapter, we assume a Cobb-Douglas functional form for the production frontieras follows:

$$\ln \hat{Y}_{ij} = \hat{\beta}_{0j} + \sum_{k=1}^{K} \hat{\beta}_{kj}\, lnX_{ik} + \hat{v}_{ij} - \hat{u}_{ij} \tag{4.9}$$

In equation (4.9), Y_{ij} is a single aggregated output produced by farm *i*. X_{ik} is a vector of K inputs used by the farm in the production of the output, and $\hat{\beta}_{0j}$ and $\hat{\beta}_{kj}$are parameters to be estimated.$\hat{v}_{ij}$, and $\hat{u}_{ij}$ are the random shocks and the inefficiency term, respectively.[27] The subscript j refers to the different classes, meaning that a different set of parameters is estimated for each of the classes identified in the LCSF model.

We use a representative cross-sectional sample of Irish dairy farms from 2018. The data comes from the Teagasc NFS, which operates as part of the EU Farm Accountancy Data Network (FADN). Teagasc has published the NFS on an annual basis since 1972. Approximately 900 farms are surveyed by a professional data collection team annually. These farms represent a farming population of about 92,000 farms. This analysis restricts the data to specialised dairy farms, which resulted in 288 farms in 2018 that represent approximately 15,500 Irish dairy farms.[28] Beyond standard farm accountancy

[27] We also estimated a *translog* functional form, but the model produced a singular Hessian. Therefore, the model did not converge in the second derivative of the production function.
[28] Since a robotic milking parlour cannot add these ancillary automated technologies, we excluded four observations that reported a robotic milking parlour in our sample.

measures, the Teagasc NFS also captures farm labour through self-reported hours and work units (unpaid and paid). Table 4.1 illustrates the variables included in the LCSF model.

Table 4.1 LCSF model production function variables

Production function variables

Variable	Description	Mean (SD)
Total output	The value of output that includes milk, cull cows and calves, sheep, beef, and crops in hundreds of euros	2499.52 (1614.26)
Capital	Machinery, buildings and livestock in hundreds of euros	2984.80 (2156.82)
Labour	Paid and unpaid annual hours of labour on the farm	3690.14 (1451.99)
Land	Total farm area in hectares	70.20 (36.81)
Miscellaneous inputs	Direct costs incurred in farm production in hundreds of euros	1563.84 (1122.01)

Table 4.1 Continued

Source: Teagasc NFS data from 2018.

From Table 4.1, we build a single aggregated output category for each farm based on the value of total outputs produced. It groups the value of output that includes milk, culled cows and calves, sheep, beef, and crops as production on the farm. We aggregate farm inputs into four categories: capital, labour, land, and miscellaneous inputs. Capital comprises machinery, buildings, and livestock based on a replacement cost methodology. The methodology adds the value of machinery and buildings and all livestock units, calculated according to the end-of-the-year valuation. We do the above because capital as input is both a flow of income and a stock. Thus, we get unbiased output elasticities for the capital input (Martinez-Cillero et al., 2019). Labour input is measured in total labour hours working on the farm. Land is measured as utilised agricultural area in hectares. Miscellaneous inputs are direct costs and other inputs involved in farm production. These inputs include purchased seeds, building repairs, livestock expenses (e.g. feed costs), veterinary and AI expenses, farm insurance, and advisory fees. Finally, we standardise the input variables by geometric means (e.g., Filipini et al., 2018; Martinez-Cillero et al., 2019). This standardisation allows for a logarithmic transformation of the variables.

4.5.1 Class membership separating variables

We include separating variables to capture the influence of these variables in defining farm latent classification. These variables parameterise the prior probabilities described in equation (4.3). Table 4.2 reports the separating variables included in our LCSF model specification.

Table 4.2 LCSF model prior probability results

	Class membership separating variables	
Variable	Description	Mean (SD)
Labour intensity	Total labour hours divided by total livestock units	32.96 (20.92)
Farm stocking rate	Total livestock units divided by utilised agricultural area in hectares	2.05 (0.53)
Specialisation dairy	The dairy gross output divided by the farm gross output in euros	0.75 (0.13)

Source: Teagasc NFS supplementary survey 2018

In defining class membership variables, we must be careful to exclude the level of inputs as this could lead to collinearity problems since the inputs are also included in the production function (Sauer and Morrison, 2013; Martinez-Cillero et al., 2019). To avoid this issue, we include class membership variables as shares (Alvarez and del Corral, 2010; Sauer and Morrison, 2013; Martinez-Cillero et al., 2019).

More specifically, using automated technologies aims to be labour-saving, especially for labour-intensive tasks (Graetz and Michaels, 2018). Therefore, we include labour intensity (i.e., labour hours per livestock unit) as a class membership variable. If the labour intensity is significant as a class separating variable, we would expect more labour-efficient farms (i.e., fewer labour hours per livestock unit) with higher adoption of automated technologies to be classified together.

Moreover, farm intensification correlates with higher use of capital and automation (Alvarez et al., 2012; DeLay et al., 2022). Thus, we also include farm stocking rate (i.e., total livestock units per hectare) as a class separating variable. Finally, in this chapter, we focus on specialised dairy farms. However, as shown in Table 4.1, we explore the farm's total output, including non-dairy outputs. Consequently, we include dairy specialisation (i.e., dairy gross output share) as a class membership variable to explore if the degree of specialisation plays a role in farms' latent classification.[29]

4.5.2 TE drivers

The variables included in the Z_i vector of the inefficiency effects model in equation (8) are described in Table 4.3.

Table 4.3 Efficiency driver variables

Variable	Description	Mean
Automated parlour feeders	1 if the farm uses the automated technology; 0 otherwise	0.57
Automated cluster removers	1 if the farm uses the automated technology; 0 otherwise	0.31
Automated scrapers	1 if the farm uses the automated technology; 0 otherwise	0.63
Automated washers	1 if the farm uses the automated technology; 0 otherwise	0.30

Source: Teagasc NFS and supplementary survey 2018

As mentioned, our main objective is to explore the role of automated technologies in TE. To this aim, we include the use of automated parlour feeders, scrappers, cluster removers, and washers as separating variables available from a supplementary survey in 2018 that elicits more detailed data on milking facilities.[30] All of these technologies aim to reduce the workload and increase the overall efficiency of the farm in previously identified labour-

[29] In the LCSF model, to avoid collinearity issues, the variables included in the class membership and efficiency-drivers specifications have to be different variables (Weller et al., 2020).
[30] Unfortunately, we do not know the year farmers adopted these automated technologies, as this question was not included in the survey.

intensive tasks in the milking process (Deming et al., 2017; Deming et al., 2018; Dillon et al., 2022). Therefore, obtaining positive correlations in increasing the TE of the farm could give confidence to farmers in adopting one of these automated technologies, given their milking facilities, labour intensity, and running costs.

4.6 Results and discussion

4.6.1 Class characteristics and membership probabilities

We start the discussion of our results with the class membership probabilities. Based on the AIC and the HQI criterion results, a two class LCSF model is preferred over a single frontier or a three class model.[31] Therefore, we report the results obtained from a two-class model. We display the coefficients and the sign of the separating variables included in the LCSF model in Table 4.4. The sign of the separating variables indicates the direction of the probability of being classified in class 2.

[31] We also estimated an LCSF model with four classes, but it failed to converge. This result indicates that such a model could be over-specified (Alvarez and del Corral, 2010; Martinez-Cillero et al., 2019).

Table 4.4 Separating variables

Variable	Coefficient (SE)	Direction of probability of belonging to class 2
Labour intensity (Labour hours/livestock units)	-8.501* (5.051)	-
Farm stocking rate (livestock units/uaa size)	7.662*** (2.033)	+
Dairy specialisation (dairy gross output/farm gross output)	1.413 (2.872)	
Constant	2.494 (3.572)	

Source: LCSF model prior probability results using Teagasc NFS and additional survey 2018. The exclusion of the separating variables was rejected by a likelihood ratio test at the 1 percent significance level; therefore, the relevance of the separating variables is confirmed for our LCSF model. Only the direction (sign) of the coefficients of the separating variables can be interpreted directly. The coefficients of the separating variables cannot be directly interpreted. Marginal effects can be manually computed (Martinez-Cillero et al., 2019). *** p<0.01, ** p<0.05, * p<0.1

In Table 4.4, statistical significance of a variable indicates that it helps to classify the sample. Therefore, as labour hours per livestock unit increase (i.e., labour intensity), the probability of a farm belonging to class 2 decreases. As farm stocking rate increases, the probability of a farm being classified in class 2 increases. The dairy specialisation membership variable is not significant. Therefore, farms in class 2 would be, on average, more labour efficient and have higher stocking rates.

4.6.2 Class characteristics

Next, we continue our results with the characteristics of the classes identified in the LCSF model. Table 4.5 reports the comparison in mean values of relevant variables for farm production and farm and household characteristics by class.

Table 4.5 Descriptive statistics by class

Variables	**Class (1)** Smaller, less intensive farms	**Class (2)** Larger, more intensive farms
Production function variables		
Capital (€)	213,107.23	378,123.08
Capital per ha (€/ha)	3,492.98	4,799.73
Labour hours	3,642.00	3,735.03
Miscellaneous inputs (€)	107,251.07	202,219.11
Miscellaneous inputs per ha (€/ha)	1762.35	2,566.88
Utilised agricultural area (ha)	61.01	78.78
Other farm production variables	**Smaller, less intensive farms**	**Larger, more intensive farms**
Hired labour (D)	0.52	0.77
Hired labour (hours)	152.70	426.03
Labour intensity (labour hours/livestock units)	36.97	20.01
Farm stocking rate (Livestock units/ha)	1.61	2.37
Livestock units	98.50	186.67
Herd size	62.96	115.39

Table 4.5 Continued

Automated technologies (efficiency drivers)	Smaller, less intensive farms	Larger, more intensive farms
Automated parlour feeders (D)	0.47	0.66
Automated cluster removers (D)	0.17	0.44
Automated scrapers (D)	0.50	0.74
Automated washers (D)	0.24	0.35
Farm and household characteristics	**Smaller, less intensive farms**	**Larger, more intensive farms**
Farm gross output per ha (€/ha)	2,949.33	4,356.03
Family farm income per ha (€/ha)	870.31	1,261.40
Farm stocking rate (Livestock units/ha)	1.61	2.37
Dairy specialisation (dairy gross output/farm gross output)	0.74	0.76
Total grants and subsidies per ha (€/ha)	348.92	376.00
Farmer age	54.71	51.85
Household members	3.30	3.53
Region of the farm[a]		
Region 1. Eastern and Midland	0.12	0.29
Region 2. Northern and Western	0.23	0.08
Region 3. Southern	0.65	0.63
Observations	139	149

Source: Teagasc NFS and supplementary survey 2018. The variables in the production function section on this table divided by hectares are shown for descriptive purposes. (D) Indicates a dummy variable. Family farm income per hectare is the gross output less total net expenses, it represents the total return to the family labour, management, and capital investment in the farm business (Dillon et al., 2022).[a] The region of the farm indicates the percentage of farms in each class by region (i.e., the numbers add to 100% in each class).

In Table 4.5, smaller, less intensive farms (see Column 1) have lower mean values for capital, miscellaneous inputs, and farm size. The difference between classes in total labour hours on the farm is small (i.e., 93 hours a year which represent 1.8 hours a week on average). Also, farms in class (1) are less likely to hire labour on the farm and hire fewer additional labour hours than farms in class (2) (see Column 2). Nevertheless, the average hours of labour per livestock unit (i.e., labour intensity) are higher in class (1). This result suggests that, on average, farms in class (2) are less labour-intensive than farms in class (1). The size of the farms can explain these differences in each class and their level of farm intensity (i.e., farm stocking rate is 1.61 in class 1 whereas stocking rate is equal to 2.4 in class 2). Therefore, class (1) represents smaller, less intensive farms. Then, we name the class identified in Column (2) as the larger, more intensive class.

For the automated technology variables, farms in the larger, more intensive class are more likely to adopt automated technologies. The differences in the use of automated technologies between the classes is around 20-25% for automatic parlour feeders, cluster removers, and scrapers. This difference is around 10% between the groups for automatic washers.

The larger, more intensive farms have higher farm gross output and family farm income per hectare. Dairy specialisation is similar to the average of the total sample displayed in Table 4.2 (i.e., 0.75). Larger, more intensive farms received higher average subsidies per hectare. Moreover, farmers in the larger, more intensive class are marginally younger, while both classes are found to have similar number of household members. Regarding farm location, in both classes, more than 60% are in the southern part of the country (as is the case for the national population of Irish dairy farms). Also, the LCSF model performed well regarding the distribution of the observations by class. Finally, the results in Table 4.5 confirm the results about separating variables shown in Table 4.4 since more labour-efficient farms and more intensive farms (i.e., farm stocking rate) are classified in the larger, more intensive class.

4.6.3 TE scores by class

Based on the estimated posterior probabilities described in equation (4.6), the LCSF model computes farm-specific TE based on each farm's most likely frontier. The estimated average posterior probabilities are 89% and 91% for each class. Therefore the LCSF model did a good job splitting the sample since these probabilities reflect the uncertainty of the researcher regarding the actual partition of the dataset (Martinez-Cillero et al., 2019). We display the estimated average TE scores, the median and the first and third quartiles from the LCSF model in Table 4.5.

Table 4.6 Mean and quartile technical efficiency scores by class

Stats	Single frontier	Smaller, less intensive class	Larger, more intensive class
Mean	**0.870**	**0.820**	**0.911**
1st Q	0.850	0.741	0.890
Median	0.881	0.830	0.932
3rd Q	0.913	0.921	0.970

Source: Teagasc NFS and supplementary survey 2018

In Table 4.6, note that the estimated TE score for each farm uses their respective class frontier in the LCSF model. Therefore, the TE scores are not directly comparable across classes (Dapko et al., 2021b). The score in the first Column corresponds to a model estimated assuming a single frontier (i.e., homogeneous technology) for all farms in the sample. The following two Columns display TE scores for farms classified in each class by the LCSF model (i.e., accounting for technology heterogeneity). When we implement the LCSF model, the total average TE level is higher for the larger, more intensive class and lower for the smaller, less intensive class compared to the single frontier model. This result confirms that not accounting for technological differences generates biases in the TE scores (Alvarez and del Corral, 2010; Martinez-Cillero et al., 2019). On average, the larger, more-intensive farms produce closer to their frontier with minor variation in TE within their class. This result also implies that at the current level of input use, larger, more intensive farms could obtain a 9 per cent increase in output if fully efficient. Farms in the smaller, less intensive class obtained a lower average score, suggesting they have more scope for efficiency improvement. This result means that, if fully efficient, smaller, less intensive farms would obtain an 18% increase in output at the current input level.

4.6.4 Efficiency drivers

In Table 4.7 we report the effects of the automatic technologies as efficiency drivers included in the inefficiency effects model described in equation (4.8). Note that coefficients and marginal effects indicate the direction of the effect of each control variable on farm inefficiency. Philosophically speaking, an effect that reduces technical inefficiency may not necessarily mean improving efficiency. However, for ease of interpretation and consistency with the literature, this Chapter considers technical inefficiency as the flip side of TE (Martinez-Cillero et al., 2019). Therefore, a positive coefficient for a given variable in technical inefficiency implies a negative effect on TE and vice versa.

Table 4.7 Coefficients and marginal effects of efficiency drivers in technical inefficiency

	Smaller, less intensive class		Larger, more intensive class	
	(1) Coefficients (SE)	(2) Marginal effects	(3) Coefficients (SE)	(4) Marginal effects
Automated parlour feeders	0.151 (0.271)		-1.431** (0.70)	-0.031**
Automated cluster removers	-0.69*** (0.242)	-0.031***	0.220 (0.694)	
Automated scrappers	-0.620* (0.360)	-0.040*	-0.204 (0.78)	
Automated washers	0.05 (0.301)		-2.382 (3.773)	

Note: *** p<0.01, ** p<0.05, * p<0.1

In Table 4.7, our results suggest that automated technologies have a heterogeneous effect on farms TE depending on their class membership. Specifically, in the smaller, less intensive class (i.e., Columns (1) and (2)) we observe that automated cluster removers and automated scrappers have a significant positive effect on farm TE. When a farm in the smaller, less intensive class adopts automated cluster removers in its milking facility, it is associated with a 3% increase (marginal effect) in TE on average. Since automated cluster removers efficiently and faster remove clusters when cows are milked, our results are consistent with Deming et al. (2017; 2018), where the milking process is identified as one of the most labour-intensive tasks in smaller farms. Therefore, our results suggest that, adopting this technology in the farms that are yet to use it (i.e., 83% of farms) would significantly aid in increasing the efficiency of smaller, less intensive farms.

Furthermore, on average and all else constant, adopting an automatic scraper is associated with a TE increase by 4% in smaller, less intensive farms. Half of the farms in the smaller, less intensive class report not adopting this type of technology. Therefore, there is room to improve their farm TE by adopting an automated scraper. Since cleaning the slurry is a labour-intensive task requiring few labour skills, our results suggest that the improvement in TE may outweigh the investment needed to adopt this technology. Finally, our results suggest that adopting an automated parlour feeder and an automated washer do not significantly correlate with farms' TE in this class. These non-significant results might be because these automated technologies are designed to reduce the increased workload, mainly associated with larger herd sizes.

In the case of the larger more intensive farms (Columns (3) and (4)), automated parlour feeders are associated with increases in TE. Since an automated parlour feeder can be easily adapted to milking systems (Ryan and Donworth, 2021), if a farm adopts this technology, it is associated with a 3% increase in TE (see Column (4)). Importantly, changing the milking facilities is a long-term decision (e.g., the milking facilities in Ireland have an average life span of 40 years) (Ryan and Donworth, 2011). Thus, investing in automated technologies tend to be auxiliary technologies to improve the existing milking facilities. Since the data on automated technologies are measures as discrete choice, adopting an automated technology represents a one-off TE gain. The rest of the automated technologies do not significantly correlate with farms TE in this class. The result may be explained by the high number of adopters in this class in which the efficiency gains might have already been made.

4.6.5 Output elasticities by class

In the last part of our analysis, we focus on the estimated Cobb-Douglas production function results. Table 4.8 reports the output elasticities and returns to scale by class.

Table 4.8 Output elasticities and returns to scale by class

Variable	Smaller-less-intensive class	Larger-more-intensive class
Capital	0.127***	0.162***
	(0.008)	(0.039)
Labour	0.037	0.076**
	(0.045)	(0.036)
Miscellaneous inputs	0.641***	0.487***
	(0.011)	(0.055)
Land	0.191**	0.221***
	(0.101)	(0.055)
Returns to scale	0.906	0.993
Constant	0.006**	0.101
	(0.002)	(0.079)

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. We also included regional dummies in the production function; none of the coefficients were significant. We also estimated other two specifications of the LCSF model as a sensitivity analysis of the output elasticities results (not reported here). First, we estimated a LCSF without class membership variables; then, we estimated an LCSF model without class membership variables and without efficiency drivers. In both specifications we obtained similar results in magnitude and significance of the output elasticities of each class.

Since we divide the variables included in the production function by their geometric means prior to estimation, the estimated parameters can be interpreted as output elasticities evaluated at the geometric mean of the sample. All elasticities have positive signs at the means, and except for labour input in the smaller, less intensive class, all input coefficients are statistically significant. Labour has also been found not statistically significant in previous SFA applications in the Irish dairy sector; for example, Carroll et al. (2011)

and Gillespie (2015). In these previous studies, it is attributed (paradoxically due to the presence of labour shortages) to the possible underemployment of labour (Loughrey and Hennessy, 2014; Loughrey et al., 2022).

The variation in the significance of the elasticity depending on the class indicates the existence of different technologies (Martinez-Cillero et al., 2019), and confirms our modelling choice. More specifically, in the case of smaller, less intensive farms, the labour elasticity is not statistically significant. In the case of the larger, more intensive farms, the labour elasticity is positive and statistically significant. This result can be explained by the mean differences in the characteristics and technologies of the farms' and households' shown in Table 4.4. That is, a possible explanation for this difference in the significance of labour elasticity could be that (given that larger, more intensive farms adopt more automated technologies on average) the use of automated technologies could have a labour-productivity effect (Acemoglu and Restrepo, 2018). Furthermore, in the larger, more intensive class, the average hours of labour per livestock unit (i.e., 20 hours) is less than the mean for the entire sample (i.e., 33 hours) and less than the figure for the other class (i.e., 37 hours). So, our combined results from Table 4.4 and Table 4.8 may provide evidence that automated technologies have a labour-productivity effect (Acemoglu and Restrepo, 2017; 2018).

Finally, the sum of all the elasticities in each class gives a measure of the returns to scale. Both classes operate, on average, with slightly decreasing returns to scale in 2018. This result suggests that all farms have room to improve economic performance by adjusting their size in relation to utilised inputs.

4.7 Conclusions

This chapter explored the role of automation in TE of Irish dairy farms after a significant structural change initiated by the EU milk quota abolition. We estimated a latent class stochastic frontier (LCSF) model developed by Dakpo et al. (2021b), and applied it to a unique representative sample of Irish dairy farms that includes detailed data on automated technologies. Our model identified two latent classes of farms, smaller, less intensive and larger, more intensive farms with a different technology underlying their production.

Furthermore, we observed considerable differences between the latent classes regarding TE scores. Consistent with the literature, we find general high TE scores of Irish dairy farms (Carroll et al., 2011; Gillespie, 2015; Bradfield et al., 2021). However, larger, more intensive farms produce closer to their frontier (i.e., TE score of 91% compared to 82% in the other class). Larger, more intensive farms are, on average more labour efficient (i.e., 20 hours of labour per livestock unit compared to 36 hours in the other class) and adopt more automated technologies (i.e., the average adoption rate of 55% against 34% in the other class). These differences highlight the importance of addressing technology heterogeneity when estimating TE (Dakpo et al., 2021a).

We find an overall positive association between adopting automated technologies and farms' TE; however, this effect is heterogeneous and depends on farms' classification. Automated cluster removers and scrapers are associated with higher TE scores on smaller, less intensive farms. In the case of larger, more intensive farms, automated parlour feeders are positively associated with higher TE scores on these farms; everything else held constant.

These findings have important practical and policy implications. In relation to smaller, less intensive farms, these farms have greater scope to increase their TE. Specifically, our findings suggest that one way to increase their efficiency is through adopting automated cluster removers and automated scrapers. Farms in this class have a relatively low adoption rate of automated cluster removers (i.e., 17% against 44% in the other class). Adopting these automated technologies could help reduce the time spent milking and increase the efficiency of the farm. Furthermore, half of the farms in this class do not use automated scrapers. Removing slurry is an essential and highly labour-intensive task on any dairy farm. Therefore, farmers with smaller, less intensive class farm characteristics may invest in these automated technologies to achieve farm efficiency gains, which may then outweigh the investment costs.

In relation to larger, more intensive farms, automated parlour feeders would help increase the efficiency on these farms. These farms are already labour efficient, have high TE scores and are likely using many other automated technologies for their milking facilities. Therefore, investing in an automated parlour feeder could represent the last necessary *push* for these types of farms to be fully efficient and face the challenges with improved productivity.

The further development and social sustainability of the dairy sector requires farm automation investment to ensure the sector's continued viability and efficiency. For instance, 55% of farmers are highly stressed due to increasing workload (Buckley and Donnellan, 2021; Brennan et al., 2021); therefore, investing in labour-saving technologies could aid in easing dairy farmers' workload related stress while increasing the efficiency of the farm. Moreover, automated parlour feeders can also be used to detect herd related health disorders, allowing farmers to identify and implement prevention and treatment protocols at earlier stages. Hence, policymakers should see the adoption of automated technologies as a multidimensional resource that will not only bring overall efficiency gains but also aid in easing labour-intensive related stress and improving milk quality and the herd's general health.

As such, a farm automation agenda targeting farms that are yet to adopt automated technologies would bring broad benefits for the future of the Irish dairy sector. The success of farm automation could be augmented by putting equal emphasis on other efficiency-enhancing factors as providing and expanding farm extension services (Buckley and Donnellan, 2022). Moreover, creating grants or expanding available grants that ease access to automated technologies, e.g., the Targeted Agricultural Modernisation Scheme (TAMS) (Nolan, 2018; 2022; Conlon, 2021), could be prioritised in the suggested automation agenda. The dissemination of the benefits of automation can also be prioritised in discussion groups since farmers may be keener to take advice from peers than from other sources of advice (Läpple and Barham, 2019).

Finally, the cross-sectional nature of our data set does not allow for the inclusion of time in our estimates. For example, assessing the year of adoption of automated technologies and allowing a farm to move from one classification to another over time is not possible (Alvarez and Arias, 2015). Moreover, since the environmental impact of dairy production is a growing concern (Dillon et al., 2022), exploring the role of automated technologies on farms environmental efficiency using panel data would be a compelling extension for future research.

Chapter 5 - Shadow wage of family labour and its role in hired labour demand: evidence from Irish dairy farms

5.1 Introduction

Agriculture increasingly faces significant challenges relating to sustainability and food security (EU Commission, 2020). A particular challenge for family farms is the ability to produce efficiently and profitably in the presence of labour shortages (McGrath, 2021; Dillon et al., 2022). Therefore, the increased demand for labour has become a concern, especially in the dairy sector (Kelly et al., 2020; Weber et al., 2021). Amongst other factors, this increased demand for labour is motivated by the significant restructuring of the dairy sector due to the abolition of EU milk quotas in 2015, and the subsequent increase in milk production in some member EU countries (e.g., the Netherlands and Ireland).

Despite the general decline in the number of people engaged in farming, family farming remains the predominant farm type (95%) in the EU (Eurostat, 2020). The Food and Agriculture Organization of the United Nations (FAO) defines a family farm as an agricultural property managed and operated by a household that predominantly provides agricultural labour (FAO, 2021). Therefore, family labour is crucial to EU agricultural sustainability and rural development.

Ireland is among the countries that experienced significant structural change due to the abolition of EU milk quotas. Recent structural change on Irish dairy farms is reflected in the fact that more than 80% of farms have expanded production, through an increase in average herd size and milk yield per cow since 2010. This has resulted in more than one-third of dairy farms reporting an average herd size of more than 100 cows, and are responsible for 60% of production (Dillon et al., 2022).[32] Since family farms are the predominant farm type in Ireland (99.7%), 93% of the workforce relates to the farmer and members of the farm household (CSO, 2018). The reliance on family labour in an enlarged dairy sector is not sustainable, with workload and labour shortages being of significant concern to dairy farmers (Brennan et al., 2021; Brennan et al., 2022). Additional hired labour is also required. Therefore, the mismatch between increasing herd size and labour availability has become a further impediment for dairy farmers (Kelly et al., 2020; Brennan et al., 2021).

Although hired labour is promoted as a practical resource to relieve stress related to the increasing workload (Farrell and Clarke, 2017; Brennan et al., 2021), hired labour remains underutilised on Irish dairy farms (Garcia-Covarrubias et al., 2022). The apparent lack of available skilled labour is one reason for this underutilisation, and is influenced by factors such as an uneven demand for labour due to the seasonal calving system in Ireland, the location of the farm and farmer characteristics (Loughrey and Hennessy, 2014; Kelly et al., 2020). For instance, data from a 2018 labour survey indicates that 73% of farmers reported problems hiring labour, with 14% unable to hire additional labour despite requiring it (O'Brien et al., 2019).[33]

This chapter estimates the economic value i.e., shadow price of family labour on Irish dairy farms. A shadow price is an estimated exchange value for a good, input or service for which no market price exists (Czichowsky et al., 2017; Yu et al., 2017). The literature highlights the importance of the shadow price (i.e., wage) of unpaid labour in the economic performance of family farms (Ooms and Peerlings, 2005; Peerlings and Ooms, 2008; Almeida and Bravo-Ureta, 2019). However, several studies analysing the family labour shadow wage assume perfectly competitive and complete labour and input markets (Peerlings and Ooms, 2008; Blanc et al., 2008; Thorne et al., 2017). In studies where perfectly competitive labour and input markets are assumed, observed market wages are used as imputed values for the shadow wage of

[32] The milk yield per cow (litres) increased from 5,099 to 5,744 from 2010 to 2021. The herd size increased from an average of 65 to 90 cows (Dillon et al., 2022).
[33] 2018 was a particularly challenging year for dairy farming due to bad weather and its consequent impact on farm income.

family labour.[34] Under the assumption of a perfectly competitive market structure, the observed market wages are identical to the shadow wage of family labour. However, this perfect market assumption is usually violated, and imperfections prevail in the labour market (Singh et al., 1986; Almeida and Bravo-Ureta, 2019). Then, the shadow wage of family labour deviates from the observed market wage (Singh et al., 1986; Thorbecke, 1993; Le, 2010). Therefore, neglecting the possibility of labour market imperfections would lead to biased shadow wages of family labour and potentially misleading practical and policy implications (Skoufias, 1994; Almeida and Bravo-Ureta, 2019). Consequently, estimating the family labour shadow wage addressing labour market imperfections becomes essential to analyse the economic performance of family farms.

Furthermore, assuming perfectly competitive labour markets might be a wrong assumption in agriculture for several reasons. Firstly, farm labour is often a lifetime decision due to frictions and imperfections in the labour markets and the cost of migration (Lopez, 1984; Le, 2010). Secondly, the productivity of family and hired labour may differ due to agricultural education, experience, and monitoring cost (Le, 2010; Almeida and Bravo-Ureta, 2019). Thirdly, several individuals become farmers because they enjoy farming which tends to lower the shadow wage of farm labour (Le, 2010; Howley et al., 2014). As a result, labour supply and demand decisions are typically non-separable in the sense that they involve the valuation of both production and consumption activities by the farm household (Le, 2010; Almeida and Bravo-Ureta, 2019).

Two key contributions distinguish this study from the existing literature. Firstly, following the seminal work of Jacoby (1993) and Skoufias (1994), we estimate the shadow wage of family labour on Irish dairy farms from a representative panel data set from 2005 to 2019. Using this methodology, we take account of potential imperfections in the labour market. More specifically, we estimate shadow wages from a production function

[34] The agricultural market wage, all sectors market wage, wages paid to hired labour on the farm, or farmer/spouse wages in the off-farm market if involved in off-farm activities are the observed market wages commonly used in previous studies as imputed values for the value of family labour.

accounting for the opportunity cost of family labour, which is determined by the farm household rather than by market forces (Le, 2009; Almeida and Bravo-Ureta, 2019). The latter results in the use of the marginal product of family labour to calculate its shadow wage, assuming that the production and consumption decisions of the family farm are non-separable (Lopez, 1984; Skoufias, 1994; Almeida and Bravo-Ureta, 2019). Then, we provide detailed descriptive evidence of shadow wage by herd size and returns to formal agricultural education. Furthermore, to the best of our knowledge, family labour shadow wage has yet to be estimated for Irish dairy farms, as only imputed values are available to approximate the economic value of family labour (e.g., Thorne et al., 2017; McCormack, 2020). This chapter fills this knowledge gap.

Secondly, we use the estimated shadow wage to explore its role in the demand for hired labour. To do so, we use a censored variable semiparametric approach that controls for the self-selection bias stemming from the opportunity cost of family labour. Thus, we obtain consistent estimates of all the parameters we report. Moreover, only a handful of studies have recently examined the demand for hired labour in family farms (e.g., Benjamin and Kimhi, 2006; Blanc et al., 2011). Therefore, our hired labour demand estimation provides insights into the relationship between hired and family labour in a family farming context in an evolving dairy sector. Finally, we aim to assess whether or not the role of shadow wages affects the demand for casual and permanent hired labour on the farm differently.

The rest of this chapter is organised as follows: Section 5.2 provides the conceptual framework utilised in this article. Section 5.3 presents the relevant literature on family labour shadow wages and hired labour demand, while Section 5.4 describes the data utilised. Section 5.5 provides an overview of the methodology, and Section 5.6 presents the results and discussion, followed by concluding remarks as the final section.

5.2 Conceptual framework

The conceptual framework for the shadow wage estimations in this study draws on the seminal work of Gronau (1977) and Rosenzweig (1980) and the adjustments made by Jacoby (1993) and Skoufias (1994).

The neoclassical approach establishes that farm household production and consumption decisions are independent. Thus, the neoclassical approach heavily relies on the separability assumption. The separability assumption states that farmers first maximise profits and then decide how much income is allocated to the consumption of goods/services (including hired labour) and leisure (Barrett et al., 2008; Almeida and Bravo-Ureta, 2019). The separability approach also assumes that agricultural markets (i.e., inputs and output) are perfectly competitive and that family and hired labour are perfect substitutes with equal productivity (Lopez, 1984; Tocco et al., 2012a; Almeida and Bravo-Ureta, 2019). This approach also assumes that equal utility is associated between off-farm and on-farm work. In empirical studies that estimate shadow wages, there is no consensus around the separability assumption (Tocco et al., 2012a; Almeida and Bravo-Ureta, 2019).

The separability of farm production/consumption decisions is too strong an assumption for the Irish dairy sector. Firstly, Ireland's grass-based dairy production creates an uneven demand for labour that generates friction in the labour market due to the demand peaks (Deming et al., 2018; Bradley et al., 2021). Since most of the workload is undertaken in the first four months of the year due to the spring calving production system, the most time-consuming activities are related to calving, breeding and milking (Deming et al., 2017; Dillon et al., 2022). Thus, assuming equal productivity between family and hired labour might be too strong an assumption since they tend to perform different tasks on the dairy farm (Deming et al., 2018).

Secondly, the recent exponential growth of dairy production in Ireland inevitably increases the need for additional labour on the farm (Anderson, 2020; Buckley and Donnellan, 2022). Therefore, additional hired labour becomes essential for dairy production (Anderson et al., 2020; Kelly et al., 2020). Due to the seasonal nature of labour demand in the Irish dairy sector

(Läpple et al., 2020), the farm's region, the farmers' demographics, and hired labour availability (Carroll et al., 2011; Loughrey and Hennessy, 2014; Kelly et al., 2020), sourcing hired labour has become an additional challenge for farmers in the sector. Therefore, assuming that all farmers have the same ease of hiring additional labour is a misplaced assumption. Consequently, the above suggests that the market for hired labour in the Irish dairy sector might not be perfectly competitive and complete. Therefore, using wage rates for hired labour as imputed values for family labour's economic value may bring biased results and misplaced practical and policy implications.

Thirdly, latent unemployment in rural areas creates additional imperfections in the labour market. The lack of opportunities for off-farm jobs may cause (paradoxically to the labour shortages) labour underemployment on some Irish farms (Loughrey and Hennessy, 2014; Loughrey et al., 2016). In addition, since most farmers/spouses involved in off-farm work are mainly driven by individual preferences rather than financial reasons (Howley et al., 2014), assuming that the value of family labour is empirically equal to the market wage rate may be a wrong assumption. For instance, if a dairy farmer/spouse chooses to work off-farm but is constrained by structural conditions (i.e., farm location, farm size of neighbouring farms); then, in principle, the value of family labour should be different from the market wage rate (Howley et al., 2014; McCormack et al., 2020). Therefore, the average market wage rate may not be empirically equal to the opportunity cost of working on the farm. In other words, the on-farm and off-farm markets are incomplete in economic terms, and the marginal utility of both types of labour might differ. Consequently, imputing the values of the observed market wages as a proxy to family labour's value would be a mistake, both theoretically and empirically.

In conclusion, relaxing the separability assumption becomes crucial for empirically estimating shadow wages irrespective of market imperfections (Singh et al., 1986; Almeida and Bravo-Ureta, 2019). Specifically, if labour markets are not perfect, then the shadow wage of the farmer/family labour is expected to equal their on-farm labour marginal product. Then, using the market wage is no longer correct to approximate the economic value of their work time (Jacoby, 1993; Skoufias, 1994). Therefore, estimating a farm production function allows the researcher to derive the shadow wage for unpaid on-farm work, and the shadow wage can be calculated from the marginal product of labour on the farm (Skoufias, 1994; Almeida and Bravo-Ureta, 2019). Finally, based on this approach, we interchangeably use *opportunity cost of labour* to refer to the shadow wage of family labour

5.3 Literature review

5.3.1 Shadow wage of family labour in Irish agriculture

To the best of our knowledge, there are no empirical studies on the shadow wage of family labour in Irish agriculture. Only imputed values are used (e.g., Thorne et al., 2017; McCormack, 2020). Thorne et al. (2017) focus on exploring the competitiveness of Irish agriculture. They analyse the Farm Accountancy Data Network (FADN) and use hired labour wages as imputed values for the wage of family labour. McCormack et al. (2020) use Central Statistics Office (CSO) data and develop a total factor productivity (TFP) analysis based on economic indices. They use agricultural output, input and income data from the CSO to construct a labour price index based on the Compensation of Employees figure using 2010 as a baseline (CSO, 2020). The labour price index reported by McCormack ranges from 92% in 2006 to 109% in 2016 (McCormack et al., 2020, p.131). Moreover, McCormack et al. (2020) acknowledge that family wages may be higher than hired labour. However, due to the absence of differential data on hired versus family wages, they use the same labour price index for both types of labour in their TFP analysis.

Moreover, Thorne et al. (2017) reckon that the use of the observed agricultural wage to value owned family labour may, in some instances, overvalue (due to underemployment) or undervalue (due to managerial or entrepreneurial ability) family labour. Therefore, determining an appropriate opportunity cost for family labour is always an issue in studies examining production costs on Irish farms (Thorne et al., 2017). Consequently, the need to approximate an unbiased estimation of the value of family labour becomes crucial to analyse the economic performance of Irish dairy farms.

Finally, on the theoretical side, Donnellan and Hennessy (2012) define a model for labour allocation decisions assuming perfect and complete labour markets. Its main objective is to analyse the possible impact of decoupled subsidies on the hours allocated by Irish farmers to work on-farm. Their findings suggest a contradictory effect of subsidies on labour allocation. On the one hand, subsidies in their model represent more income on the farm, in which case the farmer can allocate less hours to work on the farm. However, subsidies reduce farming opportunity costs, which may lead the farmer to substitute off-farm work for on-farm work (Donnellan and Hennessy, 2012).

5.3.2 The demand for hired labour on family farms

Previous studies that estimate agricultural shadow wages do so to estimate the off-farm labour supply (e.g., Skoufias, 1994; Le, 2010; Almeida and Bravo-Ureta, 2019). However, the role of shadow wages in the demand choices of farm households is also essential for understanding the economic performance of family farms.

Several studies have examined the demand for hired labour in EU family farms (e.g., Benjamin and Kimhi, 2006; Blanc et al., 2008; Lips et al., 2013; Darpeix et al., 2014) and other countries (e.g., Fredrick et al., 2007; Luo and Escalante, 2017). The empirical results from the majority of these studies find a strong correlation with the human capital characteristics of the farmers (i.e., age, formal agri-education, experience) and with the farm production characteristics (Benjamin and Kimhi, 2006; Blanc et al., 2008; Tocco et al., 2012a). Although, some studies have found that age does not significantly influence the demand for hired labour (i.e., Fredrick et al., 2007; Darpeix et al., 2014).

Regarding farm and household characteristics, the higher the number of family members on the farm, the lower the demand for hired labour (Benjamin and Kimhi, 2002; Tocco et al., 2012a). However, increasing household members typically shares a stronger correlation with extra hired labour (Blanc et al., 2008). Larger farms are generally associated with higher demand for hired labour (Blanc et al., 2008; Tocco et al., 2012a; Darpeix et al., 2014).

The role of family labour on hired labour demand has also been explored. In general, hired and family labour have been found to be substitutes on the farm (Blanc et al., 2008). Specifically, the degree of substitution between hired and family labour increases with the economic size of the farm (Blanc et al., 2008). The demand for hired labour also may increase depending on the productivity of family labour (Steeneveld et al., 2012; Lips et al., 2013). Lips et al. (2013) suggest that hired labour is a substitute for farmer and family labour, especially at lower levels of family labour productivity. However, hired labour can substitute for family labour when the productivity of the farm is high (Tocco et al., 2012a; Steeneveld et al., 2012). Therefore, the role of the productivity of family labour on hired labour demand remains unclear.

5.4 Data

We use representative panel data (664 farms; 5,264 observations) from the Teagasc National Farm Survey (NFS) spanning the years 2005 to 2019. Teagasc collects NFS data as part of the EU Farm Accountancy Data Network (FADN) database. The NFS was established in 1972 and published on an annual basis. Approximately 900 farms are surveyed annually by a professional data collection team, representing a farming population of about 90,000. These 900 representative farms belong to six different farm systems, i.e., cattle rearing, cattle other, sheep, specialised dairy, tillage and mixed livestock. In this analysis, we focus on the data of specialised dairy farms, which results in approximately 375 farms per year that represent about 15,500 Irish dairy farms.

Beyond standard farm accountancy measures, the NFS also captures annual farm labour hours. These hours include paid, i.e., casual and permanent hired labour, and unpaid labour, i.e., farmers' and family labour. The NFS also reports hired labour hours on the farm. Besides, the NFS reports whether the farmer and their spouse are involved in off-farm waged activities. Nevertheless, the earned wages in off-farm activities by the farmers and family labour are unavailable in the NFS. Table 5.1 includes the labour input variables used in this analysis and other relevant production farm and household characteristics.

Table 5.1 Descriptive statistics on labour and farm and household characteristics

Variables	Description	Mean (SD)
Total value farm output (TVFO) [a]	Average total value of the farm in thousands of euros (i.e., milk, crops, sheep, livestock, calves)	172.52
		(115.74)
Family labour	Average farmer/family labour yearly hours on the farm	4,093.37
		(2675.49)
Hired labour dummy	Dummy variable for hired labour on the farm	0.60
		(0 .48)
Hired labour	Annual hired labour hours on the farm	492.35
		(983.78)
Casual hired labour	Percentage of casual hired labour to total hired labour hours	0.82
Permanent hired labour	Percentage of permanent hired labour to total hired labour hours	0.18

Table 5.1 Continued

Capital [a]	Value of machinery and buildings and herd size in thousands of euros	105.77
		(84.18)
Miscellaneous inputs [a]	Value of direct inputs for dairy production in euros[b].	854.41
		(57.51)
Land	The size of the farm in hectares	64.3
		(35.28)
Rented land [a]	Land rent per hectares in euros	82.1
		(7.92)
Household members	Number of household members	3.68
		(1.67)
Farmer off-farm work dummy	1 for off-farm labour by the farmer	0.09
		(0.29)
Spouse off farm dummy	1 for off-farm labour by spouse	0.43
		(0.49)

Table 5.1 Continued

Grants and subsidies	Total of all non-capital grants and subsidies in euros per hectare.	413.65
		(164.01)
Agricultural education	1 if the farmer reports formal agricultural education	0.78
Herd size	Annual average herd size on the farm	68.90
		(42.31)
Geographical location		
Region 1	1 if the farm is located in the east or midland of Ireland	0.18
Region 2	1 if the farm is located in the north or west of Ireland	0.16
Region 3	1 if the farm is located in the south of Ireland	0.67

Note: [a] Deflated values with price indices from the Central Statistics Office (CSO, 2020; base year = 2015). [b] The list of miscellaneous inputs includes concentrates, seeds, and crops related expenses, farm insurances, among others. Means and standard deviations in parentheses. Teagasc NFS 2005-2019.

In Table 5.1, the total value of farm output (TVFO) is the sum of the deflated values in euros of total milk production, calves, cull cows, beef cattle sold, sheep sold, and crop sales. On average, a dairy farm in the sample produced

172,521 euros annually from 2005 to 2019. Family labour amounted to 4,093 labour hours per year, which represents approximately 78.71 hours a week of family labour on the farm. Moreover, 60% of Irish farms hire some labour annually. On average, Irish dairy farms hired 492 hours of labour, representing 10% of the total labour on the farm in the period. From total hired labour, 81% is casual and 19% is permanent labour.[35]

Capital comprises machinery, buildings, and livestock as follows: the aggregated value of machinery and buildings and the value of the dairy herd, calculated according to the end-of-year valuation based on a replacement cost methodology. Capital on Irish dairy farms is valued, on average, at 105,778 euros from 2005 to 2019. Miscellaneous inputs (854.41 euros per year on average) are direct costs incurred in dairy production, such as concentrates, fertiliser, purchased seeds, building repairs, livestock expenses, veterinary and artificial insemination expenses, farm insurance, and advisory fees, among others. Land refers to the total agricultural area utilised in hectares. Finally, the average farm size is 64 hectares in the period.

5.5 Methodology

Following Jacoby (1993); Skoufias (1994) and Almeida and Bravo-Ureta (2019), the first step in our econometric strategy is to estimate the marginal value of family labour for on-farm activities using an agricultural Cobb-Douglas production function model.

$$TVFO_{it} = \hat{\beta}_{0,i} + \hat{\beta}_1 labour_{it} + \hat{\gamma} hired_{it} + \hat{\beta}_2 X_{1,it} + \hat{u}_{1,it} \quad (5.1)$$

Where $TVFO_{it}$ is the total value of farm output for the for the *ith* farm in time *t*. The variables $labour_{it}$ and $hired_{it}$ are the logarithm of family and hired labour hours on the farm.[36] The vector $X_{1,it}$ includes inputs and control variables including capital, land, miscellaneous inputs, off-farm work of

[35] Casual labour are part-time workers that are normally on standby to do work as required without fixed hours or attendance arrangements. A casual worker has less than 13 weeks of continuous service or are casual based on a collective agreement (DJEI, 2001).
[36] Due to zero values recorded for hired labour we apply the log-transformation suggested by Cameron and Trivedi (2010). This log-transformation consists in approximating a gamma constant to the zero values in the sample to keep the logistic distribution of the variables.

farmers and spouses, among other farm and household characteristics.[37] $\hat{\beta}_{0,i}, \hat{\beta}_1, \gamma, \hat{\beta}_2$ are parameters to be estimated and $\hat{u}_{it}$ is the error term. We estimate Eq. (5.1) with fixed effects and robust standard errors. All the variables included in equations (5.1) to (5.5.1) are described in Table 1 in the data section.

5.5.1 Shadow wage and shadow income on the farm

We use the parameters of family labour marginal value obtained in Eq. (5.1) to estimate the shadow wages of family labour and shadow income on Irish dairy farms.

$$\widehat{W}_{it} = \frac{\widehat{TVFO}_{it}}{labour_{it}} \hat{\beta}_{1(it)} \tag{5.2}$$

$$\hat{I}_{it} = \widehat{TVFO}_{it} - \widehat{W}_{it}(labour_{it}) - W_{h,t}(hired_{it}) - misc_{inp_{it}} - rnt_{land_{it}} + grants_{subsidies_{it}} \tag{5.3}$$

In Eq. (5.2), $\widehat{W}_{it}$ represents the shadow wage for family labour on the *ith* farm in time *t*. $\widehat{TVFO}_{it}$ is the estimated total value of farm output obtained from Eq. (5.1). The term $labour_{it}$ is the family labour input of the farm measured in hours; and $\hat{\beta}_{1(it)}$ is the coefficient for family labour specified in Eq. (5.1). In Eq. (5.3), $\hat{I}_{it}$ is the shadow income of the *ith* farm at time *t*. $W_{h,t}(hired_{it})$ is hired labour wage[38]. The variable $misc_{inp_{it}}$represents the miscellaneous inputs used in the farm. $rnt_{land_{it}}$ is the land rent expressed in euros. Finally, $grants_{subsidies_{it}}$ is the total value of grants and subsidies received annually by the farm in euros.

[37] In contrast to Skoufias (1994) and Almeida and Bravo-Ureta (2019) we do not divide the family labour on the farm according to gender. The reason is that in our sample 95% of the farmers are male, therefore, there is not a sufficient number of annual observations to robustly estimate a female labour coefficient in the production function.

[38] The hourly paid wage is 12.78 euros on average.

5.5.2 Equality of markets

An important part of the shadow wage approach is to empirically test the equality of markets (Almeida and Bravo-Ureta, 2019). In the absence of market failures, the market wage received by family members who participate in the off-farm market should be equal to the marginal productivity of work on the family farm according to the assumption that households maximize utility (Skoufias, 1994; Abdulai and Regmi, 2000; Almeida and Bravo-Ureta, 2019). Jacoby (1993) proposes a test for the validity of this perfect market assumption using both shadow wage and market wages as follows:

$$\ln\left(\widehat{W}_{it}\right) = \hat{\alpha} + \hat{\rho}\ln({market_{wage}}_{it}|Z_{1,it}) + \hat{\varepsilon}_{it,j} \tag{5.4}$$

where $\ln\left(\widehat{W}_{it}\right)$ is the natural logarithm of the shadow wage for family labour. ${market_{wage}}_{it}$ is the average market wage per hour by year in Ireland (CSO, 2020). $Z_{1,it}$ is a vector of *exogenous* variables (Martinez-Cillero et al., 2019; Almeida and Bravo-Ureta, 2019; Chavas et al., 2022) that includes total grants and subsidies by hectare and time dummies for each year. $\hat{\alpha}$ and $\hat{\rho}$ are parameters to be estimated, and $\hat{\varepsilon}_{it,j}$ are the error terms. Our null hypotheses are that H_0: $\hat{\alpha} = 0$ and $\hat{\rho} = 1$. Moreover, if we reject the null hypotheses then imperfections in dairy labour markets are present and lend support to the non-separability of farm production and consumption assumption (Skoufias, 1994). In other words, if we reject the null hypothesis, we confirm that the market wage and the shadow wage of family labour are not equal (Almeida and Bravo-Ureta, 2019). We estimate equation (5.4) by a generalized method of moments (GMM) regression with bootstrapped standard errors, and we test the validity of our exogenous variables by Hansens J $\chi 2$ (Blundell and Bond, 1998; Almeida and Bravo-Ureta, 2019).

5.5.3 The role of shadow wages on hired labour demand

Finally, we estimate the demand for hired labour as a function of shadow wages for family labour and farm shadow income.

$$\widehat{hired}_{itj} = \alpha_{2ij} + \hat{\varphi}_1\widehat{W^*}_{it} + \hat{\varphi}_2\widehat{I^*}_{it} + \widehat{\varphi_3}X_{2,it} + \hat{u}_{2,it} \tag{5.5}$$

$$\widehat{W*}_{it} = \Pi_1 X_{2,it} + \hat{v}_{1it}$$

$$\widehat{I*}_{it} = \Pi_2 X_{2,it} + \hat{v}_{2it} \tag{5.5.1}$$

We estimate the structural equation (5.5) and the reduced-form equation (5.5.1) as a panel Tobit model using Newey's (1987) two-step semi-parametric estimators. As shown in Table 1, a non-trivial amount of farms in the sample do not hire labour annually (i.e., 40% on average). Therefore the probability that a farmer will hire labour on the farm should be taken into account while estimating hired labour demand and treated as a left-censored dependent variable (Fredrick, 2007; Cameron and Trivedi, 2010). To do so, in the semi-parametric Panel-Tobit we specify here the hired labour hours as a right-skewed variable (i.e., left-censored) with zero as the lower limit. In Eq. (5.5), $\widehat{hired}_{itJ}$ is a log-transformed latent variable that represents the hours of hired labour on the *ith* farm in time *t* (Cameron and Trivedi, 2010*)*. The subscript *J[1,..,3]* refers to the dependent variables: total hired labour, casual and permanent hired labour respectively.

In Eq. (5.5.1), we regress the shadow wage (i.e., $\widehat{W*}_{it}$) of family labour and shadow income (i.e., $\widehat{I*}_{it}$) as a function of a vector of variables $(i.e., X_{2,it})$ identified as determinants of hired labour demand. The variables included in $X_{2,it}$ are farm size in ha, capital on the farm, subsidies per hectare, household members and a dummy variable which indicates the farmer's formal agricultural education. α_{2ij}, φ_1, φ_2, and φ_3 are structural parameters to be estimated; Π_1 and Π_2 are matrices of reduced-form parameters, and $\hat{v}_{1it}$, $\hat{v}_{2it}$ are reduced-form error terms (Newey, 1987). Following Newey's (1987) approach, Eq. (5.5.1) is estimated non-parametrically; therefore, $\widehat{W*}_{it}$ and $\widehat{I*}_{it}$ become a non-parametric function of $X_{2,it}$ (McDonald and Nguyen, 2015; Wang et al., 2019). Since we assume that the error term in Eq. (5.5) $(i.e., \hat{u}_{2,it})$ is independent and identically distributed, we use a Wald test to confirm the validity of the variables included in $X_{2,it}$ in these equations (Newey, 1987; Cameron and Trivedi, 2010; Almeida and Bravo-Ureta, 2019). Finally, as mentioned, we also estimate Eq. (5.5) with casual and permanent labour as dependent variables, respectively.

5.6 Results and discussion

5.6.1 Production function

Table 5.2 presents the results of the Cobb-Douglas (CD) production function specified in Eq. (5.1).[39]

[39] We also estimated *translog* production functions (not reported here). However, the first order coefficient in the trans-log specification was not significant. Since the coefficient for family labour is of fundamental interest in this chapter, we opted for the Cobb-Douglas specification results.

Table 5.2 Cobb-Douglas production function results

	(1)
Variables	CD TVFO
Family labour	71.821***
	(22.311)
Hired labour	28.214***
	(6.317)
Capital	347.801***
	(23.331)
Land	205.9***
	(39.891)
Miscellaneous inputs	926.00***
	(33.001)
Constant	-9502***
	(513.381)
Observations	5,264
Number of farms	661
Overall R-squared	0.764

Note: Family and hired labour, capital, land and miscellaneous inputs are expressed in logarithms. Hausman test favoured the fixed effects at the 1% level.A complete set of results is presented in Table B.1 in Appendix B with all the variables specified in Eq. (1).Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Since the main aim of this chapter is to estimate the shadow wage of family labour on the farm, we separate the labour input into family labour and hired labour. The results in Table 5.2 show a significant coefficient for family labour on TVFO. Specifically, on average, a one per cent increase in family labour input is associated with a €72 increase in TVFO. This result is similar to those obtained by Carroll et al. (2011), Gillespie et al. (2015), and Bradfield et al. (2021), with similar coefficients for family labour on Irish farms.[40] The coefficient for hired labour is positive and significant, meaning that hiring labour increases farm output, in line with the results of the analysis undertaken by Bradfield et al. (2021). Specifically, a 1% increase in hired labour on the farm is typically correlated with an increase of €28 in TVFO. Our results for the remaining inputs for dairy production (i.e., capital, miscellaneous inputs, and land) suggest significant and positive coefficients similar to those reported by Carroll et al. (2012), Läpple et al. (2021) and Bradfield et al. (2021) for the Irish dairy sector. Finally, in Table B.2 in Appendix B we present the results for the equality of markets test specified in Eq. (4). The results suggest a significant difference between shadow and market wages, confirming the validity of the non-separability assumption in our analysis (Jacoby, 1993; Skoufias, 1994; Almeida and Bravo-Ureta, 2019).

5.6.2 Shadow wages

Following, Jacoby (1993), Skoufias (1994) and Almeida and Bravo-Ureta (2019), we use the estimates of the empirical model shown in Table 5.2 to calculate the shadow wage for family labour on Irish dairy farms. Table 5.3 presents the results of the average shadow wage of family labour and the average shadow wage by herd size quartiles.

[40] We also estimated a production function dividing the family labour variable to reflect the labour input of the farmer and other members of the family respectively. However, the coefficient for other family member labour variable was not significant. Therefore, shadow wages could not be estimated from this production function model (Skoufias, 1994; Almeida and Bravo-Ureta, 2019).

Table 5.3 Shadow wages by herd size quartiles

	Shadow wage of family labour
Mean	30.97
	(20.18)
Q1. less than 43 cows	12.17
	(18.6)
Q2. 43<herd>60	28.85
	(11.53)
Q3. 60>herd<86	37.98
	(14.81)
Q4. more than 86 cows	43.94
	(20.13)

Note: Standard deviations in parentheses. Data from Teagasc NFS. Figures in euros per hour. The median of the average herd size in the sample is 61 cows. Every quartile (Q1, Q2, Q3 and Q4) has approximately 1,316 observations each.

In Table 5.3, we observe a higher opportunity cost of family labour on the farm as the size of the farm increases. The estimated shadow wage is just under €31 per hour. In comparison, the average market wage in Ireland is €21 per hour, and the average agricultural market wage is €12.53 in Ireland and €12.10 in the EU (CSO, 2021; Eurostat, 2021). Therefore, the utilisation of any of these observed market wages as imputed values would underestimate the economic value of family labour.

However, for Q1 farms, the average shadow wage is lower than the observed market wage. Therefore, in terms of shadow wages, family labour on these farms would be better paid in the off-farm job market. This result suggests that, on average, these smaller farms may, in theory, be more likely to exit the dairy enterprise due to the relatively low opportunity cost of farm labour. However, off-farm income may aid these farmers to remain in the dairy industry – as well as other farm/non-farm enterprises and income transfers (Howley et al., 2014; Dillon et al, 2022).

Table 5.4 presents shadow wages according to the formal agricultural education levels of the farmer as reported in the Teagasc NFS.

Table 5.4 Shadow wages by formal agricultural education of the farmer

Formal agricultural training	Shadow wages of family labour (per hour)	Percentage of farmers
Formal agricultural education (D)	33.82	78.53%
	(18.88)	
No formal agricultural education (D)	19.23	21.47%
	(21.09)	
Agricultural education type		
(1) Agricultural degree (D)	40.36	16.98%
	(17.74)	
(2) Certificate in farming (D)	36.37	22.55%
	(18.72)	
(3) Agricultural course of more than 60 hours (D)	33.13	27.34%
	(16.85)	
(4) Agricultural course of less than 60 hours (D)	32.42	7.65%
	(19.11)	

Note: (D) indicates a dummy variable. Standard deviations in parentheses. Agricultural training for the remaining 3% of farmers that declare another form of formal agricultural education is not included in these categories.

Overall, the results in Table 5.4 suggest a positive return to formal agricultural education. Specifically, on average, the hourly shadow wage of family labour for farmers reporting such training is €33.82, compared to €19.23 for those who do not. Consequently, the average return of formal agricultural education in shadow wages is the differential of €14.59 per hour.

We further analyse the shadow wages of family labour by the type of formal agricultural education. An agricultural degree includes bachelor's degrees provided by universities in Ireland, as well as higher level education programmes provided jointly between Teagasc colleges and some Institutes of Technology (Heanue and O'Donohue, 2014; O'Donohue and Heanue, 2018).[41][42] In Table 5.4, an agricultural college degree results in a mean shadow wage of €40 per hour. Therefore, our results suggest that the average return in shadow wages of an agricultural degree compared to not having an agricultural education qualification is €21.37 per hour.

Table 5.4 also indicates that the average return from the completion of a certificate in farming (compared to no agricultural education) is €17.50 per hour. The certificate in agriculture is considered the necessary foundation qualification for farmers due to its practical orientation, which includes a 12-week farm placement (Heanue and O'Donohue, 2014; O'Donohue and Heanue, 2018).[43]

Finally, Teagasc provides shorter training courses through its education offices across the country. Some examples of such courses for dairy farmers include *The Dairy Start-Up Course* and *Best Practice in Milking.*[44] The available training courses are categorised as either more or less than 60 hours. Although we observe a positive return to shadow wages for these types of

[41] Some examples of these degrees are the Bachelor of Agricultural Science (Hons) in Dairy Business and the Bachelor of Agricultural Science delivered at University College Dublin (UCD). The Bachelor of Science in Horticulture at Dublin City University (DCU) and the College of Amenity Horticulture, National Botanic Gardens.

[42] Cork Institute of Technology; Dundalk Institute of Technology; Atlantic Technological University; Waterford Institute of Technology; Limerick Institute of Technology; Athlone Institute of Technology; and Tralee Institute of Technology. Detailed information on Teagasc REC is available at https://www.teagasc.ie/education/local-education-centres/

[43] Teagasc provides this training through its Regional Education Centres (REC) or agricultural colleges, both Teagasc and privately run. These courses can be completed on a full-time or part-time basis.

[44] For a complete list of examples of available training courses for farmers, please see the online Teagasc Education Courses website at https://www.teagasc.ie/education/courses/.

training courses when compared to the absence of agricultural education, there is a difference of less than €1 per hour in average shadow wages between the longer and shorter courses. Nevertheless, Table 5.4 suggests an average positive return of €14 in shadow wages by having either one of these courses in comparison to those farmers who do not. Overall, our findings suggest that formal agricultural education is essential to increase the farmer returns in shadow wages.

5.6.3 The role of family labour shadow wages on hired labour demand

The final component of this analysis focuses on the role of shadow wages and shadow income on hired labour demand. We present the results of a semi-parametric panel Tobit model with hired labour as the dependent variable in Table 5.5 Column (1). Additionally, in Columns (2) and (3), we divide the hired labour demand by casual and permanent labour on the farm.

Table 5.5 Semi-parametric Panel Tobit model with fixed-effects

	(1)	(2)	(3)
Variables	Total hired labour	Casual labour	Permanent labour
Shadow wage▪	1.078***	1.765***	0.203**
	(0.289)	(0.337)	(0.0940)
Shadow income▪	-0.230***	-0.114**	-0.0302
	(0.0654)	(0.0571)	(0.0232)
Constant	1.620	-2.047	2.421***
	(1.413)	(1.643)	(0.511)
Observations	4,670	4,670	4,670

Note: Newey (1987) two-step semi parametric approach. "▪" are the endogenous variables. Shadow wages and shadow income are expressed in logarithms so the observations with negative shadow wages (n=594) are not considered in the model. A complete set of results, including the control variables for hired labour demand specified in equations (5) and (5.1), is available in Table B.3 in Appendix B. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5.5 suggests a substitution and an income effect on the demand for hired labour.[45] More specifically, in Column (1), for a 1% increase in the shadow wage of family labour, the demand for hired labour increases by a similar magnitude. This result means that as the price of family labour increases, the need to hire additional labour increases. Therefore, on average, the results suggest that family and hired labour are substitutes on Irish dairy farms.

Moreover, Table 5.5 suggests that for each percentage increase in the farm's shadow income, the latent demand for hired labour decreases by 0.23%

[45] As a reminder, a substitution effect means the decrease in the demand for a good or service that can be attributed to consumers switching to cheaper alternatives when its price rises (Nicholson and Snyder, 2021). An income effect is the resultant change in demand for a good or service caused by an increase or decrease in a consumer's purchasing power (income) (Varian, 1992).

(Column (1)). In other words, this result means that there is also an income effect of shadow wages on the demand for hired labour. As mentioned, shadow income is the total farm output once family and hired labour are subtracted and subsidies and grants are added. Therefore, shadow income is similar to the FADN definition of Farm Net Income minus the cost of family labour.[46] Since the coefficient of shadow income indicates a fall in demand for hired labour as shadow income increases, the remaining shadow income after hiring labour (i.e., investment) may go to other sources. These other sources can be automated technologies or the upkeep of machinery and buildings.

Furthermore, the total effect of shadow wages on hired labour is the addition of the substitution and income effects. In conclusion, in Column (1), the total effect of a 1% increase in shadow wages on hired labour demand is an increase of 0.85%. Therefore, our findings suggest that the demand for hired labour increases slower than the shadow wages of family labour. This result suggests that family and hired labour are *weak* substitutes on Irish dairy farms.

In Column (2), we observe a substitution effect of greater magnitude for casual hired labour demand when compared to the demand for permanent hired labour. The total effect of shadow wages on demand for casual hired labour is 1.765. In the case of permanent hired labour, the coefficient is 0.20 (Column (3)). Therefore, this result suggests that the demand for casual hired labour responds faster than the increase in shadow wages compared to the demand for permanent hired labour. In other words, the demand for casual labour is more sensitive to movements in the family labour shadow wage.

Two closely related reasons could explain this result. Firstly, the seasonal nature of labour demand on Irish dairy farms is a driver due to the increase in labour-intensive tasks related to calving and breeding in the spring. Secondly,

[46] Remuneration to fixed factors of production of the family (work, land and capital) and remuneration to the entrepreneur's risks (loss/profit) in the accounting year. Farm net value added -Total external factors + Balance subsidies and taxes on investments. FADN variables definition is available at https://agriculture.ec.europa.eu/data-and-analysis/farm-structures-and-economics/fadn_en (FADN, 2022).

as the shadow wage increases, it might not be efficient to *pay themselves* (farmer and family labour) a high shadow wage to perform these labour-intensive tasks. Therefore, it might be a better option to substitute their own labour with hired labour. Also, anecdotal evidence suggests that casual hired labour is used by farmers when they take time-off from farm work. It might be relatively easier for the farmer to hire casual labour compared to permanent labour for a number of reasons. Firstly, existing programmes that facilitate access to hired labour (e.g., Farm Relief Services in the Irish case) and, secondly, the fact the farmer is required to pay less taxes when hiring casual labour rather than permanent labour (Dillon et al., 2022). Therefore, the farmer might substitute their family labour relatively easier using more temporary labour, especially during the months of peak workload.

5.7 Conclusions

This chapter estimates the shadow wage of family labour and explores its role in the demand for hired labour on Irish dairy farms. We use a representative farm-level panel sample of from 2005 to 2019. We apply a two-step production function framework while assuming the non-separability between consumption and production decisions on the farm (Skoufias, 1994; Almeida and Bravo-Ureta, 2019). Firstly, using a production function we estimate the shadow wages on Irish dairy farms and the shadow income from the marginal product of family labour (Almeida and Bravo-Ureta, 2019). Then, we regress the shadow wage and shadow income on a panel semi-parametric Tobit model (Newey, 1987; Cameron and Trivedi, 2010) to assess their role in the demand for hired labour.

Our findings in this chapter suggest that using imputed values instead of shadow wages would result in an underestimation of the value of family labour. Specifically, the estimated shadow wage shown in this chapter is approximately €31 per hour. This compares to an average agricultural market wage and general market wage in Ireland of €12.53 and €21 respectively (CSO, 2021).

Moreover, the findings suggest that as the herd size increases, so too does the average shadow wage of family labour does also. The average shadow wage of larger farms (more than 43 cows, 75% of the sample) ranges from €28 to €43. However, for the remaining 25% of farms (with less than 43 cows), the shadow wage is €12.17. Therefore, the majority of Irish dairy farms hold a relatively high opportunity cost (i.e., shadow wage) of family labour.

Importantly, in our results, we observe returns to formal education in agriculture. We observe that the level of formal agricultural education increases the return to education in terms of shadow wage. Specifically, our results suggest that the return to education is larger for an agricultural degree when compared to farm certificates and shorter courses in agriculture. Our results go hand in hand with previous findings in the sector where returns to formal agricultural education in terms of farm output per hectare and income are observed (Heanue and O'Donohue, 2014; O'Donohue and Heanue, 2018).

Our findings suggest a substitution and income effect between family and hired labour. That is, as the shadow wage (i.e., price) of family labour increases, the demand for hired labour increases (i.e., substitution effect), and as the shadow income increases, the demand for hired labour decreases (i.e., income effect). The total effect of shadow wages on hired labour demand is the subtraction of the substitution and income effects. Our results show a small and positive total effect of shadow wages on hired labour demand. Thus, on average, our results suggest that family and hired labour are *weak* substitutes on Irish dairy farms. However, the substitution effect is stronger in terms of the demand for casual hired labour on the farm.

Our findings have several policy implications. The effects of the abolition of milk quotas and the objectives set in the 2030 EU Climate Target Plan are some of the contextual factors that mark the present and future challenges faced by dairy farmers (EU Commission, 2020; Läpple et al., 2021; Buckley and Donnellan, 2022)[47]. There is a longstanding and widespread agreement that agricultural education is paramount in a rapidly changing technological, economic and environmental context such as that currently at play in the dairy sector (Heaunu and O'Donohue, 2014; EU Commission 2020). Therefore, our

[47] The main aim of the 2030 EU Climate Target Plan is to reduce GHG emissions in the sector (Buckley and Donnellan, 2022).

findings support the premise that policy efforts designed to increase the formal agricultural education of farmers are vital for the future of the dairy sector.

Furthermore, there are several policy instruments available in Ireland geared towards incentivising the modernisation and sustainability of the sector, but all of them require a minimum level of formal agricultural education as part of their mandatory qualifying criteria (Heanue and O'Donoghue, 2014; O'Donohue and Heanue, 2018).[48] Hence, providing grants and financial aid programmes for agricultural training and further facilitating access should be an important policy priority.

In addition, programmes that facilitate access to hired labour (i.e., Farm Relief Services, Macra Land Mobility Service) should be expanded (O'Brien, 2022). Our findings imply that smaller farms may need financial aid to hire farm labour. Part of the policy agenda aimed at increasing the profitability and sustainability of the sector could include specific grants and subsidies for smaller farms to hire additional casual labour. In this way, smaller farms would have access to hired labour to meet labour demand peaks in the sector (in case they consider requiring it) (O'Brien et al., 2019). Therefore, this suggested policy to facilitate casual labour needs may help in securing the permanence of these smaller farms in the dairy enterprise.

Finally, the method that we apply in this chapter is replicable. To date, research previously conducted by others, (e.g., Donnellan, 2012; Thorne et al., 2017 and McCormack, 2020) uses imputed values for family labour on the farm to analyse its impact on different economic and environmental metrics. Thus, using FADN data for Ireland, our approach provides unbiased farm and time-level-specific shadow wages for family labour. In conclusion, the contribution of this chapter provides a compelling direction for further research considering the role of shadow wages in other sectors.

[48] Some examples of the policy instruments available that require some level of formal agri-education include the Stamp Duty Exemption, Stock Relief, and the Newbie Network. Other programs requiring formal agri-education that are no longer available are Allocation of Milk Quota to New Entrants, Installation Aid, the Early Retirement Scheme and the Single Payment Scheme – National Reserve for New Entrants (Heanue and O'Donohue, 2014).

Chapter 6 - Conclusion

6.1 Main research findings

This PhD thesis assesses the role of labour as factor of production and its role in increasing efficiency using newly available data from Irish dairy farms. Overall, the research contributes to the literature in five main ways. First, by isolating the positive effect of hired labour on farms technical efficiency (TE), the thesis provides evidence that hired labour is skilled and suitable for the workload challenges on family farms (Chapter 3). Second, greater insights are gained into the positive role of automation on farm efficiency, given particular farm and automated technology characteristics (Chapter 4). For instance, the empirical evidence from this thesis suggests that adopting labour-saving technologies (i.e., automation) is also an alternative method by which to increase TE (Chapter 4). Third, this thesis estimates the shadow wage of family labour on Irish dairy farms, a figure not previously available. Fourth, this thesis finds a positive relationship between the level of formal agricultural education and the shadow wage of family labour (Chapter 5). Finally, this thesis provides evidence that hired labour demand increases as the shadow wage of family labour grows, thus, suggesting that, on average, family and hired labour are substitutes on Irish dairy farms (Chapter 5).

The current chapter presents the main findings and recommendations of this this PhD thesis in more detail in section 6.2. Limitations and potential avenues for future research are then discussed in section 6.3.

6.2 Detailed research insights and recommendations

6.2.1 The role of hired labour and automated technologies in improving farm efficiency

As previously mentioned, this PhD thesis demonstrates clear economic efficiency benefits from hiring labour and using automated technologies on family farms (Chapter 3 and Chapter 4). More specifically, the findings outlined in Chapter 3 show that hired labour has a positive marginal effect on farm TE, which suggests that hired labour is skilled and suitable to face the evolving labour challenges in the sector. In Chapter 4, the results indicate that automated technologies could increase farm TE if the particular characteristics of the technologies and farms themselves are carefully considered. In addition, combining hired labour and adopting automated technologies is a good fit to increase efficiency for farms with larger herds. Overall, the research reinforces previous findings in the literature that emphasised the role of skilled labour and automated technologies in enhancing the efficiency and productivity of family farms (Alvarez et al., 2008; Cabrera et al., 2010; Kelly et al., 2013: Kloss and Petrick, 2018). Furthermore, the findings provide novelty to the literature given the labour constrained environment in which the farm sector is currently operating in.

The positive effect of hired labour on TE shown in Chapter 3 is relatively small and decreases as herd size increases. Two main explanations are presented. First, the findings (Chapter 3 and Chapter 4) regarding TE scores are consistent with the literature that Irish dairy farms are highly technically efficient (Carroll et al., 2013; Gillespie, 2015; Thorne et al., 2017; Bradfield et al., 2021). Therefore, it is unsurprising that for high TE scores, any consequent marginal effect on TE is small. Second, larger farms already tend to have higher levels of hired labour employed on the farm (Benjamin and Kimhi, 2006; Blanc et al., 2008 Kimhi, 2009), and an increasing herd size further increases the need for additional labour (Benjamin and Kimhi, 2006; Blanc et al., 2008). Therefore, although the efficiency effect of hired labour might be economically small, results from Chapter 3 suggest that hiring labour is a *win-win* strategy for dairy farmers as it aids in increasing farm efficiency and assists in the management of an increasing workload.

Furthermore, this thesis provides evidence that using automated technologies is a suitable alternative strategy (to increasing hired labour) to improve TE. However, the particular characteristics of both the farm and the automated technology in question must be considered in determining the role of automation in improving efficiency at the farm level. As such, the findings in Chapter 4 suggest that automated parlours and feeders assist in increasing TE on farms with a larger herd size. These automated technologies in particular are designed for farms with larger herds, therefore, the size of the herd, the more beneficial they are (Ryan and Donworth, 2011). Data from the NFS indicates that such technologies are already being utilised on many farms.[49] This research suggests that farms with larger herds who have yet to invest in such technologies would improve their farm efficiency by doing so. Moreover, since the results from Chapter 4 confirm that larger farms tend to be more technically efficient (average TE score 91%), adopting these automated technologies could represent the *last push* to optimise their milking and feeding processes and ease their overall workload.

The analysis also supports the role of selected automated technologies in increasing farm efficiency on smaller farms (with herds of less than 80 cows), providing evidence for the adoption of automated cluster removers and scrapers in milking facilities. These technologies are related to labour-intensive tasks that do not require much technical knowledge (i.e. removing clusters after milking and cleaning animal waste). In other words, these activities must be assigned work time regardless of the farm's level of production. In addition, results from Chapter 4 show that despite having relatively high TE scores (average of 82%), smaller farms have more room to improve their efficiency overall. Hence, based on the findings, these technologies could be adopted on smaller farms to improve their efficiency with a labour-saving effect by allowing them to dedicate their work time to other more productive tasks or leisure.[50]

The findings on the benefits of hired labour have several policy implications. The results from Chapter 3 suggest that existing programmes that facilitate access to hired labour for all farms (e.g. Farm Relief Services) should be expanded upon. Also, anecdotal evidence suggests that dairy farmers (more used to managing family labour) may be reluctant to hire labour because it

[49] For instance, in 2018, 60% of farms reported using automated scrapers for their farm operation.

[50] These automated technologies may increase farmers' management time to operate them. However, anecdotal evidence suggests that organising the workload on the farm in the early months of the year with a defined schedule for every labourer (i.e., family and hired labour) makes the farm a more attractive place to work (Breecher et al., 2021). Having a clear guideline on the workload during the year may optimise the positive effect of automated technologies on farm efficiency and its labour-saving effect.

may reduce farm productivity. Therefore, circulating factual information about the role of hired labour and its positive effect on agricultural efficiency may help mitigate this reluctance. In this way, farmers in need of hiring more labour due to their farm plans (i.e. expansion) and farm characteristics (i.e. larger herds) can be more confident that the available hired labour is indeed suitable for their farm. This information could be disseminated by extension agents and other agricultural support services.[51] However, as individuals may be more willing to accept advice from their peers than from expert advisors (Läpple and Barham, 2019); disseminating the benefits of hired labour in improving farm efficiency should also be considered farmer networks such as discussion groups.[52]

Furthermore, our findings suggest that an automation agenda is necessary for the sustainable development of the dairy sector. Therefore, the expansion of existing financial assistance through grant aid would be beneficial e.g., in an Irish context the Targeted Agricultural Modernisation Scheme (TAMS) (Nolan, 2018; 2022; Conlon, 2021). In addition, the automated technologies explored in this thesis can be easily adapted to a herringbone milking system, which is the predominant type on Irish dairy farms (78% in 2018) (Deming et al., 2018; Dillon et al., 2019; Prendergast et al., 2022). Therefore, farmers can be sure that by investing in automation, their farm efficiency will improve, and that the time spent on the milking process will be reduced. Finally, very large farms (>250 cows) often have a rotary milking system (Prendergast et al., 2022). With such systems, the majority of the milk production process (75%) is dedicated to milking, with the remaining time being allocated to cleaning tasks (Prendergast et al., 2022). Therefore, the utilisation of technologies such as automated cluster-removers would help improve their overall efficiency based on this analysis.

Finally, using automated technologies on dairy farms would have broader benefits in addition to improved TE. Some of the automated technologies

[51] For example, in Ireland, Teagasc, Farm Relief Services or Macra Land Mobility Services.

[52] 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 (Läpple et al., 2015; Balaine, 2020). Discussion groups are often seen as an improved extension model compared to *top-down*, one-to-one systems (Davis et al., 2012; Prager and Creaney, 2017; Balaine, 2021).

(i.e., automated parlours and feeders) analysed can be used to detect herd-related health disorders, allowing farmers to identify and implement prevention and treatment protocols at earlier stages (Ryan and Donworth, 2011). Hence, policymakers should see the adoption of automated technologies as a multidimensional resource that will bring overall efficiency gains, improve work-life balance, and enhance milk quality and the general health of the herd. In conclusion, a policy agenda that expands and prioritises the use of automation on dairy farms would aid in ensuring the continued productivity and sustainability of the sector.

6.2.2 The economic value of family labour

The analysis in Chapter 5 revealed that estimating shadow wages is a better alternative, rather than imputed values, to assess the economic value of family labour. Prior to this study, research exploring the economic value of unpaid family labour on Irish dairy farms used observed market wages as imputed values (i.e., agricultural market wage, market wage, salaries paid to hired labour) (e.g., Thorne et al., 2017; McCormack, 2020). This thesis shows that such an approach (compared to estimating shadow wages) leads to an underestimation of the value of family labour. This bias is eliminated in Chapter 5 because the shadow wage is directly derived from its marginal contribution to farm output. Therefore, in terms of economic theory, the shadow wage is closer to the actual economic value of family labour (Lambert and Magnac, 1997). In addition, this value is unbiased because it is estimated regardless of market imperfections and constraints that are usually prevalent in the agricultural labour market (Skoufias, 1994; Almeida and Bravo-Ureta, 2019).

Additionally, Chapter 5 is consistent with previous findings on the positive returns of formal agricultural education regarding farm output and income (Heanue and O'Donohue, 2014; O’Donohue and Heanue, 2018). Specifically, the findings reveal positive returns to the shadow wage of the farmer as a result of their level of training. These positive returns increase as the academic level of this formal agricultural education increases.

These results have some practical and policy implications in the context of the current challenges faced by dairy farmers in Ireland and other countries with pasture-based dairy systems (e.g., Australia, New Zealand), the shortage of farm labour (e.g., US, Canada, and some EU Member States) within a predominantly family farming system (e.g., the EU). The increasing need to improve the environmental footprint of farming poses another challenge at the farm level. This has resulted in the requirement to achieve agreed GHG emissions reduction targets in some countries, including Ireland (EU Commission, 2020; Läpple et al., 2021; Buckley and Donnellan, 2022). To this end, there is a role for education and training in equipping farmers with adequate knowledge pertaining to sustainable practices and suitable technologies as previously demonstrated in the literature (by Heanue and O'Donohue; 2014, O'Donohue and Heanue; 2018, and Ruzzante et al., 2021). Therefore, our findings support the premise that policy efforts designed to increase the formal agricultural education of farmers are critical for the sustainable future of the dairy sector.

There already exist a number of policy initiatives in Ireland to incentivise farmer engagement with agricultural education. For instance, the Young Farmers Scheme provides financial assistance to farmers aged below 40 years with relevant qualifications, to facilitate intergenerational transfer.[53] Further dissemination of the benefits of formal agricultural education and continuous professional development to farmers should be encouraged through farm advisory services and other networks such as farmer peer groups.

6.2.3 Hired labour demand in family farms with seasonal labour demand

The findings from Chapter 5 suggest that, on average, family and hired labour are substitutes on Irish dairy farms. As the shadow wage (price) of family labour increases, the demand for hired labour increases. This substitution is stronger in the case of casual labour compared to permanent labour.

[53] Young Farmers Scheme description available at https://www.gov.ie/en/service/6e97d8-young-farmers-scheme/

More specifically, the seasonal nature of production in the Irish dairy sector serves as an explanation for this. As mentioned, the uneven nature of labour demand on Irish dairy farms results in the need for additional labour in the spring (due to calving). Also, as the shadow wage increases, it might not be efficient to adequately remunerate farmer and family labour due to its high shadow wage. Therefore, it may be preferable to substitute with additional hired labour. In addition, it may be relatively more manageable for the farmer to opt to hire casual (compared to permanent) labour due to existing programmes (in Ireland) such as Farm Relief Services.[54] Therefore, the farmer might substitute their family labour more easily using more temporary labour, especially due to the seasonal peak workload.

Moreover, Chapter 5 also calculates shadow income on the farm, and the findings reveal that as shadow income increases, the demand for hired labour decreases. Since shadow income is capital remuneration, after family and hired labour are paid, it is a figure that represents an investment on the farm. Therefore, this finding suggests that such investment may be allocated to other sources such as automated technologies or the upkeep of machinery and buildings. Then, once additional labour is required, investment may be redirected towards automation as a strategy to confront labour constraints. As mentioned, it is more likely that larger farms exhibit a higher demand for hired labour (Kimhi, 2009). These findings corroborate this, and align with the fact that farms with already high levels of hired labour are more likely to adopt automated technologies (Chapter 4). However, further research is needed to explore this type of investment on farms and the relationship with particular farm and farmer characteristics.

These findings can inform the design of farm labour policy recommendations, again reinforcing the need for programmes facilitating access to hired labour and training. As such, the design of tax incentives could be explored. In this way, farms facing increasing workloads could have easier access to hired labour to meet labour demand peaks if required.

[54] Also, hiring casual labour might be more financially attractive for farmers than permanent labour since the former does not require commitments around social insurance (PRSI).

Finally, a contemporary examination of the Irish dairy sector is a fascinating case study. First, the sector has been in a phase of significant expansion and intensification due to the removal of EU milk quota in 2015 (Eurostat, 2021; Läpple et al., 2022). The subsequent structural change brought with it significant labour challenges for some farms in transition with a growing herd size and predominantly family labour (Eurostat, 2021). As such, the increasing workload and the demand for skilled labour are particular discussion points in Ireland (Kelly et al., 2020; Brennan et al., 2022).

The recent expansionary phase within the Irish dairy sector is expected to slow due to agreed reduction targets for agricultural emissions framed in The Climate Action and Low Carbon (Amendment) Act 2021 (DAFM, 2020; Climate Action Plan, 2021; Food Vision 2030, 2022; Buckley and Donnellan, 2022). The main aim of the Climate Act is to reduce GHG emissions from 22% to 30% from a 2018 baseline, particularly as the agricultural sector is responsible for one third of Irish GHG emissions (DAFM, 2020; CSO, 2022). To this end, a Food Vision Dairy Group (FVDG) (established as part of the Food Vision 2030 Strategy) was recently tasked with proposing an agreed set of relevant recommendations.[55][56] The requirement for an improved sustainability pathway for Irish dairy farming is increasingly evident compared to the ambitious expansionary objectives of earlier policies such as Food Harvest 2020 and Food Vision 2025.[57]

Despite the expected slowdown in dairy expansion, farm labour challenges look set to continue in the context of an increasingly tight labour market. Indeed, consideration of farmer workload and wellbeing in terms of overall social sustainability is emphasised (Dillon et al., 2022; Brennan et al., 2022). Overall, this PhD thesis highlights the strategic importance of farm labour,

[55] The Food Vision 2030 Strategy is a ten-year Strategy for the Irish agri-food sector (taken to include primary agriculture, food and drink processing and manufacturing, fisheries, aquaculture and fish processing, forestry and forestry processing and the equine sector). The main aim of the strategy is to make Ireland a world leader in Sustainable Food Systems (SFS). See https://www.gov.ie/en/publication/c73a3-food-vision-2030-a-world-leader-in-sustainable-food-systems/#food-vision-2030 .

[56] The recommendations are also in line with those established in the Roadmap Towards Climate Neutrality Report by DAFM (2020) available at https://assets.gov.ie/109097/2090f877-85bd-430c-8506-aa829f5930df.pdf

[57] The Food Wise 2025 strategy (Food Wise, 2015), published in 2015, pursued a similar course of action to Food Harvest 2020 (Food Harvest 2010), leading to further increased production levels in the dairy sector (Balaine et al., 2022).

automation, and education as critical factors for the sustainable development of an evolving dairy sector. Therefore, providing solutions to productivity and efficiency concerns at the farm level remain critical (Kelly et al., 2020; Dillon et al., 2022).

6.3 Limitations and future research

The absence of detailed data on labour input on the farm by individual tasks is an important limitation of research aiming to analyse its role in farms' economic performance. The NFS is the primary source of data analysed in this thesis. The NFS captures farm labour input through self-reported hours and calculates AWU annually, in line with the EU FADN methodology. A professional data collection team surveys around 900 farms annually (representing a farming population of 92,000 farms) to ensure data quality. Farm labour is divided into paid, i.e., any hired labour and unpaid, i.e., family labour. However, these measures are cumulative numbers that do not provide insight into time spent on individual tasks. Although most agricultural studies that explore labour input on farms are also based on aggregated numbers (e.g. Benjamin et al., 1996; Benjamin and Kimhi, 2006; Kostov et al., 2018), the potential for systematic over-reporting of on-farm hours could be countered using the time-use methodology (Fall and Magnac, 2004). Therefore, an advantage of such a methodology is that it may aid in informing more specific best practices on the farm and providing precise evidence-based recommendations to contribute to policy changes (Charmes, 2020).

From the perspective of the findings from this thesis, the use of aggregated labour data presents a significant limitation. As mentioned, it has been found in case studies with non-statistically representative primary data that hired labour usually carries out labour-intensive activities related to the calving-breeding season and cleaning (Deming et al., 2018; Santhanam-Martin et al., 2021; Hogan et al., 2022). Therefore, the findings concerning the substitution effect between family and hired labour (Chapter 5) only hold under a specific assumption. That is to say, the substitution effect holds if it is assumed that the farmer substitutes their labour for hired labour on the farm for other types of labour tasks that might not be related to the seasonal demand peak (i.e., office business tasks), leisure, or off-farm work. On the other hand, if during the peak workload months, the farmer/family hires more labour and dedicate their time to the same labour-intensive activities on the farm related to milking, calving, calf care and feeding, then the addition of hired labour would complement family labour instead of substituting it. In order to clarify this result, it is necessary to have a breakdown of labour data on the farm by type of labour and tasks undertaken.

In this instance, as an initial plan of this PhD research project, a pilot time study has been conducted to better understand farm labour allocation across various tasks (NFS, 2020). Using insights on farm labour input from previously published work (Deming et al., 2017; 2018), a detailed booklet to record all labour input on NFS farms (i.e., farmer/manager, family labour, and hired labour) has been designed for this time-use study. This booklet listed 18 typical tasks, e.g. milking, calving, and grass management.[58] Alternatively, participating farmers could use a dedicated smartphone/tablet to record their labour time use with the Hubstaff app (Hubstaff, 2020). Finally, the project planned farm visits to further explain the use of the booklet and the smartphone/tablet app to participating NFS farmers. The original plan for the farm visits and the data recording of the time study was set from February to June 2020.

The time-use study beginning at the onset of the global pandemic set a difficult challenge for farm visits and data collection. Specifically, due to the lockdowns put in place, farm visits were impossible to carry out. Despite this significant drawback, data on N=30 farms could be collected with the help of the NFS team, data recorders and the postal service. Besides, being a pilot study is another challenge to perform a quantitative analysis. The relatively low number of participating farmers who completed the data recording (N=27) provide some valuable insights but make the collected observations insufficient to perform an econometric analysis.

[58] The complete set of tasks includes: calving, herding pre and post milking ,milking, washing post-milking ,cleaning yards/cubicles, feeding heifers and cows, calf care and feeding, AI, grass measurement and management, heat observation, fertiliser spreading, slurry/soiled water spreading, general herding tasks, buying/selling stock, land, building, machinery upkeep, veterinary, office/business tasks, and other dairy tasks.

Furthermore, despite not being a representative sample of Irish dairy farms, a summary benchmarking report has been provided to participant farmers.[59] The pilot time-use study results provide two important insights. First, the results from the pilot suggest that farmers can quickly adapt to recording farm labour input manually or using a device. The participant farmers found it relatively easy to fill out the booklet or the device at the end of their working day on the recording days of each month. Second, it validates the increased workload and seasonal labour requirement, as found by Deming et al. (2017) and Deming et al. (2018). From February to April, the pilot time-use study confirmed that calving, calf-care and feeding, and milking-related tasks, including rearing and cleaning, consume most of the labour hours on the farm.

Moreover, the results from this time-use study confirm that larger farms (>84 cows) use more hired labour on the farm. Results also suggest that hired labour complements family labour in general herding, cleaning yards and cubicles, and calf-care-related tasks and substitutes family labour in slurry oiled water and fertiliser spreading. Overall, even with the limitations imposed by the COVID-19 pandemic, there is a case to be made for scaling up the study to a nationally representative sample, thus providing a clear direction for future research regarding the use of more detailed data on farm labour.

Therefore, if more disaggregated data on farm labour becomes available, the research conducted as part of this thesis can be further explored to obtain more detailed insights into labour input and its role in enhancing farm efficiency. For instance, the efficiency of farms can be benchmarked regarding the time dedicated to specific tasks by type of labour (i.e., farmer/family and hired). In this way, insights could be obtained on the optimal allocation of labour by the task in terms of farm efficiency, given the characteristics of the farm, the use of automated technologies, and the type of labour. Moreover, in the context of the challenges agriculture faces due to climate change, deteriorating water quality, and biodiversity loss (Eurostat, 2022; Buckley and Donnellan, 2022), further exploration of the findings of this PhD work in

[59] The template for the benchmark report provided to farmers is presented in Figure C.1 in the Appendix for Chapter 6.

terms of environmental benefits is an additional compelling direction for future research. For example, regarding water quality, exploring the role of farm labour and the use of some automated technologies (e.g., automated scrapers) in ensuring water quality on environmental efficiency could be explored.

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Appendices

Appendix A. Supplementary material for Chapter 3

Table A. 1 Relevant descriptive statistics Irish dairy farm by year

Year	Milk output	Capital	Labour	Misc. inputs	Land	Herd size
2000	1206.61	1346.70	1996.42	452.61	53.76	45.29
	(643.79)	(1056)	(980.78)	(320.97)	(30.27)	(26.87)
2001	1295.39	1381.52	1985.46	471.33	54.83	47.28
	(671.54)	(1066.6)	(922.60)	(340.97)	(29.81)	(26.37)
2002	1281.32	1426.87	1923.30	462.20	56.25	49.04
	(671.23)	(1149.2)	(901.32)	(343.15)	(33.15)	(29.22)
2003	1350.68	1433.89	1916.50	460.03	56.52	49.64
	(698.17)	(1048.5)	(915.26)	(301.19)	(33.05)	(28.32)
2004	1376.36	1507.81	1930.14	466.62	57.81	50.57
	(715.37)	(1201.5)	(908.65)	(331.38)	(33.21)	(28.62)
2005	1381.09	1402.28	1716.04	409.38	58.34	52.17
	(687.21)	(1116)	(864.36)	(294.36)	(33.49)	(29.8)
2006	1446.68	1469	1744.08	441.85	59.53	54.06
	(743.11)	(1140.9)	(861.11)	(318.73)	(34.83)	(30.69)
2007	1503.09	1669.24	1925.23	478.68	61.20	58
	(734.94)	(1293.6)	(927.22)	(336.75)	(34.1)	(34.1)
2008	1517.90	1704.75	1937.15	467.50	62.12	60.13
	(779.96)	(1333.2)	(956.26)	(357.89)	(34.79)	(34.85)
2009	1482.90	1664.66	1691.21	404.79	62.66	62.05
	(803.25)	(1317.9)	(863.19)	(322.97)	(35.49)	(37.04)
2010	1556.55	1828.37	1933.50	510.83	63.45	63.74
	(764.79)	(1402.3)	(977.99)	(399.42)	(33.6)	(38.07)
2011	1643.65	1700.50	2003.17	505.08	63.84	66.62
	(750.29)	(1257.1)	(949.12)	(369.35)	(34.14)	(38.98)
2012	1619.54	1603.28	1879.37	501.94	64.69	67.66
	(780.63)	(1175.3)	(860.47)	(353.82)	(33.97)	(37.70)
2013	1682.72	1680.11	2044.59	592.95	64.54	68.82
	(752.19)	(1195.1)	(920.50)	(397.81)	(33.83)	(38)
2014	1777.32	1764.76	2055.72	601.87	64.91	70.69
	(801.60)	(1207.4)	(931.9)	(401.87)	(34.25)	(37.85)
2015	2079.31	1899.76	2032.85	609.37	65.45	75.90
	(956.30)	(1319)	(932.1)	(417.83)	(34.96)	(42.56)
2016	2098.12	2029.43	2026.80	660.25	68.44	82.89
	(967.28)	(1423.4)	(979.63)	(455.87)	(37.71)	(47.54)
2017	2163.38	2267.29	2283.02	781.79	69.60	86.17
	(956.29)	(1605.8)	(1099.4)	(541.13)	(37.41)	(49.91)
2018	2311.18	2321.18	2315.02	894.51	70.50	88.97
	(1051.6)	(1746.3)	(1146.3)	(639.4)	(37.27)	(53.54)

Table A.1 Continued

Year	Hired labour share < 80 cows	Hired labour share > 80 cows	TE scores for farms < 80 cows	TE scores for farms > 80 cows	Herd expansion	Percentage of farms in herd expansion
2000	8%	41%	0.77	0.78	.	.
	(14%)	(24%)	(0.08)	(0.07)	.	.
2001	8%	33%	0.78	0.80	0.05%	60.56%
	(14%)	(26%)	(0.08)	(0.06)	(12.11%)	
2002	8%	34%	0.77	0.78	1.50%	58.37%
	(14%)	(26%)	(0.08)	(0.06)	(11.99%)	
2003	8%	34%	0.78	0.80	2.13%	64.87%
	(15%)	(25%)	(0.07)	(0.06)	(13.43%)	
2004	7%	33%	0.78	0.78	0.67%	55.48%
	(14%)	(26%)	(0.08)	(0.07)	(14.28%)	
2005	7%	32%	0.78	0.78	0.61%	61.14%
	(14%)	(25%)	(0.07)	(0.05)	(14.86%)	
2006	7%	32%	0.79	0.80	0.51%	56.86%
	(14%)	(24%)	(0.06)	(0.06)	(11.49%)	
2007	7%	32%	0.77	0.79	1.32%	62.07%
	(13%)	(22%)	(0.09)	(0.06)	(15.41%)	
2008	7%	30%	0.79	0.80	1.85%	60.77%
	(12%)	(23%)	(0.07)	(0.06)	(12.06%)	
2009	5%	26%	0.81	0.84	0.65%	56.23%
	(11%)	(23%)	(0.07)	(0.05)	(11.38%)	
2010	5%	28%	0.77	0.79	0.33%	55.52%
	(12%)	(24%)	(0.08)	(0.06)	(12.24%)	
2011	6%	28%	0.80	0.81	2.84%	65.13%
	(12%)	(23%)	(0.07)	(0.06)	(11.87%)	
2012	6%	26%	0.80	0.81	2.24%	61.11%
	(12%)	(24%)	(0.06)	(0.06)	(12.42%)	
2013	5%	27%	0.76	0.76	2.09%	63.45%
	(10%)	(23%)	(0.07)	(0.06)	(10.61%)	
2014	6%	26%	0.78	0.77	3.71%	67.25%
	(10%)	(22%)	(0.06)	(0.06)	(10.45%)	
2015	5%	23%	0.82	0.84	8.38%	80.30%
	(9%)	(23%)	(0.07)	(0.05)	(16.12%)	
2016	5%	23%	0.81	0.82	6.01%	73.48%
	(9%)	(23%)	(0.06)	(0.05)	(11.15%)	
2017	4%	24%	0.77	0.79	3.47%	68.57%
	(8%)	(23%)	(0.09)	(0.06)	(12.13%)	
2018	5%	25%	0.74	0.79	2.47%	65.54%
	(9%)	(24%)	(0.07)	(0.06)	(10.51%)	

Note: Mean and standard deviations in parentheses. Milk output is the total milk produced by the average dairy farm in hundreds of euros. Capital comprises machinery, buildings, and livestock in hundreds of euros. Labour measures total labour on the entire farm including both unpaid and paid labour. Miscellaneous inputs are direct costs incurred in dairy production. Land is dairy forage area in hectares. Herd size is the average number of cows in the dairy herd over a twelve-month period. Hired labour share is the percentage of hired labour to total labour on the farms. The TE score is the overall TE. Herd expansion is the average annual growth rate of herd size. The percentage of farms in herd expansion includes farms with a positive herd growth rate per year.

Appendix B. Supplementary material for Chapter 5.

Table B. 2 Cobb-Douglas production function all variables results

Variables	(1) CD TVFO
Family labour	71.82***
	(22.31)
Hired labour	28.21***
	(6.317)
Capital	347.8***
	(23.33)
Land	205.9***
	(39.89)
Miscellaneous_inputs	926.0***
	(33.00)
Additional control variables	
Young household members (<=20 years old)	18.97***
	(7.28)
Adults household members (>20 years old)	7.68
	(7.95)
Farmer off-farm labour	-23.72
	(27.70)
Spouse off-farm labour	55.78***
	(20.55)
Age of farmer	-13.46***
	(3.47)
Age squared	0.115***
	(0.036)
Time trend	22.56***
	(1.731)
Region	-70.27
	(162.3)
Constant	-9502***
	(513.38)
Observations	5,264
Number of farms	661
Overall R-squared	0.764

Note: Family and hired labour, capital, land and miscellaneous inputs are expressed in logarithms. We tested random effects and fixed effects to estimate the production functions. We estimated translog production functions (not reported here; however, the first order coefficient in the trans-log specification was not significant. Hausman test favoured the fixed effects at the 1% level. Married dummy and formal agricultural education omitted because of collinearity. Robust SE in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B. 3 Test for inequality of markets

Variables	(1) Shadow wage of family labour
Ln Market wage	2.62***
	(0.18)
Constant	-22.37**
	(1.84)
Wald test	35.74***
F-test	52716.4***
Hansens J $\chi 2$	17.50
Observations	3,987

Note: The sample includes farms that report at least one week of off-farm labour by year (Almeida and Bravo-Ureta, 2019). Due to possible measurement errors in market wages it is necessary to have exogenous variables in the regressions (Le, 2010; Almeida and Bravo-Ureta,2019). The exogenous variables for the GMM regressions are grants and subsides per ha and dummies per year. The Hansens J χ 2 confirms the validity of the variables. F-Test under the Ho of α=0 and rho = 1. Bootstrap standard errors in parentheses.*p < 0.10, ** p < 0.05, *** p < 0.01.

Table B. 4 Hired labour demand function complete set of results

Variables	(1) Total hired labour	(2) Casual hired labour	(3) Permanent hired labour
Shadow wage▪	1.078***	1.765***	0.203**
	(0.289)	(0.337)	(0.0940)
Shadow income▪	-0.230***	-0.114**	-0.0302
	(0.0654)	(0.0571)	(0.0232)
Control Variables			
		Mac	
Farm size in ha	0.016***	0.020***	0.005***
	(0.004)	(0.004)	(0.001)
Machinery, buildings and herd size	0.068	0.138	0.076
	(0.315)	(0.367)	(0.110)
Subsidies per ha	0.0002	0.0003	-0.0002*
	(0.0003)	(0.0003)	(0.0001)
Household members	0.086**	0.074	0.009
	(0.043)	(0.051)	(0.015)
Formal agri-education farmer	11.38***	11.04***	0.523
	(0.574)	(0.838)	(0.906)
Constant	1.620	-2.047	2.421***
	(1.413)	(1.643)	(0.511)
Censored observations	1,860	1,860	1,860
Uncensored observations	2,810	2,810	2,810
Observations	4,670	4,670	4,670

Note: Newey (1987) two-step semi parametric approach. "▪" are the endogenous variables. Variables specified in the non-parametric reduced equation for endogenous variables are capital on the farm, total grants by hectare, household members, farm size, farmers' formal agri-education, and a time trend. The Wald test for exogeneity confirms the validity of our variables included in Eq. (5) and (5.1). Co-ownership variable omitted due to multicollinearity. We omitted the square term for age from the table since it shows no statistical significance. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix C. Supplementary material for Chapter 6

Figure C.0.1 Template for benchmark report to farmers

Figure C.1.1. Front cover of benchmark report for farmers

Labour time use study report
Teagasc National Farm Survey

Farm Code

Individual farm comparative analysis report

The data collected on farms has been divided into two herd size groups – above and below 84 cows. The results from your farm are presented alongside these.

Year
2021

teagasc
Agriculture and Food Development Authority

1

Note: Cover letter of Benchmark report to participant farmers in Time-use study NFS (2020).

Figure C.1.2. Page 2 of benchmark report for farmers

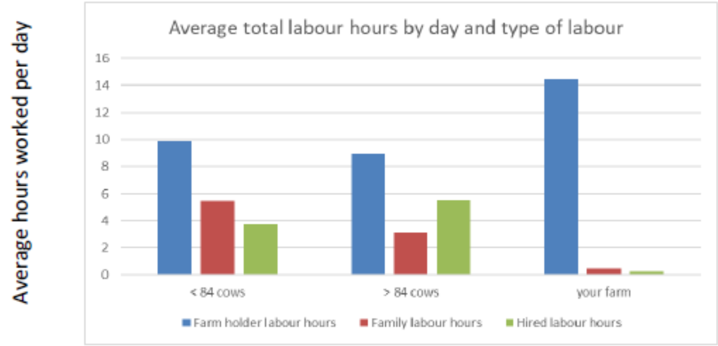
Farm level analysis			
Average total labour hours by day and type of labour			
Herd size	less than 84	more than 84	your farm
Farm holder labour hours	9.86	8.95	14.46
Family labour hours	5.47	3.14	0.47
Hired labour hours	3.75	5.5	0.25

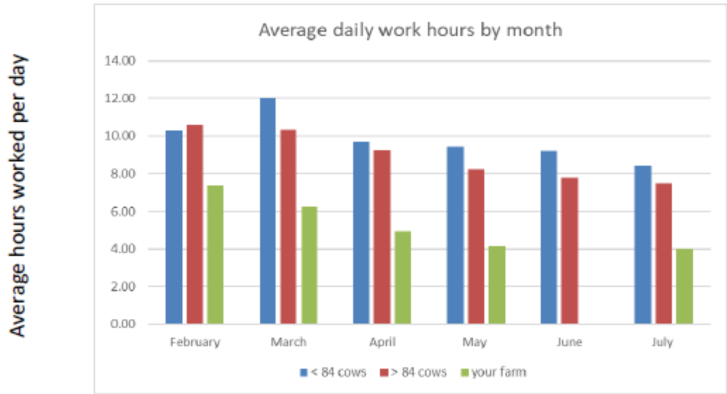
Average total hours by month and type of labour	Farm holder			Family labour			Hired labour		
Month/Herd size	<84	>84	your farm	<84	>84	your farm	<84	>84	your farm
February	10.32	10.61	20.55	4.43	2.52	0	3.28	8.61	1.5
March	11.99	10.33	17.33	6.31	2.77	1.33	3.65	5.75	0
April	9.67	9.26	14.08	5.33	4.01	0.83	3.85	4.43	0
May	9.47	8.26	11.75	6.23	2.74	0.67	4.87	4.82	0
June	9.20	7.79	11.16	5.16	3.74	0	2.77	4.59	0
July	8.43	7.49	11.91	5.49	3.47	0	3.69	5.16	0

The results in these tables are displayed in the graphs on the next page

Note: Page 2 in Benchmark report to farmers includes general descriptive statistics of the individual farm compared to other farms by size. It also includes the breakdown of type of labour (farmer/family/hired) by month.

Figure C.1.3. Page 3 of benchmark report for farmers





3

Note: Page 3 in Benchmark report to farmers includes the average total labour hours by day and type of labour for the individual farm compared to smaller and larger farms. It also includes the benchmark by farm size of the average daily work hours per month.

Figure C.1.4. Page 4 of benchmark report for farmers

Average hours worked per working day by activity
(ranked by the time spent on these tasks on your farm)

Herd size	less than 84 cows	more than 84 cows	your farm
Slurry/soiled water spreading	2.15	2.38	6.67
Other dairy tasks	1.88	2.35	2.25
Milking	2.59	3.06	1.72
Fertiliser spreading	2.96	4.07	1.46
Land, Building, Machinery Upkeep	2.28	2.45	1.07
Buying/Selling Stock	1.28	1.42	1.00
Herding Pre & Post Milking	1.64	1.96	0.90
Feeding Heifers & Cows	1.08	1.05	0.68
Office/business tasks	1.10	1.38	0.67
Calf care and feeding	1.86	1.22	0.67
Calving	0.73	0.75	0.67
Grass measurement and management	0.60	0.78	0.65
Veterinary	0.58	0.75	0.56
Cleaning yards/cubicles	1.13	0.79	0.54
Washing Post-Milking	0.97	0.74	0.54
General Herding tasks	0.56	0.59	0.52
Heat Observation	0.97	1.21	0.31
AI (artificial insemination)	1.04	0.82	0.30

Note: Page 4 in Benchmark report to farmers includes the comparison of the individual farm of labour hours worked by task to smaller and larger farms.

Figure C.1.5. Page 5 of benchmark report for farmers

Average hours worked by activity and month in your farm

(Ranked tasks as in the time use study booklet)

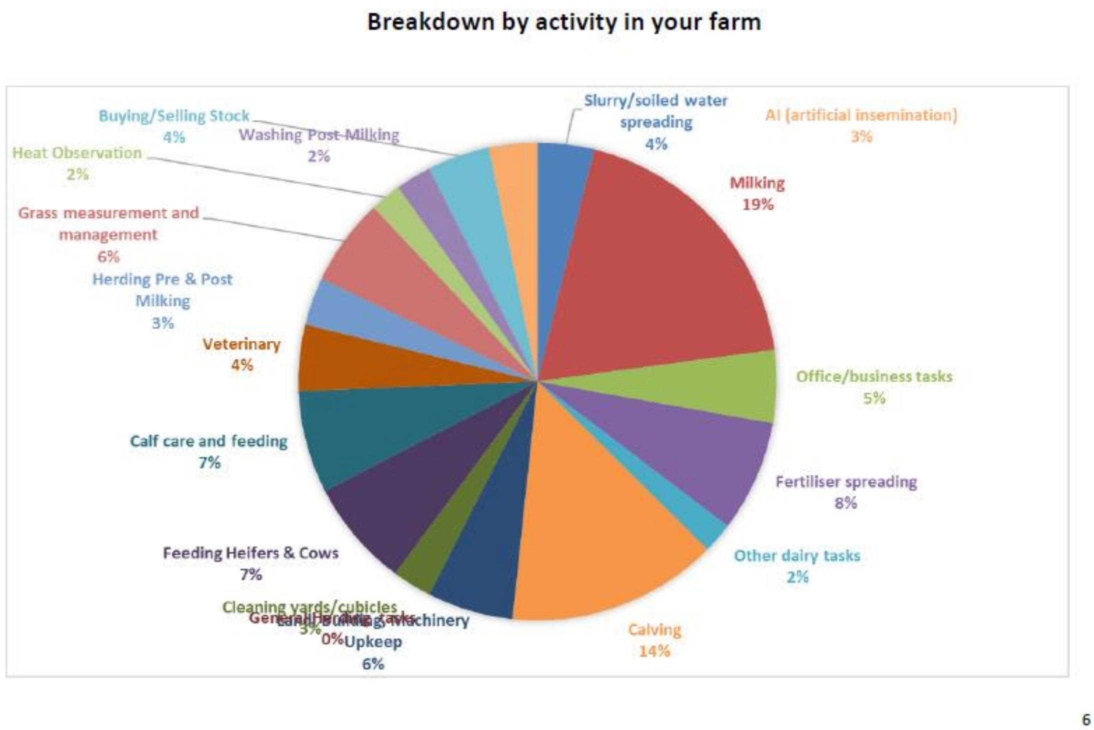
Activities in your farm	February	March	April	May	June	July
Calving	7	4	0.5			
Herding post milking	1.5	0.5	0.5	0.75	0.75	0.75
Milking	4.75	4.75	4.25	4.5	4.5	4.5
Washing post milking	0.75	0.75	0.75	0.5	0.5	0.5
Cleaning yards and cubicles	2.5	0.5	0.5	0.25	0.25	0.25
Feeding heifers and cows	2	2	1.5			
Calf care and feeding	2	4	2.5	2		
AI Artificial insemination			0.5	1	1	0.5
Grass Measurement		1.25	1.25	1.5	1.5	1.5
Heat Observation			0.5	0.5	0.5	0.5
Fertiliser spreading		2	2	2	2	1.5
Slurry oiled water spreading	0.5	1	0.5	1		1.5
General herding tasks						
Buying selling stock		1	1	0.5		1.5
Land building machinery upkeep					2	2
Veterinary			0.5	1		2.5
Office business tasks	2	2	1.5	1	1	1
Other dairy tasks	0.5	0.5	0.5	0.5	0.5	0.5

The results in these tables are displayed in the graphs on the next page

5

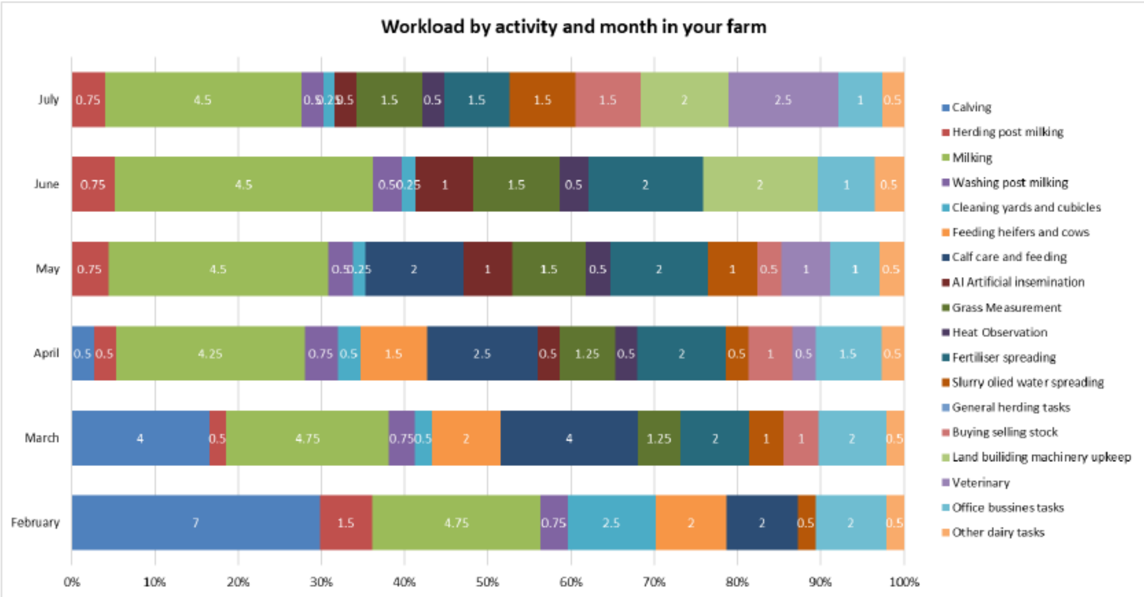
Note: Page 5 in Benchmark report to farmers includes the average labour hours spent on specific tasks by month in of the individual farm.

Figure C.1.6. Page 6 of benchmark report for farmers



Note: Page 5 in Benchmark report to farmers includes the graph in percentages for the table included in Page 4 for the individual farm.

Figure C.1.7. Page 7 of benchmark report for farmers



Note: Page 6 in Benchmark report to farmers includes the graph in percentages for the table included in Page 5 for the individual farm with the aggregated working time in the full period of the study (February to June 2020).