Assessing the use of chemical inputs in UK agriculture and its impact on farm productivity and labour requirements

Stuart Ian Henderson

A thesis submitted to The University of Kent for the degree of

Doctor of Philosophy in Agri-Environmental Economics

School of Economics

December 2023

Abstract

Agricultural policy is shifting in England to a model based on public money for public goods. Chapter 2 assesses the broader socio-economic effects at the territorial level of farms adopting ecological approaches to farming. These ecological approaches are growing in popularity and include low-input, organic, regenerative, conservation and agroecological farming. This chapter explores their potential growth over the next decade in two heterogeneous regions of South East England, namely North Kent and the High Weald. Q-methodology and Delphi Exercise are two stakeholder based approaches used to investigate the perspectives of different groups of farming related stakeholders. Results emphasise that there will need to be an increase in the skill level of the farm workforce in order to facilitate changes in farm practices. Therefore, policy may want to address the provision of education and experience as well as sourcing migrant labour depending on the farming context.

Chapter 3 estimates Total Factor Productivity (TFP) in a Cobb-Douglas production function framework. The estimation strategy applies generalised method of moments accounting for the use of chemical inputs which is absent in previous GMM estimations of TFP in the literature. Data is used from the Farm Accountancy Data Network for cereal crop farms from 2004-2018. As agricultural policy in the United Kingdom is heading towards the Environmental Land Management Scheme, some farmers might be encouraged to farm with a lower chemical intensity thereby making estimations adjusting for this variable more important within production function estimations.

Chapter 4 examines the farmer's return to education differentiating between organic and conventional farming. By using the 1972 Raising of the School Leaving Age as a quasi-experiment with a Regression Discontinuity Design, we identify a causal relationship for the farmer's return to education on farm economic performance. Using data from a sample of English farms between 2011 and 2018 from the Farm Business Survey, we show: (i) a positive return to education on farm performance (ii) a higher education return in organic farming in comparison with conventional farming.

Declaration

I hereby declare that this thesis has been realised under normal supervision, and all sources used have been acknowledged.

I declare that this work has not already been accepted in substances, nor is it currently being submitted in candidature for any other degree.

Chapter 2 has been submitted as part of an European Union Horizon 2020 Deliverable (Bailey *et al*., 2021). The deliverable combined research from organisations across Europe for which I designed the studies, implemented them in England and wrote up these English results. This chapter focuses on the studies in the English regions rather than a pan-European comparison study.

Chapter 4 is a joint paper with a co-author, Lionel Védrine, who is based at CESAER, INRAE, Institut Agro Dijon, UBFC and Université Clermont Auvergne, AgroParisTech, INRAE, VetAgroSup in France. We both contributed to the identification strategy and interpretation of the results while the rest of the paper was led by me.

Acknowledgements

There are many people who have helped and supported me along my journey to completing the research for this thesis. First, for giving me the opportunity and the many, many meetings along the way I wish to thank my supervisors Sophia Davidova and Alastair Bailey. They gave me constant support and guidance throughout this journey, I have learned a lot from them and benefited from their encouragement.

The research in this thesis contributed to the Low-Input Farming and Territories (LIFT) project. This work was supported by the European Union's Horizon 2020 research and innovation programme [grant number 770747]. I am grateful to the European Commission for the financial support and granting access to data from the Farm Accountancy Data Network. In addition, I am grateful to many of the consortium partners who helped give me constructive feedback and guidance especially Laure Latruffe, Joseph Tzanopoulos, Peter Matthews, Kato Van Ruymbeke and Lionel Védrine. A special thanks goes to Lionel who became a valued coauthor and who willingly offered me assistance with my research.

I am also grateful to my examiners Iain Fraser and Marian Rizov who provided numerous insightful comments and feedback to improving my thesis.

I have enjoyed my time spent at the School of Economics at the University of Kent, and I thank all the lecturers and staff who have passed on their knowledge over the years with a truly unforgettable experience due to their care and attention. I thank the many friends who have supported me along the way and in particular Rowan Cherodian for his mentoring and support in completing this thesis.

My family have been the foundation who have seen me grow in my time here at the University of Kent, they always believed me and would always provide a place of respite when needed along the way. Last, but not least, I would like to thank my wife, Hannah Henderson, who has always been there for me during my PhD journey. Hannah has been my waypoint, a place of refuge and hope. A lot of our time together has run alongside my PhD, and we were married during it, an unforgettable day.

Contents

List of tables

List of figures

List of abbreviations

BPS - Basic Payment Scheme

CAP – Common Agricultural Policy

CF – Control Function

CSA - Case Study Area

DEA – Data Envelopment Analysis

ELMS – Environmental Land Management Schemes

EG – Environmental Goods

ES – Ecosystem Services

EU – European Union

FADN – Farm Accounting Data Network

FBS – Farm Business Survey

GMM – Generalised Method of Moments

MCMC - Markov Chain Monte Carlo

NCAs – National Character Areas

PCA – Principal Component Analysis

PG – Public Goods

RDD – Random Discontinuity Design

ROSLA – Raising of the School Leaving Age

SFA – Stochastic Frontier Analysis

SI – Sustainable Intensification

TFP – Total Factor Productivity

UAA – Utilised Agricultural Area

UK – United Kingdom

Chapter 1 – Introduction

Background

Policy has shifted from boosting food output post Second World War when the general population faced rationing, through to the general population being well fed and an oversupply of food, a time of 'butter mountains' and 'lakes of milk and wine' in the 1970s. Now policy is moving away from subsidising food production and instead shifting towards promoting public goods (PG) and environmental services (ES) such as soil quality, water quality and wildlife biodiversity (European Commission, 2020). Through incentives from the policymaker, and/or of their own volition, farmers may seek to provide PG and ES whilst maintaining some level of food production. In doing so, they may adopt certain ecological practices, e.g. direct or minimum tillage, integrated pest management, setting aside wildflower and buffer strips, rotation between a larger set of crop varieties and integrating crops and livestock. These practices may in themselves provide PG and ES, but may also reduce the input intensity of chemical (and polluting) inputs. The replacement for the European Union's (EU) Common Agricultural Policy (CAP) in the United Kingdom (UK), the Environmental Land Management Schemes (ELMS) (DEFRA, 2023), aims to withdraw the Basic Payment Scheme (BPS) and replace it with subsidies promoting ecological practices to replace agrochemical inputs (Barnes et al., 2022). As the BPS is being withdrawn so farmers will need to either provide PG and ES in order to receive payment, cut costs, increase sales of food or else go out of business.

When designing ELMS the government would have considered its 25 Year Environment Plan. 5 of the 10 goals introduced in this plan, namely air quality, water quality, waste, biodiversity and carbon are directly impacted on by farming practices of which the use of chemicals are included (Helm, 2022). In shaping the three tiers of schemes which make up ELMS, government may be promoting the type of farming where chemical input use is being limited.

Adjusting farming practices and reducing chemical input use in order to pursue environmental goals will influence the farm's demand for labour. Increasing farm labour is itself a policy goal (Dries *et al.*,

(2012) and Garrone *et al*., (2019a)) whereby more farm jobs and a higher income would help create thriving rural communities with more demand for local goods and services and the wider non-farm economy (Rizov *et al*., 2018). As a farm's demand for labour increases, new jobs are created, and farms aim to employ more labourers. The issue for farms is to then find the workers willing to supply their labour and fill these farming job positions. Labour supply may also be an issue in the adoption of ecological farming practices.

Ecological practices are understood here broadly as low-input practices and/or practices that are environmentally friendly, and therefore comprises not only existing farming approaches (e.g., organic farming, agroecological farming) but other approaches not yet labelled as well. When considering ecological approaches to agriculture, the literature most often refers to organic and conventional farming approaches. Indeed, chapter 4 of this thesis further adds to this comparison between organic and conventional farming. The reason for this is that there are data more readily available, and this in itself is as a result of a clearer definition for organic farming than the broad meaning that can be associated with either ecological agriculture or low-input farming.

The organic agriculture literature finds that organic farms tend to require more farm labour to substitute for reduced chemical use (Offermann and Nieburg (2000); Morison *et al*., (2005); Green and Maynard (2006); Moakes *et al*., (2015)). Therefore, as farms reduce their chemical input intensities, then difficulty in recruiting the necessary numbers of farm workers and hours to be worked may be a barrier to adopting these practices. These practices may in particular require skilled labour for which recruitment may be of greater difficulty. The farmer may need to increase wages to attract this skilled labour, which if successful may further support rural communities with additional income.

Gaps in this literature include exploring a heterogenous effect on labour, if there are differences in skilled or non-skilled labour as well as gender differences or differences in full-time and part-time employment.

The main objective of this thesis is to explore how outputs and inputs, in particular labour, change in response to a change of farming practices towards a reduction in chemical input use. Labour is explored in greater detail through investigating the impact of additional education. This additional education leads to an increase in skill level of the farming workforce and their impact on farm productivity is studied including a comparison between organic farms and all farms in the sample. This comparison is made to explore if there are greater benefits to education in a farming approach which uses fewer chemical inputs in comparison with a more conventional farming type.

Theoretical Foundations for Technology Adoption in Agriculture

A number of different factors contribute to the adoption of technology in agriculture. New technologies may include precision agricultural technologies (Barnes *et al*., 2019) and conservation tillage (Brown *et al*., 2020). Barnes *et al*., (2019) find that the main barrier to adopting new technologies is the high cost of entry – this would especially be the case for precision technologies where the necessary machinery would be very expensive. Given the large expense, larger farms will find It easier to invest in these new technologies. Another aspect in adopting these precision technologies is that the farmer will require more knowledge in order to adjust to using a different machine in the first place, but also in response to the heterogeneity of the farming landscape. Brown *et al*., (2020) agree that the size of the farm allows the farm to benefit from economies of scale and thus benefit from labour saving technologies, the incentive to save on labour cost is increased when output prices become lower.

Continuing from Barnes *et al*., (2019), a couple papers emphasise the importance that education has in the adoption of new technology. Huffman (2001) find that more education results in an increase in farmers' information acquisition and technology adoption. The definition for education that Huffman uses is one of producing general intellectual achievement which comprises abilities and knowledge and is created through increased schooling, better quality schooling, innate ability and the learning environment. Chavas and Nauges (2020) study the role of uncertainty, learning and information transmission on technology adoption and they find that farmers who are stronger at obtaining and processing information are usually early adopters of a technological innovation, whilst those who are weaker tend to be late adopters. This suggests that receiving more education may result in an earlier adoption of a new farming technology.

Thesis Outline

Chapter 2 studies interactions between outputs and inputs, rural communities as well as considering the different points of view of farmer and policymaker. This chapter uses stakeholder-based approaches to imagine future scenarios of ecological agriculture adoption. The approaches are namely Delphi exercises and Q-methodology. Here, stakeholders explain how they perceive people and other productive assets being employed and remunerated following 10 years of farms adopting ecological approaches to agriculture. The stakeholders are the economic agents closest to innovations and changes in the field. They are experiencing the changes as they happen and are naturally looking forward to how these changes may impact upon the future of farming. A mixture of qualitative and semi-quantitative methods are used here to explore stakeholder perceptions. These methods allow us to explore stakeholder opinions whilst the factor analysis component of Q-methodology introduces some rigour. ELMS is demonstrated to be a considerable uncertainty for farmers and their future planning.

Chapter 3 estimates Total Factor Productivity (TFP) in a Cobb-Douglas production function framework. The Cobb-Douglas production framework is chosen due to being relatively easier to estimate than CES or translog functions where these alternate functions may generate multiple spurious solutions (Biagini et al., 2023)[1]. In addition, Ackerberg *et al.*, (2023) demonstrate that TFP estimates are not improved significantly through the choice of alternative functional form. Within the chapter there is a discussion of what approach may be best suited to estimating TFP in agricultural settings. The approaches considered include Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA),

[1] For a further discussion on the choice of functional form see (Biagini et al., 2023).

Control Function (CF) methods and Generalised Method of Moments (GMM) (Biagini et al., 2023). GMM is the chosen method as it is found to control for endogeneity more effectively than SFA and DEA approaches (Mary (2013); Khafagy and Vigani (2022)) and in contrast to CF methods it avoids the risk of evaluation errors in case of choosing the incorrect instrumental variables (Biagini et al., 2023). The contribution of this paper to the literature is that it accounts for the use of chemical inputs which is absent in previous GMM estimations of TFP in the literature. Data is used from the Farm Accountancy Data Network (FADN) for cereal crop farms from 2004-2018. Including chemical inputs in the specification makes little difference to labour and capital productivity, but it has a large effect in reducing the coefficient on land productivity. Other papers use materials as another variable in the estimation, but given the policy environmental policy context, chemical inputs may also be worth considering.

Chapter 4 considers the heterogenous returns to education for organic and conventional farming. The chapter addresses the shortfall of a lack of studies on the returns to education in agriculture and in particular in the context of organic farming. The comparison between organic farming and conventional farming is an attempt to study if farmers benefit more from additional education as they reduce their use of chemical inputs or not. This chapter exploits the 1972 Raising of the School Leaving Age (ROSLA) in a regression discontinuity design (RDD) setting. ROSLA was a policy enacted in 1972 where pupils had to stay in school till they were the age of 16, whereas before then students could leave school after turning 15. When estimating the relationship between output and education there is often a problem of endogeneity. Given that education comprises both number of years of schooling and innate ability (Huffman, 2001), an example of the possible endogeneity here is that students with more innate ability may choose to stay in school for longer and, in addition, students who have more innate ability may perform better managing a farm and produce more farm output. RDD exploits a natural experiment whereby a treatment and a control group are created where the participants are separated into these two groups by those who had to stay in school for longer (the treated group) than those who could leave school earlier (the control group). The RDD is estimated in two stages. First, it estimates the number of years of schooling depending on the birth year of the farmer which aims to confirm that those in the treated group did indeed receive more education. Second, an RDD estimation for farm output uses Two Stage Least Squares with the dummy variable for those required to stay in school for longer or not used as an instrument for the number of years of schooling. This approach is applied to estimate returns to agriculture across all farms in the sample as well as the organic farms. The RDD model is extended through using a Correlated Random Effect model and in estimating the organic farming a heterogeneous local average treatment effect (HLATE) approach is used. A limitation with this analysis is the plausibility that an additional year of schooling from 1973 onwards resulted in a meaningful increase in farm output 40 years later. It may be possible that receiving this additional education at this point might result in a greater appreciation for additional education and training opportunities which may lead to this treated group following a different learning trajectory over time compared with the control group.

Lastly chapter 5 concludes the thesis.

Chapter 2: Stakeholder insights from two case studies in England on the regional socio-economic effects of ecological agriculture

Abstract

This chapter assesses the broader socio-economic effects at the territorial level of farms adopting ecological approaches to farming. These ecological approaches are growing in popularity and include low-input, organic, regenerative, conservation and agroecological farming. This chapter explores their potential growth over the next decade in two heterogeneous regions of South East England, namely North Kent and the High Weald. Q-methodology is an explorative, semi-quantitative approach that investigates the perspectives of different groups of stakeholders. In this study it was used to capture the perspectives of local stakeholders in two steps. First, stakeholders have in mind an 'adoption scenario' – what they consider would be the adoption rate and pattern of lower chemical input practices on farms. Second, what would be the socio-economic effects of their 'adoption scenario'. A concurrent Delphi Exercise using the same 10-year frame, adoption scenario and involving additional stakeholders is used to supplement the interpretation given from the Q-studies. Results emphasise that there will need to be an increase in the skill level of the farm workforce in order to facilitate changes in farm practices. Therefore, policy may want to address the provision of education and experience as well as sourcing migrant labour depending on the farming context.

2.1 Introduction

There is a need to assess the broader socio-economic effects at the territorial level of farms adopting ecological approaches to farming. It is difficult to separate out different socio-economic effects at the territorial level into individual pieces of research due to multiple interrelating effects and this is especially so when discussing ecological approaches to farming. The environmental impacts as well as the social and economic consequences of an increase in ecological farming at a regional scale are still unclear. One reason for this is the lack of assessment at a regional scale, due to the complexity of methods and substantial amount of data needed (Graymore *et al*., 2008). This chapter contributes to shedding light on this issue, with an approach based on stakeholders' perceptions.

Ecological practices are understood here broadly as low-input practices and/or practices that are environmentally friendly, and therefore comprises not only existing farming approaches (e.g., organic farming, agroecological farming) but other approaches not yet labelled as well.

Q-methodology (henceforth Q) is an explorative, qualitative approach that allow experts who are closer to innovations on the ground to explain how they perceive the industry changing in light of further attention regarding ecological approaches to farming. Using Q as a research method allows the researcher to investigate similar or diverging subjective perspectives held by groups of people on a specific topic (see Stephenson (1935); Stephenson (1953); McKeown and Thomas (2013)). This method is increasingly recognized in social sciences and has been applied to elicit views on a variety of topics.

Examples of using Q in the literature include Cuppen *et al.,* (2010) where the authors apply Q to identify stakeholder perspectives on energy production from biomass in the Netherlands. Zepharovich *et al*., (2020) make use of Q to investigate the perceptions of stakeholders (large-scale producers, small-scale farmers, indigenous peoples, governmental actors, civil society) on deforestation in the province of Salta (north-west Argentina). Mahlalela *et al*., (2022) use Q to identify and analyse perspectives held by different stakeholders on wetland ecosystem services in Hawane Dam and Nature Reserve (in Eswatini, South Africa), to guide policymakers (i.e., conservation management initiatives). Vecchio *et al*., (2022) apply Q to understand agricultural entrepreneurs' perspectives in Italy on precision farming and to analyse the role and importance of precision farming tools for the sector. Alexander *et al*., (2018) employ it to explore 35 rice farmers' viewpoints on their production goals and potential to adopt technologies to improve productivity in Southern Lao PDR. Also, with this method, Iofrida *et al*., (2018) explore, in the Calabrian region, the perceptions of various actors, including local and supply chain stakeholders to identify room for innovation towards sustainability. Lehrer and

Sneegas (2018) explore stakeholders' views about pesticide use and associated risks for on-farm workers in Washington State's tree fruit industry.

As an explorative exercise, the approach frames the research in a 10 year forward perspective and explores how stakeholders believe farms in a given Case Study Area (CSA) will adopt ecological farming approaches. The timeframe of 10 years was chosen in part to recognise that adoption of new technologies and changes on farms can take some time. Farming policies in the UK are undertaking a generational change which may require a few years for policy to settle and farmers to adapt. In addition, 10 years from the study coincides with the Sustainable Development Goals target of 2030. Some stakeholders even felt that 10 years was not long enough a timeframe, whilst others thought it too far in advance leaving 10 years as a balancing point in the middle. The two CSAs were chosen to reflect heterogeneity in UK farming landscapes and to capture a wide range of farm types given the available resources.

Within this 10-year horizon, stakeholders are encouraged to explore two fundamental questions that outline: 1) would a low or high percentage of farms in the area adopt ecological practices? And 2) would the pattern of adoption of ecological farming form a cluster or be randomly spread across the territory. Given these adoption scenarios, we use Q and Delphi to investigate their socio-economic effects.

The chapter presented here is structured as follows. First, the two CSAs used in the Q and Delphi are described with an explanation regarding their economic and geographical contexts. Second, the methodology describing the application of the Delphi and the Q are presented. Third, there is a discussion of the results from each CSA and for each methodology. Finally, this chapter concludes.

2.2 Methodology

This section proceeds by first presenting brief descriptions of the CSAs involved in the Q and the Delphi Exercise. Second, it outlines the Delphi Exercise. Third, it explains Q. Fourth, it discusses how the statements were selected. Fifth, it describes the participants. Sixth, an explanation is given of how the analysis was carried out.

2.2.1 Case study area descriptions – High Weald and North Kent

The CSAs of the High Weald and North Kent were chosen to reflect heterogeneity in English regions where each CSA is unique, varying in climatic conditions, land cover, relief and topography (flat or mountainous etc.), and population. These differences in the farming landscape inevitably result, firstly, in variations in the prevalence of different farm types existing in the CSAs (whether that be cereal crop, livestock, horticulture etc.) and, secondly, to the ecological farming approaches that best suit these different farms. Given the variety and breadth of farming types that the CSAs incorporate, they are an interesting focus for stakeholders to discuss the future of the effects of ecological approaches to agriculture because they may have implications for impacts in other UK regions. However, given that these CSAs are unique, a limitation must be placed on the lessons that can be learnt and applied to other UK regions.

Both CSAs are located in South East England – one of the most populous region in the UK, and within commuting distance of London, with approximately 9.4m inhabitants, 13.9% of the UK total, and relatively densely populated at 492 inhabitants/km^2 against a UK average of 279 inhabitants/km^2 (ONS, 2024). Figure 1 is a map showing the location of the CSAs in South East England[2].

The CSA of North Kent is an area of diverse agricultural systems, with a mix of arable, livestock and horticulture farms comprising three National Character Areas (NCAs) (Natural England, 2024). The North Kent Plains, one of the NCAs, contain fertile loam soils, thus, is characterised by arable,

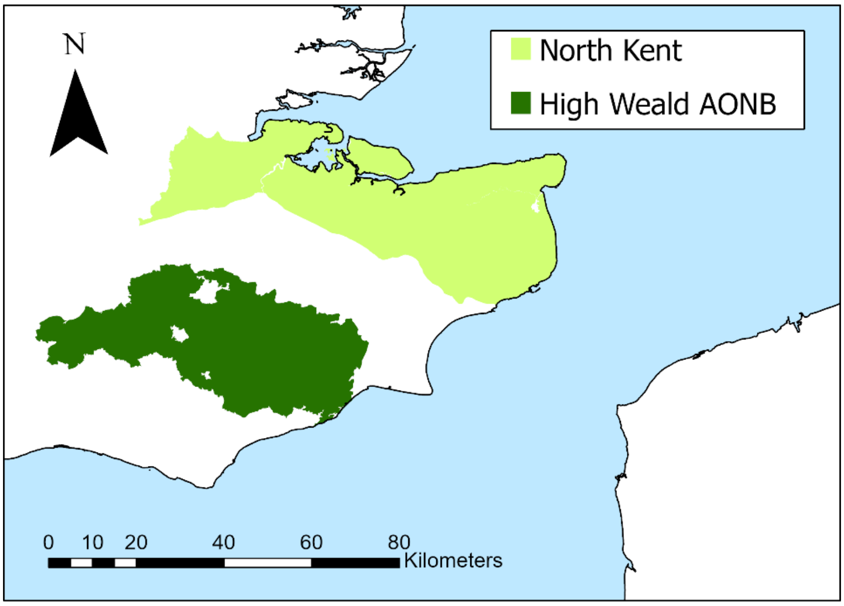
---

[2] *© Natural England copyright. Contains Ordnance Survey data © Crown copyright and database right 2023*. Data for the High Weald was accessed from: https://www.data.gov.uk/dataset/8e3ae3b9-a827-47f1-b025-f08527a4e84e/areas-of-outstanding-natural-beauty-england and for North Kent from https://www.data.gov.uk/dataset/21104eeb-4a53-4e41-8ada-d2d442e416e0/national-character-areas-england.

traditional orchards, and soft fruits and vegetables. Grazing marsh is typical in the Great Thames Estuary (another NCA) and mixed farming is widespread on the North Downs (the final NCA).

In contrast, the High Weald CSA largely comprises pastoral agriculture with areas of horticulture on higher ground, while the low lying, flat areas towards the east contain concentrations of arable farmland. This landscape was granted Area of Outstanding National Beauty status in 1983, recognising the unique High Weald landscape of a mosaic of small farms, the highest concentration of woodland in England (26%) and ridge-top villages.

Figure 1: Location of the two English CSAs



Farms are on average larger in the North Kent study area, 99.4 hectares (ha), in comparison with 52.6 ha in the High Weald (DEFRA, 2024)[3] and the total farmed area is larger in North Kent (148,637 ha against 97,609 ha in the High Weald). This is not surprising bearing in mind that a large proportion of farms in the High Weald tend towards the smaller end of the national farm size scale i.e. less than 20ha in size (49.9% less than 20 ha versus 43.5% in North Kent and nationally 40.9%) while there are a significant number of farms in North Kent larger than 100 ha (25.7% versus 13.6% in the High Weald

[3] Land area are authors' own calculations using geographical data broken down by NCA from the June 2021 census.

and 23.6% nationally). Compared to the High Weald, North Kent has a far larger proportion of cereal[4] farms (23% against 7.2%), but a much lower importance of grazing livestock (32.6% against 46.1%).

2.2.2 Delphi Method

The Delphi method attempts, first, to collect the views and opinions of a number of informed people and, second, to harmonise these views across a panel of experts (Börjeson *et al*., 2006). Gallego and Bueno (2014) define Delphi as a type of questionnaire, which, through feedback, organises and shares opinions. According to the authors there are four main characteristics of Delphi. First, it is anonymous (each stakeholder does not know the response of another). Second, it iterates through rounds of sharing opinion and feedback. Third, controlled feedback is given (responses are summarised by researchers and presented again to the stakeholders). Fourth, a group response is produced statistically.

Delphi was implemented in the two UK case study regions and the interview questions can be found in the Appendix to this chapter. The questionnaire was constructed in combination with project partners involved in the Horizon 2020 LIFT project and the full results are presented in Bailey *et al*., (2021). Approximately 10 stakeholders were involved in each region in the Delphi analysis. 10 stakeholders were approached in order to gather a wide range of information, but as the questionnaire is detailed and administered over three rounds, a relatively small sample size was chosen given the available resources. The objective was to have a balanced representation by years of experience and occupation – advisory system officers, researchers, land agents, farmers, civil servants, non-government organisation representatives – therefore an aim of covering 2 stakeholders from each occupation. Also found in the Appendix to this chapter is the Delphi Information sheet for participants in North Kent.

[4] Farm types are classified using standard output, percentages are authors' own calculations.

As a first step we provided a representative model of a typical ecological farm in each of the case study regions and asked the stakeholders to describe the changes in the farming practices they foresee in comparison to a typical conventional farm in their area. A scenario of a hypothetical pattern of adoption (including high, low, clustered, random pattern) has been suggested to the respondents and they had to choose the pattern they expected to be the most probable for their region. Second, the participants were asked about their opinion on what might happen in factor markets, especially considering whether there would be any second-round effects on the labour market. Third, we summarised these opinions and presented them again to the stakeholders, asking them if there were any revisions to be made. Finally, we looked for signs of convergence and consensus.

Figure 2: Summary of Delphi process

Round 0:
- Send participants an information sheet presenting average statistics comparing ecological and conventional farm characteristics in the area
- Stakeholder panel finalised

Round 1:
- Interview stakeholders round 1 questions
- Anonymise and synthesise results from round 1 in form of qualitative summary and statistical indicators

Round 2:
- Present results from round 1 to stakeholders
- Interview stakeholders round 2 questions
- Anonymise and synthesise results from round 2 as done above

Round 3:
- Present anonymised results from round 2 to participants
- Interview round 2 questions again
- Aggregate responses into consensus from round 3 and analyse

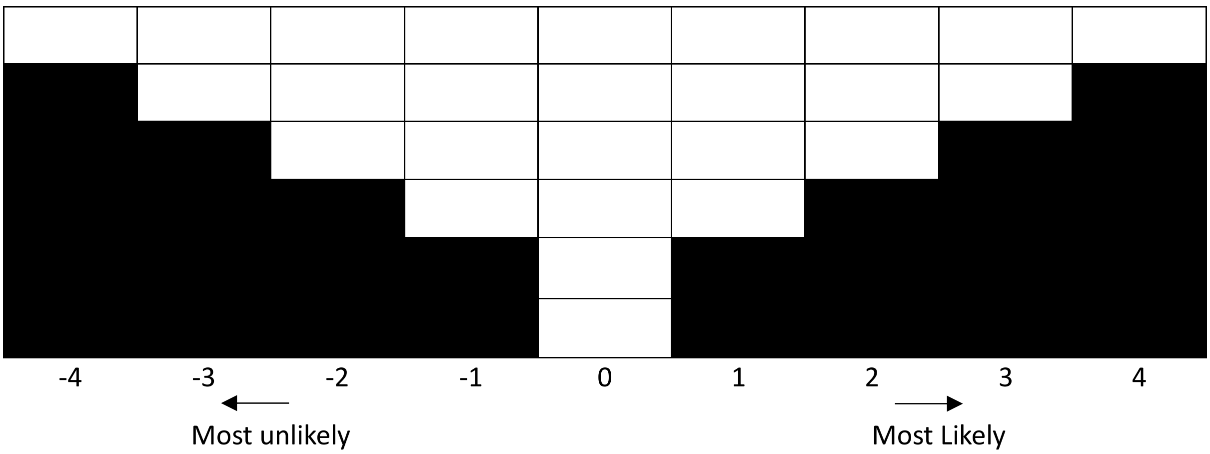
After this first step, three rounds of Delphi were implemented. In the first round, participants were asked to characterise ecological approaches to agriculture as they may develop in a 10-year timeframe in their region; the second round enquired about the socioeconomic effects of these ecological approaches and the third round repeated the questions of round 2 presenting a summary of round 2 to participants.

2.2.3 Q Study Design

Q attempts to measure attitudes (Cross, 2005) and human subjectivity (Kampen and Tamás, 2014). An advantage of Q is that it is designed to manage a small sample size (Giannoulis *et al*., 2010). Giannoulis *et al*., (2010) used Q on a sample of 23 journalists from 9 different newspapers to study beliefs on environmental issues. Another study uses a sample of 61 Mexican American women to sort 36 images of children into weight categories to investigate perceptions of childhood obesity (Bayles, 2010). In another study on the perceptions of rurality, the sample size was of 10 people (Duenckmann, 2010). Another example from a brief examination of the Q literature is of a paper with sample size of 75 engaged in a stakeholder dialogue (Cuppen *et al*., 2010). The authors use this dialogue in order to gain the perspectives of the stakeholders on energy from biomass and Q is used as a method to select stakeholders for these dialogues. Both Cuppen *et al*., (2010) and Bayles (2010) use a mix of different stakeholders, including farmers, academics and local councillors, in their use of Q. Additional publications, Grimsrud *et al*., (2020) and Zepharovich *et al*., (2020) respectively use 15 participants to sort 46 statements and 25 participants for 36 statements. A statistically robust analysis in Q requires at least 1 participant for every 3 statements (Webler *et al*., 2009).

In this chapter, Q was used to gather the attitudes of stakeholders on the adoption and socio-economic effects of ecological farming approaches. This methodology attempts to rank-order statements along a continuum, for example, from ‘agree’ to ‘disagree’ (Cross, 2005). The statements are sorted into what may resemble a normal distribution, the shape depicted in Figure 3 with each square being one statement, where the tails are the extreme statements that sit closest to agreement with the stakeholder or disagreement on the other tail. The distribution forms ‘a model of subjective preference’ (Cross, 2005, p. 209). For the topic area being studied, the data from the Q-sort is what the stakeholders make of a ranking of items, or statements, that are presented in front of them. Q typically uses cut up pieces of paper or cards with statements on them for participants to sort. The following section describes how the statements were selected. An information sheet for the High Weald case study area, as presented to study participants is included in the appendix for this chapter.

Figure 3: Distribution grid for Q-sorts

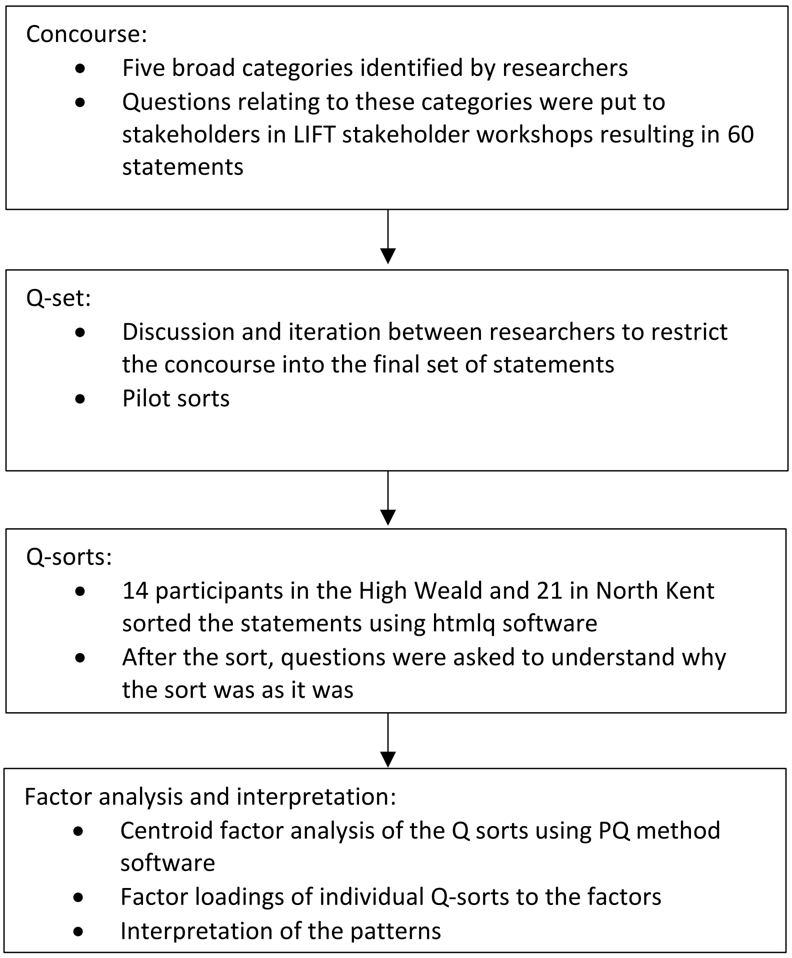


The sample of items that make up the ‘Q-set’ usually comprises of 10 to 100 items and this ‘set’ and ‘sampling’ need to take place to create this ‘Q-set’ (Cross, 2005). We adapt this ordering of statements: from ‘fully agree’ to ‘fully disagree’, instead becomes from ‘most likely’ to ‘least likely’. A grid, Figure 3, is used as a visual aid to help stakeholders sort these statements along a Likert scale where -4 is ‘least likely’ and +4 is ‘most likely’. This rank-order is in anticipation of how the adoption scenario embedded among the statements would relate with socio-economic effects 10 years in the future.

2.2.4 Selection of statements in the Q set

This Q-study aimed to study a wide range of topics starting with five broad categories as described in Bailey *et al*., (2021). These categories were identified by researchers to firstly understand the future of pattern and rate of adoption of ecological farming approaches and as a result of the prevailing pattern and rate of adoption, their socio-economic effects. The five categories that were chosen: adoption pattern and rate, ecosystem services, nature of farm labour, labour market and the wider rural economy. Including ecosystem services allows participants to identify how ecological and conventional farming approaches may have different impacts, framing the concourse relative to these different approaches. Statements fitting into adoption pattern and rate allow participants to quantify how these aspects may further impact socio-economic effects. The nature of farm labour helps to outline how attractive the farming industry is for employees. Statements in this category cover peak work (need for seasonal and possibly migrant labour), a varied job may be more interesting than one which is repetitive and a more physical, whereas a manual job may be less attractive and at a territorial level this may have a different impact from farm level. The focus of this chapter on socio-economic effects thereby focuses on labour and the wider rural economy.

Figure 4: Summary of Q method design



From these five broad categories, approximately 60 statements were chosen stemming from 6 stakeholder workshops organised in the LIFT project and involving 23 stakeholders (Bailey *et al*., 2021), and supplemented with statements derived from media sources that include farming radio and online news media. The statements were chosen through a process of iteration between LIFT researchers. The final Q-set of statements can be found in the results section of this chapter. In the end, 26 statements were selected: 3 statements to set out the adoption pattern and rate, 4 statements to capture effects on ecosystem services, 3 for nature of farm labour, 8 for labour market and 8 for the wider rural economy. There is no particular reason for this weighting other than the chosen statements were thought capable to capture the largest number of viewpoints, and the focus of the study is on socio-economic effects. Several pilot sorts were conducted with other researchers and a couple farmers to evaluate the statements in terms of understanding and balance. Using the Likert scale on the grid for the Q-set, as shown in Figure 3, participants were asked to fit each of their 26 statements into each of the 26 grid spaces from what they thought was 'least likely' and 'most likely'. Each individual Q-sort of the Q-set is unique to each participant.

2.2.5 Participants in the Delphi Studies and Q

The minimum number of participants in Q suggested through the literature was at least 9 participants (Webler *et al*., 2009) and we aimed to recruit around 20 participants for each CSA. These participants are also intended to have knowledge of farming practices and technologies across the CSA, but we expanded the sample to also include farmers given that they often do cooperate with others in the CSA and know the local landscape and climate. A total of 35 participants from the 2 different CSAs took part in this Q with 14 in the High Weald and 21 in North Kent. A variety of methods were used to collect Q-sorts from stakeholders that included face-to-face meetings, meetings through online video teleconferencing software, phone calls, Q-study sent over email, from May 2020 to June 2021. The consistent feature across all these meetings was the use of the htmlq software to facilitate the sorts[5]. The time period coincided with Covid and hence initially there were face-to-face meetings, but following lockdown the interviews were moved online.

Table 1: Participant information (number of participants) in the Q and Delphi exercises

	Q			**Delphi Exercise**		
	High Weald	North Kent	Total	High Weald	North Kent	Total
Gender						
Male	11	16	27	6	10	16
Female	3	5	8	4		4
Area of work						
Researcher		1	1		2	2
Civil servant	1	1	2	1	1	2
Extension officer	1	1	2	4	4	8
Farmer	4	12	16			
Land agent	2	1	3	2	1	3
NGO representative	6	4	10	3	2	5
Other		1	1			
Work experience						
< 5 years	3		3	1		1
5-10 years	1	5	6	2		2
10-20 years	4	2	6	1	2	3
> 20 years	6	14	20	6	8	14
Total	14	21	35	10	10	20

During the Q-sorts, participants were asked their thoughts on why they sorted Q statements in the way that they did. This facilitated easier interpretation, greater depth to the interpretation and a more cohesive stakeholder perspective to emerge. Table 1 presents information on the Delphi exercise and Q participants. It can be noted that there are a lot more farmers in the North Kent sample giving them

[5] htmlq software: https://github.com/shawnbanasick/easy-htmlq is now a legacy system and has been replaced by EQ Web sort: https://github.com/shawnbanasick/eq-web-sort. Here is a link to the study: https://unikentlift.netlify.app

a stronger voice in North Kent and this may be a limitation of the study. However, as a group the farmers do not seem to load onto a given factor suggesting some variance in perceptions between farmers.

2.2.6 Q Data analysis

This section describes the process for analysing data across the CSAs so that the resulting factors would be as comparable and consistent as possible.

To analyse the data, the PQMethod[6] program by Schmolck (2024) was used. Centroid factor analyses (centroid factor analysis being a type of factor analysis offered by the PQMethod program) were carried out rather than principal component analysis (PCA) due to the explorative nature of the study (Barry and Proops, 1999). Although PCA would give the 'best', single, mathematical solution, this is argued to not be the desired choice in Q given the desire to further explore the data and identify more related factors to discuss (Watts and Stenner, 2012).

A Varimax rotation was applied to the unrotated factors following papers in the literature (Grimsrud *et al*., (2020) and Zepharovich *et al*., (2020)). After selecting the Varimax option in PQMethod, we need criteria with which to choose how many factors we should rotate. Although using principle component analysis, Grimsrud *et al*., (2020) explain their decision in choosing three factors (using 15 participants) with a cut-off point aiding their decision. As a rough guide, Watts and Stenner (2012) suggest starting with 1 factor for every 6 participants which matches with Grimsrud *et al*., (2020). Our aim is to find an appropriate number of factors to maximise the number of Q-sorts that load significantly onto them and explain a significant amount of study variance (Watts and Stenner, 2012) – this might be as much art as it is science. The advised decision, and statistical, criteria for choosing a factor is that at least 2 Q-sorts load onto each factor and each factor should have an eigenvalue of at least 1. The final set of statements can be referred to in the results section for this chapter.

[6] The software can be found here: http://schmolck.org/qmethod/

2.3 Results

The below section interprets factors identified through the Q-analysis as described above. Each factor begins with a set structure to support the decision rule as identified above and how significant this factor is in terms of explained variance. In each factor, the number of Q-sorts – the rank-order combination of an individual participant – is given which load significantly onto an identified factor. The significantly loading Q-sorts will tend to correlate with each other to give numbers that indicate how likely they believe these statements to be 10 years in the future relative to each other. For the participants with significant loadings, an interpretation starts to form of the viewpoint or factor based on the Q-items in the Q-set and how they correlate with each other. To supplement this correlation, the thoughts of participants of these significantly loading Q-sorts strengthen the interpretation. The Delphi Exercise is also used to supplement the interpretations of these factors. Once these interpretations have been discussed – a summary heading is offered by the researcher of this viewpoint. In the following interpretations for each factor, the figures between brackets, e.g. (2/+3), correspond to (Statement number/degrees of agreement), and the matching statement number can be seen in the set of statements presented later in this section e.g. Table 2.

2.3.1 Delphi Exercise

Concerning the development of farming practices, respondents tended towards the proliferation of ecological farming but in parallel with the continuous existence of conventional agriculture. Concerning skills, Delphi participants argued that modern farmers are highly skilled, but to be able to adopt more environmentally friendly practices they may need to further develop their skill sets. Three main points were emphasised for skill demand.

First, ecological agriculture might result in integrating multiple farming systems onto a single farm: crops, livestock, orchards, forestry. These farms would be more complex operations requiring a variety of skills and knowledge. The larger set of skills would require a versatile farmer with a wide range of skills or workers covering the necessary range, which might result in more hired labour, particularly on larger farms.

Second, in order to provide more public goods and ecosystem services, farmers have to adopt different practices: intercropping, cover and catch cropping, holistic planned grazing, Integrated pest management, Integrated weed management. These practices require an increased understanding of biology, ecosystems and natural processes. Observation skills, and not so much the traditional repetitive manual work, would be necessary for recognising issues e.g. pest species from beneficial species. However, some stakeholders argued that the new requirements can be handled through contracting an adviser on bigger farming operations.

Third, adoption of more ecological farming practices requires knowledge of its possible impacts on soil, water, air, and skills to market the positive effects to the buyers of farm produce. Knowledge will be necessary to use the public incentives and comply with regulations with respect to public good and ecosystem service provision, and how environment management can be integrated with the farming operation. Stakeholders argued that farmers have to learn on the job, be proactive and stay informed regarding developments in the industry and should actively communicate with other farmers.

Results from Delphi in the case study regions under analysis here have indicated consensus that farmers would need new skills to operate a farm adopting ecological farming techniques. However, similar to the views covered in the literature review above, some stakeholders, although a minority, suggested that new technologies, irrespective to whether they are related to ecological farming or not, e.g. precision farming, robots, AI, may limit the requirements to skills and decision making by farmers.

Overall, the results from Delphi suggest that we may expect a need for more skills in order to successfully adopt ecological approaches to farming. However, caution is necessary since consensus has not been reached in Delphi. And, in any case, the main gap in the literature, and in our Delphi exercise, remains whether the skill sets necessary for ecological farming differ from those needed for more conventional agriculture and what would be the effect on the return to such skills.

2.3.2 Q study - High Weald

Factor 1 – Skilled ecological movement

Factor 1 is defined by 7 significantly loading Q-sorts, explaining 28% of the variance in the study and has an eigenvalue of 6.58. Table 2 presents the results for the Q in the High Weald where the Q sort values indicate how strong the stakeholders with the significant factor loadings agree (or disagree if negative and high) with that statement as part of the factor (Zepharovich et al., 2020). Meanwhile, the z-score indicates the distance the statement is relative to the middle of the sorting distribution. Starting with the pattern of adoption stakeholders identify that at least 10% of farms in the study area will be using ecological farming approaches (2/+3)[7] - indeed this proportion may already be the case - this rate will be somewhere between 10% and 50%, possibly not yet at 50% in 10 years' time (1/+1), that is of farms being regenerative. In addition, these farms employing ecological approaches are likely to form in clusters (3/+2) as farmers cooperate more with neighbouring farmers (14/+3). Stakeholders suggest local cooperation should take place for biodiversity reasons such as wildlife corridors. This increase in ecological practice participation and local cooperation is predicted to result in improved soil quality (6/-3) and as a further result, increased water quality (5/+2) as soils hold water like a sponge rather than letting water runoff into nearby water bodies with the soil nutrients. In addition, the number and size of hedgerows will increase (7/-3) where stakeholders point out they may be a source of nutrients for grazing livestock and provide a windbreak as well as homes for birds and other wildlife. An important statement in this factor (more important than in factor 2) is that farmers will need to increase their level of skills (12/+4) – more knowledge is required and following Brexit, where the CAP was seen to be prescriptive among farmers, this 'freedom' may enable farmers to rediscover knowledge on when to make interventions on farm, but in line with environmental objectives. Another statement with a strong opinion was that ecological farming approaches will be more than just a limited social movement (16/-4): there is already support in newspapers on ecological farming

[7] The numbers in the brackets correspond as follows: (Statement number/degrees of agreement)

practices, more farmers will adopt ecological practices, and more consumers will buy their food locally (15/-2). In addition, study participants foresee that rural areas will become more attractive to residents

Table 2: High Weald Q Results

No.	Statement	Factor 1		Factor 2	
		Q	Z	Q	Z
1	50% of farms will adopt ecological farming practices.	1	0.83	2	1.03
2	10% of farms in the case study area will adopt ecological farming practices.	3	1.35	-2	-0.81
3	Ecological farms will form clusters of closely connected farms within the case study area.	2	1.02	1	0.85
4	There will be little change in the landscape appearance of rural areas.	-1	-0.4	-1	-0.51
5	Water quality will improve.	2	1.04	3	1.58
6	Little change will happen to soil quality.	-3	-1.69	-4	-2.32
7	There will be no change in the number and/or size of hedgerows.	-3	-1.65	-3	-0.92
8	Employment opportunities in farming will increase.	0	0.01	1	0.47
9	The need for labour work of an individual farmer will be spread throughout the year.	0	0.11	0	-0.06
10	The farmer’s daily routine will become more varied.	1	0.82	0	-0.31
11	The wider rural economy will be more resilient.	1	0.37	2	0.91
12	Farmers will need to increase their level of skills.	4	1.97	2	0.99
13	The nature of work on farms will be more physically demanding.	-1	-0.8	0	0.33
14	Farmers will cooperate more with neighbouring farmers and farms close to them.	3	1.2	3	1.48
15	Consumers will not buy a lot more of their food locally.	-2	-0.85	-2	-0.82
16	Ecological farming will be a limited social movement and will not provide substantial ecosystem services.	-4	-1.75	-3	-1.21
17	There will be tight certification to define farms as ecological.	0	-0.17	1	0.43
18	As a proportion of household income, income from farming will decrease.	2	0.86	-1	-0.68
19	More livestock farmers will use mob/strip grazing.	1	0.82	4	2.08
20	Mob/strip grazing will decrease the requirement for labour.	0	-0.19	0	-0.46
21	Rural areas will become no more attractive for residents and users.	-2	-1.06	1	0.46
22	There will be more need of seasonal labour.	0	0.24	0	-0.31
23	The use of family labour will decrease.	-2	-0.94	-1	-0.48
24	There will be more need of migrant labour.	-1	-0.36	-1	-0.71
25	There will be no change in trade of locally sourced inputs.	-1	-0.61	-2	-0.86
26	There will be more demand for female labour for manual operations.	0	-0.2	0	-0.13

and users (21/-2), although this may be a subjective viewpoint and different to those coming from urban environments.

Factor 2 – Transformative mob grazing

Factor 2 is defined by 6 significantly loading Q-sorts, explaining 27% of the variance in the study and has an eigenvalue of 1.05. The scenario in this perspective is one where stakeholders view 50% of farms using ecological approaches as being more likely (1/+2) than a 10% adoption rate (2/-2), but also that farms using ecological approaches will form in clusters (3/+1), just at a lesser extent. The High Weald has a lot of lifestyle and hobby farmers as it is close to London and as an AONB these farmers are more likely to farm with an environmental objective in mind. Meanwhile, clusters are more likely as farmers share their experiences and future agricultural subsidies encourage cooperation among neighbours (14/+3) for wildlife corridors and increasing biodiversity. As a result of this adoption, the environmental effects are similar to factor 1 where soil (6/-4) and water quality will improve (5/+3) as well as the number and size of hedgerows (7/-3) (also receiving financial incentives). In this factor, mob grazing stands out where participants think that this will increase (19/+4) in the future as they see the practice being a better way of managing livestock and grazing: it reduces the amount of inputs that farmers need (fertiliser on the grass and medicines in animals) while increasing the livestock density the grassland is able to support. The stakeholders believe this practice of mob grazing will deliver improvements in the ecological side of the farm – soil and water quality are examples of perceived improvements and various organisations, including the High Weald AONB team, promote its use. The use of this practice is associated with an increase in skill level (12/+2) where farmers need to: more closely observe their animals; understand the biology in their soils; manage grasslands; and manage the nature around them. Farmers' labour is also perceived that it would change. Livestock are kept in barns for a shorter amount of time, therefore less time would be needed to clear it out and to feed the livestock in barns throughout the year as well as given a lower requirement for medicines, less time needed to treat animals on farms. Saving time in these ways may enable farmers to spend more time observing their livestock and manage their local environment. However, farmers would need to move livestock more often, though this may be possible through automation through using moving electric fences. These changes, including observing livestock more, enables the farmer to take better care of the livestock, but also to spend time diversifying into other enterprises and this may lead to an increase in employment opportunities (8/+1) in this scenario and factor.

2.3.3 Q study - North Kent

Factor 1 – High and clustered adoption needs skilled land managers

Factor 1 is defined by 8 significantly loading Q-sorts, explaining 23% of the variance in the study and has an eigenvalue of 5.98.

Table 3 presents the z-scores and Q sort values for the North Kent sample. This factor presents the case where the likeliest adoption rate is where 50% of farms in the CSA adopt ecological farming practices (1/+3) and their adoption pattern is likelier to be clustered than spread (3/+3). Participants argued a 50% adoption rate is likelier as subsidies might become necessary for the farm business to survive and under a change in policy, subsidies are restricted to be paid when farms provide public goods through adopting ecological practices. These practices may need to include no till farming and environmental land management. Clusters are already taking shape in the CSA where farms share best practice. Another participant refers to the Lawton review: 'Making space for nature' (Lawton *et al*., 2010) – an independent review studying England's wildlife sites and their capability of responding and adapting to climate change and other demands on the land. The review emphasises how small, isolated pockets will not be sufficient for nature conservation to succeed – bigger landscape scale clusters of farms are necessary, and this is supported through a change in government policy which is currently being finalised (at the time when the Q was taken, there were still plans and a lot more uncertainty as to the policy taking shape).

Table 3: North Kent Q results

No.	Statement	Factor 1		Factor 2		Factor 3	
		Q	Z	Q	Z	Q	Z
1	50% of farms will adopt ecological farming practices.	3	1.26	-2	-1.04	2	1.06
2	10% of farms in the case study area will adopt ecological farming practices.	0	0.36	3	1.58	1	0.59
3	Ecological farms will form clusters of closely connected farms within the case study area.	3	1.37	1	0.28	1	0.52
4	There will be little change in the landscape appearance of rural areas.	-3	-1.43	-3	-1.49	6	0.42
5	Water quality will improve.	1	0.72	3	1.42	2	0.78
6	Little change will happen to soil quality.	-2	-1.31	-3	-1.39	-1	-0.53
7	There will be no change in the number and/or size of hedgerows.	-4	-1.56	0	0.11	-3	-1.72
8	Employment opportunities in farming will increase.	1	0.68	-1	-0.49	-2	-0.89
9	The need for labour work of an individual farmer will be spread throughout the year.	2	1.01	-2	-0.69	-2	-1.17
10	The farmer’s daily routine will become more varied.	2	1.25	2	0.62	0	-0.17
11	The wider rural economy will be more resilient.	2	1.01	0	-0.12	1	0.72
12	Farmers will need to increase their level of skills.	4	1.74	2	1.23	3	1.20
13	The nature of work on farms will be more physically demanding.	-1	-0.59	-4	-1.65	-1	-0.81
14	Farmers will cooperate more with neighbouring farmers and farms close to them.	1	0.84	1	0.37	3	1.69
15	Consumers will not buy a lot more of their food locally.	-2	-1.08	1	0.29	-2	-1.26
16	Ecological farming will be a limited social movement and will not provide substantial ecosystem services.	-3	-1.39	0	-0.20	-3	-1.31
17	There will be tight certification to define farms as ecological.	0	-0.33	4	2.39	2	0.84
18	As a proportion of household income, income from farming will decrease.	0	-0.22	2	1.37	0	0.41
19	More livestock farmers will use mob/strip grazing.	1	0.88	-1	-0.47	1	0.49
20	Mob/strip grazing will decrease the requirement for labour.	-1	-0.41	0	-0.38	-1	0.46
21	Rural areas will become no more attractive for residents and users.	-2	-1.13	-1	-0.49	0	0.11
22	There will be more need of seasonal labour.	0	0.11	0	-0.11	0	-0.42
23	The use of family labour will decrease.	-1	-0.51	0	-0.06	0	0.47
24	There will be more need of migrant labour.	0	-0.41	-1	-0.54	4	1.75
25	There will be no change in trade of locally sourced inputs.	-1	-0.77	1	0.24	-4	-1.79
26	There will be more demand for female labour for manual operations.	0	-0.09	-2	-1.01	-1	-0.52

In this likelier scenario of high adoption and clusters of farms with ecological approaches, stakeholders envision there to be significant change in the landscape appearance (4/-3) as farmers would be encouraged to use cover crops, mixed rotations and companion cropping (less mono-cropping). Another example, an increase in the size and number of hedgerows (7/-4) is expected as upcoming grant schemes starting in the next 10 years' will further encourage their expansion, but a participant in another defining sort in this factor argues that hedges will not necessarily be planted, and the focus would rather be on planting woodland on infertile soils. Overall, stakeholders believe this appearance will be more attractive to residents and users (21/-2). Expanding from this perspective is that ecological farming approaches will become a pervasive social movement (16/-3) where the wider rural economy will be more resilient (11/+2) with consumers buying more of their food locally (15/-2) and farmers will cooperate more with each other (14/+1).

In order to facilitate this adoption, this stakeholder perspective highlights that farmers will need to increase their level of skills (12/+4): diversified cropping, use of artificial intelligence will increase, knowledge of biodiversity, managing recruitments. A farmer already using ecological approaches adds that they need to glean more knowledge and take more time over management decisions to make the system work. The diverse cropping and practices on farms with ecological approaches should lead to a farmer's daily routine becoming more varied (10/+2) and labour work to be more spread across the year (9/+2).

Factor 2 – Low percentage certified ecological

Factor 2 is defined by 4 significantly loading Q-sorts, explaining 11% of the variance in the study and has an eigenvalue of 1.71. In this perspective, stakeholders anticipate a lower adoption rate of ecological farming approaches, 10% being likely (2/+3) while 50% is unlikely (1/-2). This is where these farms are certified as ecological (17/+4), where they use a complete suite of ecological practices rather than adopting a few. Given this low adoption, stakeholders think soil (6/-3) and water quality will improve (5/+3) – probably as farms become more ecological, just not certifiably so. Participants consider that the Department for Environment, Food and Rural Affairs (DEFRA) will want to make sure that their grants are justifiable, and consumers are more interested in knowing about the provenance of their food. However, stakeholders believe consumers will continue to use supermarkets for their convenience (15/+1) and purchase low-cost relative to more expensive locally priced foods. With a low adoption of ecological practices, a withdrawal of BPS subsidies, and consumers not increasingly buying local, stakeholders predict income from farming will decrease as a proportion of household income (18/+2).

On farm labour, farm work in its nature is perceived to become less physically demanding (13/-4), the ecological practices will not make farm work more physically demanding and associated technologies may even further reduce the physical strain. The statement on women and physical labour received strong disagreement (26/-2) in this factor – participants highlight that what matters is the right person in terms of their skills and competencies for the job and that female labour should not be treated any differently from male labour on farms.

Factor 3 – Skilled migrant labour demanded

Factor 3 is defined by 5 significantly loading Q-sorts, explaining 13% of the variance in the study and has an eigenvalue of 1.99. As with factor 1, factor 3 presents a perspective where 50% of farms adopt ecological practices (2/+1) and these farms using ecological approaches are more likely to form into clusters (3/+1). Reflecting these clusters, farmers will cooperate more with one another (14/+3), but here is a stronger emphasis on the form of that cooperation – an increase in trade of locally sourced inputs (25/-4). This perspective explains that farms with ecological approaches will still need more migrant labour (24/+4) as the local population are perceived as unlikely to have the skills and willingness to fill the gap for seasonal labour. In North Kent, although there may be a high proportion of farms with ecological approaches, there will still be intensive cropping of soft fruits (e.g. strawberries and raspberries) and top fruit orchards, and therefore a need for seasonal migrant labour. Although in their explanations, participants highlighted that migrant labour is needed where seasonal labour is needed – the statement discussing seasonal labour features neutrally in this factor suggesting that the need for migrant labour may be more on a permanent basis in order to fill a shortfall in skill level (22/0). Indeed, skills have a higher significance (12/+3) and as put by the participant before, it may be the skills that migrant labour brings, that farmers using ecological approaches are most interested in utilising on farm.

2.4 Discussion and Conclusions

Q has allowed for the study of complex qualitative questions in a structured manner in order to forecast the socio-economic effects of adopting ecological practices after 10 years. In an ideal setting, the Delphi should have been organised in advance of the Q from where statements could be created to manage the entire discourse, but due to time management concerns, the studies were run concurrently. The results should still be valid as each study is alone sufficient, however, a stronger set of statements could have been designed through the structured approach of the Delphi exercises instead of more informal stakeholder workshops and discussions between researchers.

The complexity of adopting ecological approaches in both these English CSAs was reflected in the Q and their resulting diverse socio-economic effects. Q asked participants to sort a list of statements that outline the pattern and rate of adoption as well as possible socio-economic effects of this adoption scenario. The understanding of ecological approaches for the case study areas were similar and seemed to form an English understanding of the term where ideas seemed to coalesce around regenerative farming and conservation agricultural practices e.g. minimising soil disturbance, integrating livestock and crop farming. As participants sort these statements, they may explain to the interviewer the reasons behind their individual Q-sort which provides added material from which the subsequent factors can form a stronger interpretation.

Depending on local conditions, geography, farm type and being located in an AONB, ecological practices vary in each CSA. This leads to a variation in the pattern and rate of adoption of these practices in 10 years' time. Depending on this adoption, effects differ to be stronger in areas with higher and more clustered adoption. Meanwhile more spread and lower adoption often leads to little or no change, but skill level is something that, even given a small increase in ecological approaches, is expected to change. This finding suggests that UK and EU policy to encourage collaboration between farmers is well placed.

Four key results are taken from the Q.

First, skill level was a significant aspect in many of the factors in the Q. Following an expected change in government policies, in order to receive government subsidies farmers will need to make environmental interventions rather than rely on area payments as these are being phased out. The Delphi Exercise supports this increased need in skill level and study participants added that they expect an increase in quality of life to go with an increase in the diversity of farming enterprises, the interest generated from this, the knowledge of natural processes and biology required, engagement with nature and new machinery that is coming into the industry. Strongly related to this need for skills is a predicted increase in the number of advisers and civil servants to deal with more complicated farms and incentives as well as monitoring of ecological effects on farm.

Second, especially where farms are clustered together, Q highlights that they may support a stronger social movement, more consumers buying local food, and may increase collaboration between farmers. Supply chains are expected to become shorter as farmers sell more directly to the consumer and there are fewer intermediaries upstream of the farming sector. As farmers collaborate more with each other on environmental objectives, trading inputs and sharing best practice, farmer relationships should improve in rural communities.

Third, Q highlights that ecological practices will not mean the end of machinery and a lot more labour – often machinery will be useful in weeding and reducing physical labour as technology has significantly improved and skills are improving too in order to use these technologies. The Delphi exercise adds that contracting, machinery purchasers, and machinery traders and dealers could increase, decrease or not change – the anticipated effects are mixed. But stakeholders conclude that a greater specialisation in machinery will occur leading to changes in farm management as well as the suppliers of this machinery.

Fourth, Q highlights that where there is high adoption of ecological approaches, rural areas are expected to become more attractive as landscapes will have a much greater variety of crops instead of large fields of monocrops. This variety of crops may include agroforestry as well as intercropping. In addition, Delphi exercise respondents argued that although rural populations might be little affected from ecological farming, larger rural populations seeking a more attractive rural environment might contribute to higher local consumer demand.

A limitation in this study is that the questions and statements proposed to stakeholders did not sufficiently cover the development of private markets for carbon, nutrients and biodiversity through Biodiversity Net Gain.

Interesting policy recommendations come out from the need for more skills repeated in both English CSAs. Policymakers need to ensure there is a suitable provision of education and skill development for farmers to learn new skills relating to farming using ecological approaches. Some of the skill gap could also be filled through sourcing farm skilled migrant labour. In addition, given the introduction of the Sustainable Farming Incentive and the withdrawal of the Basic Payment Scheme, stakeholders anticipate a higher uptake of ecological practices. Stakeholders perceive that, in order to survive, many farms may need to adopt these practices which are predicted to make significant improvements in soil and water quality as well as biodiversity as a result. However, these farms still need to remain profitable, and in more fertile ground in North Kent farms may become more intensive.

Appendix

Delphi Exercise Interview Questionnaire

Delphi Round 1 Questions

1) What farm practices would an ecological farm use as opposed to a conventional farm? Would this type of farm be large or small compared to an average conventional farm in the area? Why? Please explain.

Please rank (on a scale from 1 being least important to 12 most important) the below farming practices into what is most important to defining an ecological farm		
Practice	% Top Rank	Average rating
Low tillage use		
Integrated Pest Management		
Integrated Weed Management		
Machine weeding		
Manual weeding		
Precision technologies		
Use of organic manure or compost		
Number of crops		
Extensive use of cover crops		
Strip grazing		
Integration of crop and livestock at farm level		
Alternative remedies for livestock disease management		

2) Statement	Rating
On a scale of 1-9 where 1 is significantly smaller, 5 is no change and 9 is significantly larger please indicate the size comparison of an ecological farm with a conventional farm.	

3) Is it possible to use natural processes to replace the use of chemical inputs on the farms in the area? If yes, what natural processes? If not, why?

4) If more farms became ecological in the way set out in the farm representative model, would more farms across the study area become mixed or would they remain specialised in livestock or crop production? What proportion of the region's farms would become mixed livestock with crop production farms?

5) On the farms in the study area, is it realistic or not to have a system that integrates livestock, cover and catch crops, and direct drill practices? Please explain.

6) In the study area, is it realistic or not to only have farming systems that integrate crops and livestock?

7) Would there be a large need for machinery on an ecological farm in your area?

8) Would the type of practices implemented in ecological farms require the use of more or less labour, in terms of people and number of hours worked? Why?

Delphi Rounds 2 & 3 Questions

Section 1 - Pattern of adoption

Please fill out the %s in the below table with explanations for questions 1 and 2 of this section.

	Round 2		Round 3	
	Clustered – C	*Random Pattern - R*	*Clustered – C*	*Random Pattern - R*
Low Adoption Rate (L - 10%)	L-C: %	L-R: %	L-C: %	L-R: %
High Adoption Rate (H - 50%)	H-C: %	H-R: %	H-C: %	H-R: %

1) If farms were to adopt this ecological farming system in your case study area, would these farms be clustered together or spread across the territory? Please explain.
2) Would adoption of this regional ecological farming system be closer to a low (of around 10%) or a high proportion (around 50%) of the region's farms? Please explain.

Section 2 - On-farm employment effects across the study area

Questions 4-11 provide qualitative information supporting the Likert scale below in question 3.

3) What would be the impact on the following?		Large decrease			Little change			Large increase		
		1	2	3	4	5	6	7	8	9
a)	Total farm employment across the area	☐	☐	☐	☐	☐	☐	☐	☐	☐
b)	Need for migrant labour	☐	☐	☐	☐	☐	☐	☐	☐	☐
c)	Wage level	☐	☐	☐	☐	☐	☐	☐	☐	☐
d)	Gender balance of farm heads	☐	☐	☐	☐	☐	☐	☐	☐	☐
e)	Flexibility of working hours	☐	☐	☐	☐	☐	☐	☐	☐	☐
f)	Skill level of farmers	☐	☐	☐	☐	☐	☐	☐	☐	☐
g)	Quality of life of farmers	☐	☐	☐	☐	☐	☐	☐	☐	☐

4) What would the impact be on total farm employment across the area? Please explain.
5) Would there be differences in the nature of this employment, i.e. would there be more or fewer jobs that are full-time or part-time, would more or fewer farmers become self-employed or hired on the farm or in other areas of the value chain? Please explain.
6) Would farmers in an ecological farming system be able to work hours that are more or less flexible? Why?
7) Would the quality of life change for farmers within ecological farms? Positively or negatively, how might it change?
8) Would there be an increase, decrease or no change to the need for skills in the labour force? Please explain.
9) Would there need to be more, less or no change to migrant labour? Please explain.
10) Would there be more farm heads who are female, or more farm heads who are male? Please explain.

11) What would the effect on farm wages in the area be? Please explain.

Section 3 - Employment effects on industries supporting farming

12) Would the advisory service need to increase in personnel, decrease or no change?

13) What additional skills of farm advisors would be required by ecological farming?

14) What would be additional skills of civil service required by ecological farming?

15) Which actors in the food chain – up and downstream of agriculture - need to change their skills? Please explain.

16) Rank (on a scale from 1 being least change and 8 the biggest change) the following actors in the food chain into where the biggest change in skills and knowledge for engagement with ecological farming would need to be

Actor	Rank
Farmers	
Input suppliers	
Extension agents	
Civil service	
Consumers	
Retailers	
Food and drink manufacturers	
Wholesalers	

Section 4 - Supply chain effects

17) How would this impact on trade in inputs between farms, e.g. manure, seeds, hay?

18) Considering the list of below inputs, please rank (on a scale from 1 being having least change to 7 having most change) which input will have the biggest change in trade levels between farms?

Input	Rank
Animal manure	
Compost	
Seeds and plantlets	
Bulk feed and coarse fodder	
Concentrated feed	
Shared labour	
Shared machinery or equipment	

19) What would the effect be on contract farming?

20) How would this impact the purchase of tractors and other machinery?

21) How would this change the number of traders and dealers of machinery who operate in the region?

22) Would this modify supply chains?

Section 5 - Effects on rural communities

23) Would there be a change in the size of the rural population and thereby a change in demand for rural services? Please explain what may happen.
24) How would this affect the rental/purchase price of homes in rural areas?
25) How might relationships between farmers change?

Delphi Information Sheet for North Kent

The objective of these interviews is to seek consensus between the members of an expert panel, specific for the North Kent case study area, on the socio-economic effects of a change in the territorial landscape. This change is a result of a certain level and pattern of adoption of ecological farming 10 years from now and in comparison, with the current situation of farming in the area. The survey information contributes to a research project LIFT ('Low-Input Farming and Territories'), funded by the European Commission in the frame of its programme Horizon 2020. The research project is carried out by 17 teams.

In this study, you will be asked individually of your opinion on: a/ characteristics of an ecological and a conventional farm, typical for the area; b/ how you will forecast these farms appearing in your area in terms of proportion of all farms and what will be their pattern of adoption – clustered or randomly distributed in the territory; c/ the socio-economic effects of this adoption level and pattern. Think about the area as a whole, not just a single farm. It is important to keep in mind throughout the interviews that it is the effects you think will happen in 10 years.

To give some context surrounding the characteristics of ecological and conventional farms, please see Table 1 below. The numbers in this table correspond to the North Kent case study area and are based on data – from the LIFT farm survey. Please continue to refer back to this table throughout the rounds of the interview and keep in mind that all questions are specific to effects in the whole territory of your area.

Table 4. Comparing a possible ecological farm with a typical conventional farm (data extracted from the LIFT farm survey in UK - North Kent case study area)

Ecological practices	A Conventional Farm	An Ecological Farm
Farm size (UAA[1] in ha)	306	472.4
Farm size (LSU)	6.5	81.6
Value of farm machinery (£)	414,545	357,000
Stocking density (LSU/ha)	0.25	0.17
Crop-livestock integration (% farms)	13.3	32
Inorganic pesticide use (£/ha)	247.6	155.6
Inorganic fertiliser use (£/ha)	147.1	98.5
Organic animal manure or compost (% UAA)	21.2	13.6
Green manure (% arable UAA)	26.9	19.5
Conservation or zero tillage (% arable UAA)	55.7	51.6
Crop diversity (Number of different crops)	5	5.8
Semi-natural habitats (% UAA)	6.67	7.2
Average hours of labour used (per farm, per week)	105.8	119.5
Physical nature of work (Likert[2])	3.28	3.17
Mental workload of farm work (Likert[2])	3.71	3.35
Intensity of seasonal peaks (Likert[2])	3.07	3.09
Notes: [1]UAA is utilised agricultural area, LSU is Livestock Units [2]Likert scale follows the LIFT large-scale farmer survey questionnaire in D2.2 (Tzouramani, et al., 2019) and is from 1 to 5 with 1 being large decrease, 3 no change and 5 a large increase		

Each time following a round of questions, the researchers will summarise and anonymise the responses and will present an anonymised summary again to you to see your opinion on the summary, thus, to see whether the opinions of individual members of the panel will still diverge or converge towards consensus.

This process will take 3 rounds with each individual panel participant and each round is quick to complete. Round 3 asks the same questions as round 2, but after having received an anonymised summary of responses, you have another opportunity to consider the question.

Please note the information you supply is entirely confidential, your identity remains anonymous, and the data obtained will be analysed scientifically.

The name of the researcher who will participate in your interview is Stuart Henderson and his e-mail address is sh902@kent.ac.uk.

Q Information Sheet

This is an exercise which looks at your opinions of what is more likely or less likely to happen in 10 years' time over the High Weald if ecological farming is more widely adopted. The principles for regenerative agriculture may help in defining how ecological farms are different from conventional farms – not necessarily organic, but reduced chemical use and attention given to improving the soil (e.g. minimum or no tillage practices, cover cropping, holistic planned grazing).

In 10 years' time, ecological farming may have been adopted by more farmers and this adoption could be either dispersed or clustered across the High Weald study area. This interview seeks your opinion on what the effects might be of this particular change to farming in the following areas: i) the provision of ecosystem services; ii) working conditions of farmers and hired farm workers; iii) rural labour market; iv) ecological farming if treated as a social movement. As a basic background, a typical ecological farm for the area, in comparison with a typical conventional farm, is outlined in Table 5, below. Have this table in front of you when you will give your opinion on what would happen if ecological farming were more widely adopted in comparison to the current situation.

Table 5. Comparing a possible ecological farm with a typical conventional farm (data extracted from the LIFT farm survey in UK – High Weald case study area)

Ecological practices	**A Conventional Farm**	**An Ecological Farm**
Farm size (UAA[1] in ha)	117.2	160.9
Farm size (LSU)	50.4	116.5
Value of farm machinery (£)	225,625	148,045
Stocking density (LSU/ha)	0.67	0.85
Crop-livestock integration (% farms)	0.3	0.13
Number grazing days in the same field	74.2	65
Inorganic pesticide use (£/ha)	78.3	7.3
Inorganic fertiliser use (£/ha)	108.5	18.4
Organic animal manure or compost (% UAA)	17.7	19.2
Green manure (% arable UAA)	0	2
Conservation or zero tillage (% arable UAA)	33.3	24.5
Crop diversity (Number of different crops)	4.7	6.7
Semi-natural habitats (% UAA)	2.5	5.4
Average hours of labour used (per farm, per week)	114.5	65.4
Physical nature of work (Likert[2])	3.11	3.67
Mental workload of farm work (Likert[2])	3.44	3.73
Intensity of seasonal peaks (Likert[2])	2.78	3.27
Notes: [1]UAA is utilised agricultural area, LSU is Livestock Units		

[2]Likert scale follows the LIFT large-scale farmer survey questionnaire in D2.2 (Tzouramani, et al., 2019) and is from 1 to 5 with 1 being large decrease, 3 no change and 5 a large increase

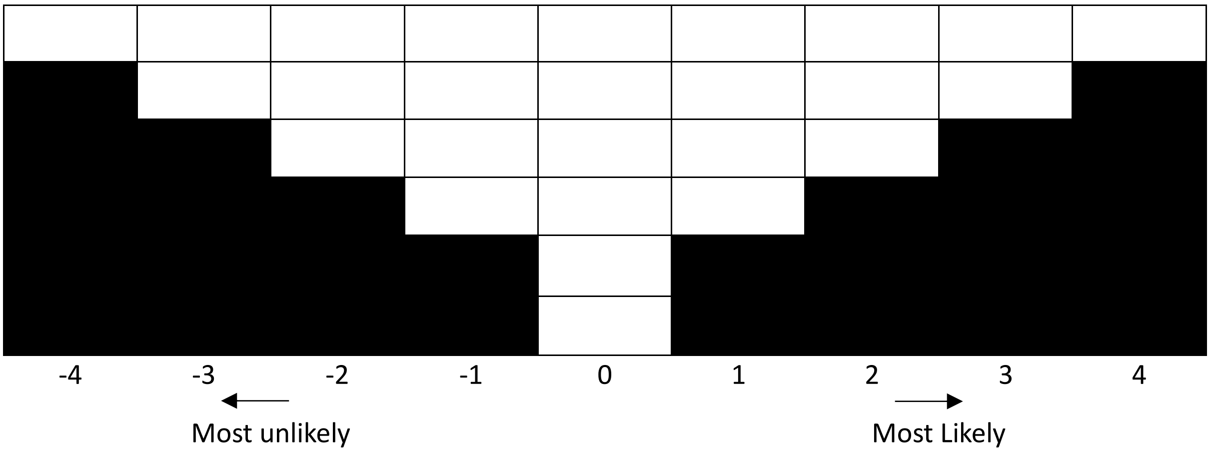
Ecological farms in table 1 were categorised as such if they receive agri-environmental payments and/or are organic, otherwise farms were categorised as conventional. This approach is problematic as for example it might be more worthwhile for larger farms to apply for the payments and/or they have more field corners that comply with payment requirements – this is possibly why ecological farms in the sample are of average larger. We are working on a better approach, but thought the above data give a useful context for different practices and differences – in any case, the use of chemicals is on average lower on ecological farms in the sample which fits with our hypothesis.

In this exercise, you are presented with 26 statements. First, sort each statement into one of three piles: likely to happen, unlikely to happen and neutral or unsure. Then, please order these statements along a continuum from most likely to least likely to happen in 10 years' time compared to the farming of today.

Statements are to fit all of the grid boxes as seen below in Figure 5. It is not possible to sort two statements into the same box, but multiple statements can go into each column. Think of this exercise as a game in which you try to place all the statements in a way that best represents your opinions. Once you have placed a statement in the grid you are still able to move it if you reconsider it in comparison with another statement. You can move up until the time you placed all statements in the grid boxes, and you are happy with your choice.

As you sort through the statements, the researcher accompanying you online may ask questions for your reasoning why this statement was placed where it was. This is to further study your opinion on the matter involved.

Figure 5: Q ranking grid



Note that background information regarding age and gender does not need to be completed.

At the end of the online study, please select 'Submit data', this will fail, but you will have 3 more options at the end, please 'Print data' and print to pdf (if this is not possible a photo or scan could be taken of the results, either of a printed paper or on-screen results). Please then send this pdf document (or scan or photo) to me.

The survey information contributes to a research project LIFT ('Low-Input Farming and Territories'), funded by the European Commission in the frame of its programme Horizon 2020. The research project is carried out by 17 teams.

Please note the information you supply is entirely confidential, your identity remains anonymous, and the data obtained will be analysed scientifically.

The name of the researcher who will participate in your interview is Stuart Henderson and his e-mail address is sh902@kent.ac.uk.

Chapter 3: Estimating Total Factor Productivity with Chemical Inputs

Abstract

This chapter estimates Total Factor Productivity (TFP) in a Cobb-Douglas production function framework. The estimation strategy applies Generalised Method of Moments (GMM) accounting for the use of chemical inputs which is absent in previous GMM estimations of TFP in the literature. Data is used from the Farm Accountancy Data Network (FADN) for cereal crop farms from 2004-2018. Including chemical inputs in the specification makes little difference to the coefficient on labour productivity, but it has a large effect in reducing the coefficient on land productivity. As agricultural policy in the United Kingdom (UK) is heading towards Environmental Land Management Scheme (ELMS), some farmers might be encouraged to farm with a lower chemical intensity thereby making estimations adjusting for this variable more important within production function estimations. Future estimations should include chemical inputs as a factor of production as it reduces the bias on the coefficients on the other input elasticities and itself is a useful indicator of the return to additional use of chemical inputs on farm production.

3.1 Introduction

Following Brexit, agricultural policy in the United Kingdom (UK) is undertaking dramatic changes. In England, the European Union's (EU) Common Agricultural Policy (CAP) is being partly replaced with Environmental Land Management Schemes (ELMS) (DEFRA, 2023). From 2021 to 2027 Direct Payments are being phased out in England: the Basic Payment Scheme (BPS) will end at the end of 2023 and will be replaced with delinked payments from 2024 to 2027. In the meantime, farmers are being encouraged to take up payments through ELMs to replace their loss in BPS. ELMS would be used as a tool for government to encourage farmers to adjust their farming practices in order to reach the government's aims outlined in its 25 Year Environment Plan. Reducing the use of chemicals within farming practices directly impact the aims of air quality, water quality, waste, biodiversity and carbon (Helm, 2022).

Studies assessing the impact of chemicals on farm productivity have existed for many years (Headley (1968); Lichtenberg and Zilberman (1986); Chambers and Lichtenberg (1994)). In an early study Headley (1968) estimates pesticides separately from the other inputs in the production function highlighting that as well as fertiliser, pesticides is a highly productive input in its own right. The literature developed to study pesticide use as a means of damage control (Lichtenberg and Zilberman, 1986) i.e. pesticides are used to minimise losses to output rather than increase output as fertiliser does. An attempt was made in the literature to reconcile econometric results, which had suggested that farms should use more pesticides, with the available entomological knowledge (Lichtenberg and Zilberman, 1986). Indeed, estimates for the productivity of pesticides are shown to have been overestimated (Lichtenberg and Zilberman (1986); Chambers and Lichtenberg (1994)).

The literature studying the relationship between reducing the use of inputs harmful to environmental performance and its effect on farm production has since grown and this is studied in a literature review in the following section. A number of different approaches are used to estimate farm productivity that include Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA), Control Function (CF) methods and Generalised Method of Moments (GMM) (Biagini et al., 2023). This chapter seeks to estimate a production function, considering the possible endogeneity issues faced by other estimation methods in the literature and includes the impact of chemical inputs on Total Factor Productivity (TFP) estimations.

The next section presents a review of the relevant literature. The following section 3 describes the model, variables and data used in the estimations. Section 4 presents the results and section 5 concludes the chapter.

3.2 Literature Review

Since the paper by Chambers and Lichtenberg (1994) the literature has developed in its study of agriculture's impact on the environment. Examples include attempts to construct an indicator, or index, to represent environmental goods, Sustainable Intensification (SI) or eco-efficiency as a ratio indicator or within frontier-based models (Lauwers, 2009). Lauwers (2009) identifies two branches of the eco-efficiency frontier-based models - two different types of models for integrated ecological-economic analysis within a production context. The first branch of models are environmentally adjusted production efficiency models, and this includes parametric models such as Stochastic Frontier Analysis (SFA) as well as non-parametric models including Data Envelopment Analysis (DEA). The second branch are frontier eco-efficiency models. Lauwers suggests a way to combine both branches of models is through the materials balance principle and thereby add a third branch to the literature. In this context, the materials balance principle is where all materials that enter the economic system will finally end up in the environment with some recycling along the way. For example, in pig production, piglets and feed go into the system and out comes meat, manure and other byproducts.

Applying a DEA approach, Gadanakis *et al*., (2015) evaluate the SI of General Cropping Farms in the East Anglian River Basin Catchment using Farm Business Survey data. Their aim is to outline a policy-making tool to assess SI at a farm level. The concept of SI at farm level is that while the farm minimises its generation of environmental pressures it simultaneously increases agricultural output per unit of input (Firbank *et al*., 2013). An aggregated index of Eco-Efficiency, a composite indicator also known as the Economic-Ecological Efficiency, is a ratio of an output (measured through the value of products) over the inputs the farm uses. The inputs are considered as a proxy for the environmental pressures generated by the farm and the indicator measures how efficiently resources are used to produce output. Linear programming techniques were used to assign weights. If the Eco-Efficiency Index goes down in value, then this means there is an increase in environmental impact while the output value is decreased or is maintained and the reverse in the case of improvement. Gadanakis, *et al*., (2015) continues with an estimation of an Eco-Efficiency frontier using DEA. The frontier is intended to characterise a trade-off between economic and ecological performance.

Omer *et al*., (2007) combines a biodiversity index with Farm Business Survey (FBS) data economic variables into a SFA framework. Over an 11-year period it derives a hypothesis about the interaction between biodiversity and optimal crop output in the longer run and in the transitional path towards a steady-state equilibrium. The authors find that there is a positive relationship between biodiversity conservation and an increase in crop output.

Areal, *et al*., (2012) and Areal, *et al*., (2018) also apply a SFA, instead using a Bayesian procedure. The former paper studies technical efficiency using a multi-output technology in the framework of an output distance function where there are the traditional market outputs as well as an output for the provision of PG and ES, or environmental goods (EG) as used by Areal. Using FBS data, the authors use a proxy indicator for EG where EG = (permanent grassland + rough grassland)/total agricultural area. Areal, *et al*., (2012) turn their distance function into a translog functional form that then allows them to use a Bayesian Markov Chain Monte Carlo (MCMC) to estimate the technical efficiency of the farms. They compare two models, one which includes EG and one which does not, where they find that efficiency measures are biased when not using EG as an output. Therefore, policymakers should rather consider a model using EG otherwise, they may support farms that would not boost a provision of EG despite this being a key policy aim in the UK and the EU. In contrast, Areal, *et al*., (2018) incorporate a novel SI composite indication with the Bayesian MCMC to analyse farm efficiency.

Another application of SFA is in a recent paper measuring the 'ecologisation' of farms and its impact on total factor productivity (TFP) (Baráth and Fertő, 2023). These authors combine a composite indicator for how ecological a farm is and a dose-response function with a random-parameter stochastic production frontier model (Baráth and Fertő, 2023). They find that as a farm becomes more ecological it reduces farm TFP.

Another approach to study TFP in agriculture is the CF method. This method has become standard practice in applied economics production estimations (Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg *et al*., (2023)). Most of the papers using this approach in an agricultural context apply the method to studying the impact of a change in CAP on TFP (Rizov *et al*., (2013); Kazukauskas *et al*., (2010); Kazukauskas *et al*., (2014). A notable exception is a Japanese application where differences between farms as well as product differentiation are studied with respect to TFP (Akune and Hosoe, 2021). The benefit of the CF method is that it adjusts for the simultaneity and selection biases that are usually found when estimating TFP and this is in direct contrast to the SFA (Kazukauskas *et al*., 2010).

Elsewhere in the literature exploring the link between chemical input use and the production technology is through contrasting conventional and organic farming (Latruffe and Nauges, (2014); Kumbhakar *et al*., (2009); Zhengfei *et al*., (2005); Gardebroek *et al*., (2010)). Latruffe and Nauges, (2014) and Kumbhakar *et al*., (2009) both compare the technical efficiency of organic and conventional farming. Meanwhile, Zhengfei *et al*., (2005) and Gardebroek *et al*., (2010) consider the production technologies based on damage abatement and risk adjusted production functions instead.

A final method considered in this chapter to estimate a farm's production function is through GMM (Mary (2013); Garrone *et al*., (2019b); Khafagy and Vigani (2022); Biagini *et al*., (2023)). Mary (2013) argues that GMM has advantages over the previously mentioned frontier-based models. Random shocks such as weather conditions affecting yields may strongly impact the production process of crop farms, the farmer may react in a way known to them but not typically known to the econometrician (Petrick and Kloss, 2018). Indeed, the DEA will not allow the econometrician to observe the effect, but this can be accounted for in GMM (Mary, 2013). In addition, Mary argues that whereas the SFA may struggle with simultaneity or endogeneity in the independent variables due to a correlation between inputs and productivity shocks, GMM can account for these problems. Khafagy and Vigani (2022) add to this critique of the SFA and DEA frontier approaches by arguing that they do not account for regional heterogeneity.

As argued by Biagini *et al*., (2023), the CF approach is not used in this chapter due to avoiding the risk of evaluation errors which may be present if the incorrect free and state variables or the wrong set of Instrumental Variables were selected. In order to correct for simultaneity in the first-differenced equations that may be a problem with SFA and DEA approaches, this chapter utilises the GMM approach whereby GMM estimators use lagged instruments and eliminates firm specific effects through taking first-differences (Blundell and Bond, 2000).

3.3 Estimation Strategy and Data

The following section first describes the data sample and explores some trends of the time period of the data. Second, it explains the methodology for estimating the production function technological parameters and third, this explain describes the procedure for estimating farm TFP.

3.3.1 Sample description and trends in the data

This chapter uses Farm Accountancy Data Network (FADN) panel data of UK cereal farms over 15 years of data from 2004 to 2018. The farms in the sample are only crop producing farms so as to limit the differences in farming practices that would be present in different farming systems (Areal *et al*., 2018).

The variables as shown in Table 6 taking monetary values, in £GBP, e.g. fuel expenditure have been adjusted by being deflated using the corresponding adjustment coefficient for each variable taken from the Eurostat Price indices. The adjustment coefficients reflect how prices for these respective variables have changed over time relative to 2015 as the base year. Values are deflated by dividing the value for each farm by the adjustment coefficient for that year. Only crop farms have been selected from the FADN UK dataset and only farms that have been surveyed for at least 4 years have been kept within the sample. Not including farms that are in the dataset for only 1, 2 or 3 years is so that in case these farms observe a random, exceptional event, their data will not lead to a measurement error in the dataset that could be controlled through the panel features of the data. Further outliers were removed following Mary (2013) and described as follows. All observations, where there is an observation of 0 output, or the log difference in the capital stock variable and/or the output variable between two consecutive years exceeds three in absolute value have been dropped. This leaves an unbalanced panel of 1,168 farms and a total of 8,053 observations across all these farms.

Table 6: Description of the variables

Variable	**Description**
Output (Y_{it})	Total output (£)
Productivity shock (Z_{it})	The residual, TFP (Calculated as part of the chapter)
Land (N_{it})	Total utilised agricultural area (UAA) in hectares
Labour (L_{it})	Total labour hours per farm
Capital (K_{it})	Total closing value (£) for machinery and equipment.
Fertiliser ($FERT_{it}$)	Total fertiliser expenditure (£)
Crop protection (CP_{it})	Total crop protection expenditure (£)

Table 7 presents the descriptive statistics for the crop farms in the FADN data sample for the years at the beginning and end of the panel. Over time both output and most inputs have on average increased. Labour in the number of hours worked has decreased on average and land and fertiliser has barely changed overall.

Table 7: Descriptive statistics comparing the farm sample in 2004 with 2018

	2004			2018		
	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.
Output (£)	12.06	0.89	505	12.47	0.92	635
Total Labour (hours)	8.42	0.79	505	8.35	0.93	635
Capital (£)	11.58	1.11	504	11.81	1.30	630
Land (ha)	5.11	0.79	505	5.18	0.76	635
Fertiliser (£)	10.08	0.90	501	10.15	0.97	631
Crop Protection (£)	9.52	1.15	498	10.02	1.10	620
Note: All variables are in logarithms.						

Figure 6 and Figure 7 show the trends in the variables used in the production function over the time period. These trends are included here to explore any underlining trends and changes in the partial productivity of different factors of production. Note that these show the average values for every year after having been deflated by the relevant price indices. As labour has fallen between 2004 and 2018 and output has increased it is unsurprising that labour productivity is shown to increase over time. Whereas capital has increased close to in line with output and thereby showing little improvement in partial productivity.

Figure 6: Panel a – Average Farm Labour Productivity and Panel b – Average Farm Capital Productivity

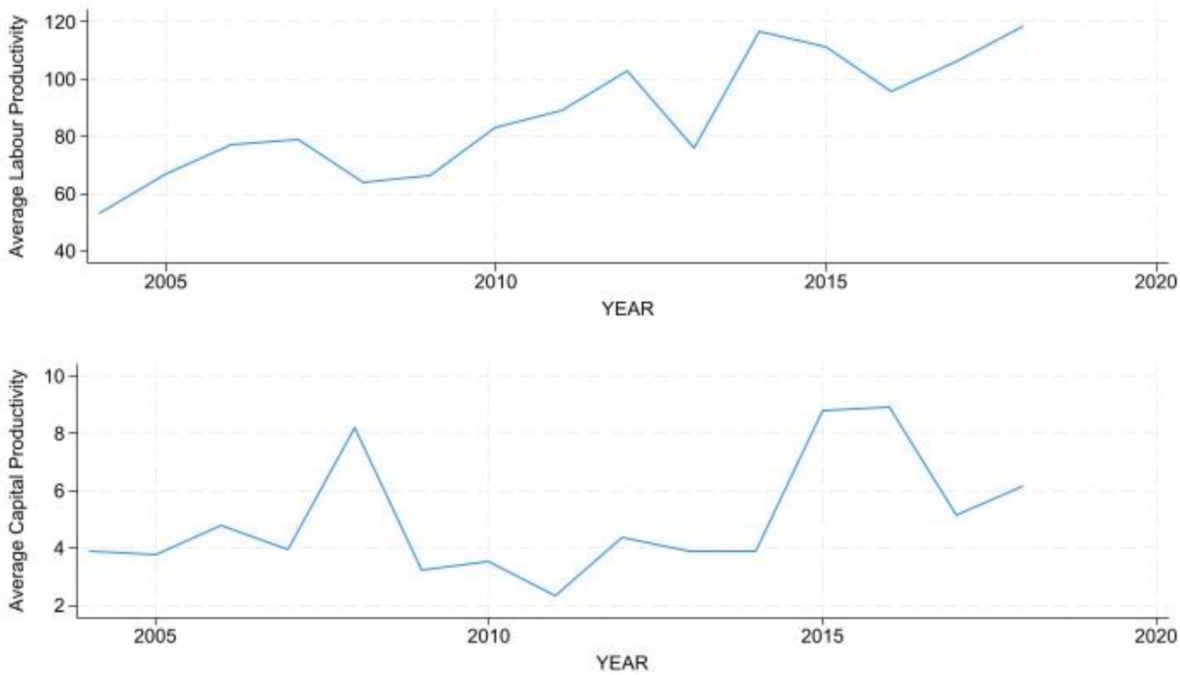


Figure 7: Panel a – Average Farm Output per ha and Panel B: Average Chemical Input expenditure per ha

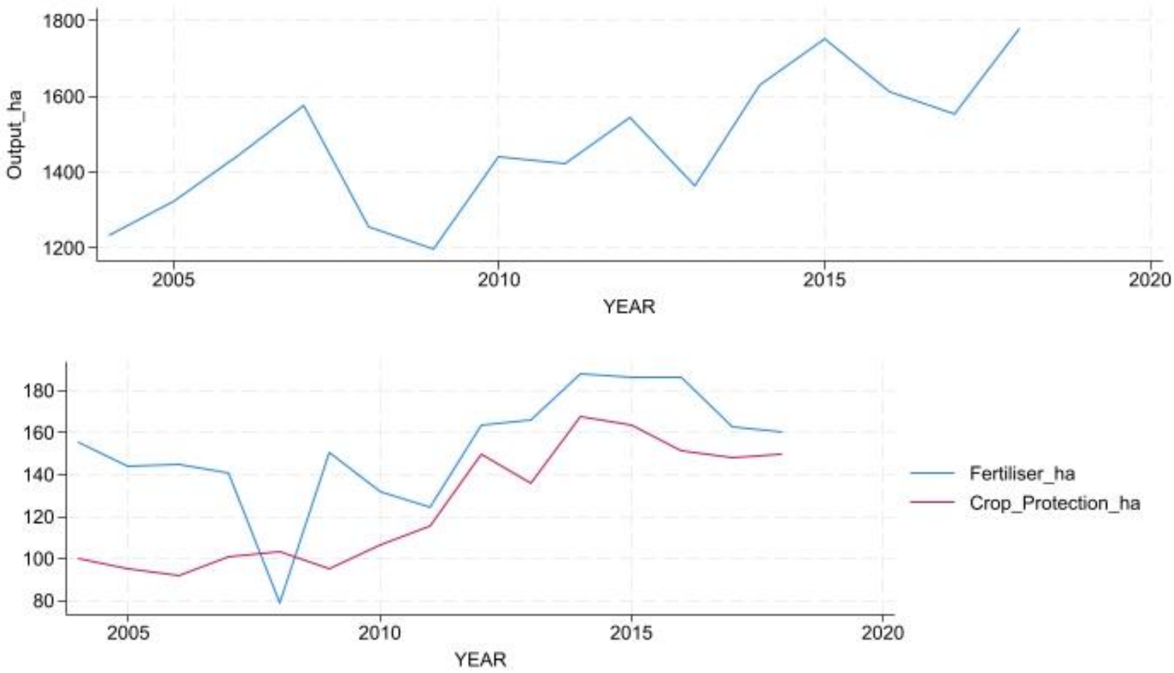


Figure 7 considers output per hectare (ha) as well as the chemical inputs, fertiliser and crop protection expenditure per ha. Shown in panel A, over time output has been increasing relative to land. Comparing 2004 and 2018 would make it appear that fertiliser expenditure has changed little over this time period, however if starting in 2008, after the financial crisis, then an increasing trend can be observed. Meanwhile there has consistently been an increasing trend in crop protection expenditure per ha from 2004 to 2018. This indicates that chemical input expenditure has been increasing in intensity relative to land, but perhaps in line with food production.

3.3.2 Econometric specification – Production Function Estimation

The production function models a continuous relationship between output and inputs (Petrick and Kloss, 2018). Estimating the production function has often encountered difficulties in terms of endogeneity where they do not account for managerial skill in decision making (Petrick and Kloss, 2018) or that there may be a random event that the farmer reacts to with their use of inputs but this is not observed by the econometrician (Latruffe *et al*., 2017); (Mary, 2013).

A sample of data contains different random variables, and the data are assumed to be the sample equivalent for the population of UK cereal farms. An example of a moment condition is the expected value of the random variable, x, is equal to the mean, μ, in the population and its sample equivalent, $\hat{\mu}$, is a parameter we may wish to estimate. When the number of parameters equal the number of equations to be satisfied, this is method of moments, but in GMM there are more moment conditions than parameters. Therefore, exact solutions cannot be found without a particular value of the parameter. Therefore, GMM attempts to construct cost functions where each function minimises the absolute deviation in the parameter values within the moment conditions (the moment conditions are a system of equations where there is one equation per instrument (Mary, 2013)).

In the context of a dynamic panel data model with a lagged dependent variable and lagged independent variables (Arellano and Bond, 1991); (Blundell and Bond, 1998), the GMM application allows for estimation where there are more instruments than there are regressors. An issue with "Difference and system GMM estimators… can generate moment conditions prolifically, with the instrument count quadratic in the time dimension of the panel T" (Roodman, 2009, p. 98).

Below a Cobb-Douglas production function is considered based on Mary (2013) which in turn is based on Blundell and Blond (2000):

$$Y_{it} = Z_{it} L_{it}^{\beta L} K_{it}^{\beta K} N_{it}^{\beta N}\,, \qquad i = 1, \dots, N; t = 1, \dots, T,$$

where each variable is indexed by individual farm, i, and time, t, table 1 describes each of the variables. The model makes the assumption that serially correlated shocks allow for a dynamic representation of the production function (Mary, 2013). Taking logarithms, we obtain:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_n n_{it} + u_{it}, \tag{1}$$

where $y_{it} = \ln(Y_{it})$, $l_{it} = \ln(L_{it})$, $k_{it} = \ln(K_{it})$, $n_{it} = \ln(N_{it})$, $u_{it} = \ln(Z_{it})$. This model is adapted to include a combined measure of fertiliser expenditure ($FERT_{it}$) and crop protection (CP_{it}) costs, where $CHEM_{it} = FERT_{it} + CP_{it}$ and thereby we obtain:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_n n_{it} + \beta_{chem} chem_{it} + u_{it}, \tag{2}$$

As discussed earlier in the introduction, pesticides are better thought as minimising damage to crop output, whereas fertiliser increases crop growth. An alternative estimation disaggregating these inputs is also used and the results are shown in the appendix. The objective here is to model the overall contribution of chemical inputs within the production function. Following on from Mary (2013) and introducing a productivity shock:

$$\begin{gathered} u_{it} = G_t + \eta_i + v_{it} + m_{it}, \\ v_{it} = \rho v_{i,t-1} + \epsilon_{it} \end{gathered} \tag{3}$$

Here G_t is a common effect to all farms, the farm specific and time invariant effect is η_i, v_{it} is an AR(1) idiosyncratic shock with ρ being the coefficient from the shock from the previous period to the current period, m_{it} are measurement errors which are uncorrelated with the rest of the equation. Estimating the parameters of the production function and including the chemical inputs gives us the following dynamic representation:

$$\begin{aligned} y_{it} = {} & \beta_L l_{it} - \beta_L \rho l_{(i,t-1)} + \beta_K k_{it} - \beta_K \rho k_{(i,t-1)} + \beta_N n_{it} - \beta_N \rho n_{(i,t-1)} + \beta_{CHEM} chem_{it} \\ & - \beta_{CHEM} \rho chem_{(i,t-1)} + \rho y_{i,t-1} + G_t - \rho G_{t-1} + (1-\rho)\eta_i + \epsilon_{it} + m_{it} - \rho m_{i,t-1} \end{aligned} \tag{4}$$

3.3.3 Econometric Specification - Total Factor Productivity Estimation

Using the estimation from Equation (4) TFP at the farm level is estimated as the Solow residual. In following this literature (Olley and Pakes, 1996); (Rizov *et al*., 2013); (Mary, 2013), but including the parameter for the chemical inputs we obtain:

$$TFP_{i,t} = \exp\left(y_{it} - \widehat{\beta_L} l_{it} - \widehat{\beta_K} k_{it} - \widehat{\beta_N} n_{it} - \hat{\beta}_{CHEM} chem_{it}\right) \tag{5}$$

The parameters for these estimates are obtained through the minimum distance estimator following (Mary, 2013) and (Biagini *et al*., 2023).

3.4 Estimation Results

This results section discusses the estimations for the above equations first for the production function and second TFP. Estimations are carried out in Stata – details and code provided in the appendix to this chapter.

3.4.1 Production Function Estimation

The production function estimates proceed in two stages. The first stage jointly controls for the pre-determined variables (k_{it} , fixed capital, in (Olley and Pakes, 1996)) and the error term (Petrick and Kloss, 2018). Table 8 and Table 9 Tables 3 and 4 present these first stage results.

The results in Table 8 attempt to replicate Mary (2013) by using similar variables in a similar model specification except using data that is more recent and with cereal farms from a UK sample rather than from France. Biagini *et al*., (2023) is another recent application of the approach used by Mary (2013).

Overall, the results below offer similar coefficients to those in Mary, except the standard errors are lower and thereby the results contain more statistical significance. Although the coefficient on the capital variable is much smaller in the UK results. Another difference compared to Mary (2013) is that the lagged independent variables in the specification are mostly significant. Mary used the SYS-GMM $t-3$ results in his subsequent analysis and the same is done here in this chapter. The interpretation from the first stage results for each variable in time t are the instantaneous effect of the variable on output now. The coefficient from $t-1$ is the impact from that time period to output in t. Bearing this in mind, $t-1$ results tend to be positive and significant suggesting an overuse of the input in the past. The lag on the dependent variable is however positive and significant which is what could be expected as a higher income last year should lead to more this year through being able to purchase more inputs for example.

Table 9 includes a similar set of variables and specification except that it also contains the contemporaneous and lagged chemical input combination of both fertilisers and crop protection costs. Including this variable in the specification slightly improves the estimates on labour, capital and land as well as being significant and positive itself. Indeed, the land variable approaches a coefficient closer to those reported in Mary(2013); (Petrick and Kloss, 2018) and (Biagini *et al*., 2023). This suggests that although GMM controls for endogeneity, there might still be some errors in terms of omitted variable bias for the production function coefficients in the estimation.

Table 12 and Table 13 in the appendix present the results from a different application of the SYS-GMM procedure. Whereas the above results used a Stata command to collapse the number of instruments and so address the problem of too many instruments (Roodman, 2009). Hence instrument numbers are reported in all the sets of results and it can be seen that they are much lower in the results in Table 8 and Table 9. Another improvement in the results in Table 8 and Table 9 is that they do not assume any of the variables to be strictly exogenous from the dependent variable. Instead, it assumes that the lagged dependent variable is endogenous and the other variables to at least be weakly exogenous whereas the other set of results only takes the dependent variable to be endogenous and assumes the others to be exogenous. A shortfall in the estimation results of Table 8 and Table 9 is that the Hansen test is strongly rejected and thereby suggesting an endogeneity issue in these results. Although the alternative results are presented as the Hansen test is not rejected here.

As described in the estimation strategy, pesticides are used by the farmer to protect output whereas fertiliser is used to increase. Therefore, Table 14 shows production function estimates for the two inputs estimated separately from each other. Here it can be seen that omitting fertiliser is the cause for the upward bias on the coefficient estimate on land and the coefficient on pesticides are insignificant. As the disaggregated result is similar to the combined result and the focus of this paper is on overall chemical impact, the focus of the discussion remains on this combined chemical result.

An estimation was also attempted using materials instead of chemical inputs to follow the estimations done in (Petrick and Kloss, 2018) and (Biagini *et al*., 2023) where they incorporate materials instead of the chemical input. Materials here comprise total annual specific costs (FADN SE281) and total annual farming overheads (FADN SE336) which respectively relate to production specific costs and capital costs (Biagini *et al*., 2023). As shown elsewhere in the literature, materials have a large production function elasticity, and the elasticity of labour and capital are much lower in these other estimations. The materials results are presented in Table 15. The land coefficient is similar to estimations using chemical inputs as another variable.

Table 8: Production Function Estimates without Chemical Input variable

	One-step		Two-step	
	(1)	(2)	(3)	(4)
y_t	SYS-GMM $t-2$	SYS-GMM $t-3$	SYS-GMM $t-2$	SYS-GMM $t-3$
l_t	0.156*** (0.037)	0.144*** (0.028)	0.166*** (0.036)	0.130*** (0.029)
l_{t-1}	-0.034 (0.024)	-0.072** (0.032)	-0.047* (0.025)	-0.110*** (0.034)
k_t	0.084*** (0.022)	0.060*** (0.018)	0.112*** (0.021)	0.072*** (0.018)
k_{t-1}	-0.044*** (0.016)	-0.059*** (0.018)	-0.040** (0.016)	-0.063*** (0.018)
n_t	0.839*** (0.089)	0.733*** (0.085)	0.739*** (0.078)	0.591*** (-0.075)
n_{t-1}	-0.045 (0.045)	-0.177** (0.079)	-0.081* (0.048)	-0.299*** (0.082)
y_{t-1}	0.227*** (0.041)	0.526*** (0.118)	0.268*** (0.041)	0.713*** (0.118)
m1 (P-value)	-13.55 (0.000)	-5.91 (0.000)	-13.52 (0.000)	-6.76 (0.000)
m2 (P-value)	0.86 (0.392)	1.67 (0.094)	1.39 (0.165)	2.28 (0.022)
Sargan, p-value (d.f.)	0.829 (16)	0.158 (15)	0.829 (16)	0.566 (15)
Hansen, p-value (d.f.)	0.000 (16)	0.002 (15)	0.000 (16)	0.002 (15)
Instruments in the first-differenced equations	Lagged levels t-2	Lagged levels t-3	Lagged levels t-2	Lagged levels t-3
Instruments in the levels equations	Lagged first differences	Lagged first differences	Lagged first differences	Lagged first differences
Number of instruments	37	36	37	36
Number of observations	8,176	8,176	8,176	8,176

Notes: Parentheses contain asymptotic standard errors. Standard errors have had the Windmeijer correction applied in all the GMM estimations. All models include year dummies.
***significant at 1%, **significant at 5%, *significant at 10%.
The Arellano-Bond tests for serial correlation for first-order and second-order serial correlation, respectively m1 and m2, are reported, asymptotically N(0, 1).

Table 9: Production Function Estimates with Chemical Input variable

	One-step		Two-step	
	(1)	(2)	(3)	(4)
y_t	SYS-GMM $t-2$	SYS-GMM $t-3$	SYS-GMM $t-2$	SYS-GMM $t-3$
l_t	0.140*** (0.033)	0.147*** (0.032)	0.147*** (0.033)	0.138*** (0.034)
l_{t-1}	-0.027 (0.024)	-0.032 (0.027)	-0.048* (0.026)	-0.070** (0.036)
k_t	0.086*** (0.019)	0.075*** (0.019)	0.103*** (0.020)	0.085*** (-0.030)
k_{t-1}	-0.030* (0.015)	-0.037** (0.016)	-0.021 (0.015)	-0.030* (0.016)
n_t	0.471*** (0.157)	0.488*** (0.132)	0.385*** (0.135)	0.292** (-0.212)
n_{t-1}	-0.037 (0.037)	-0.131* (0.070)	-0.075 (0.054)	-0.212*** (0.76)
$chem_t$	0.369** (0.147)	0.303*** (0.107)	0.385*** (0.136)	0.402*** (0.015)
$chem_{t-1}$	-0.064* (0.034)	0.028 (0.028)	-0.059* (0.036)	0.015 (0.110)
y_{t-1}	0.204*** (0.038)	0.273** (0.120)	0.237*** (0.037)	0.387** (0.178)
m1 (P-value)	-14.06 (0.000)	-4.49 (0.000)	-13.79 (0.000)	-3.48 (0.000)
m2 (P-value)	0.24 (0.807)	0.21 (0.835)	0.52 (0.601)	0.45 (0.653)
Sargan, p-value (d.f)	0.797 (28)	0.566 (26)	0.797 (28)	0.566 (26)
Hansen, p-value	0.000 (28)	0.000 (26)	0.000 (28)	0.000 (26)
Instruments in the first-differenced equations	Lagged levels t-2	Lagged levels t-3	Lagged levels t-2	Lagged levels t-3
Instruments in the levels equations	Lagged first differences	Lagged first differences	Lagged first differences	Lagged first differences
Number of instruments	51	49	51	49
Number of observations	8,053	8,053	8,053	8,053

Notes: Parentheses contain asymptotic standard errors. Standard errors have had the Windmeijer correction applied in all the GMM estimations. All models include year dummies.
***significant at 1%, **significant at 5%, *significant at 10%.
The Arellano-Bond tests for serial correlation for first-order and second-order serial correlation, respectively m1 and m2, are reported, asymptotically N(0, 1).

Table 10 presents a comparison to estimating the technological parameters and production elasticities both of one-step and two-step GMM as well as the model specification that does and does not include chemicals. All the elasticities are positive (in line with expectations) and significant suggesting that chemical inputs should be included in a production function estimation using GMM as it gives important information to the model. In addition, including chemicals in the estimation seems to improve the results whereby land is overestimated. This might be expected given that chemical inputs include fertiliser which would increase the quality of the land. The labour and capital coefficients are smaller, but closer to those reported by (Mary, 2013) than for (Biagini *et al.*, 2023). The results in the table suggest that an increase in chemical inputs result in the biggest increase in output by 0.35% with an increase in chemical expenditure by 1%.

Also presented in the appendix, Table 16, are the technological parameters with materials instead of chemical input estimated. The results are not very dissimilar from those in Table 10 except that the materials coefficient is quite large, much more so than in (Biagini *et al.*, 2023). In addition, the labour and capital coefficients are quite small.

Table 10: Technological parameters

	Not including Chemicals		Including Chemicals	
	One-step	Two-step	One-step	Two-step
β_l	0.150*** (0.0256)	0.143*** (0.0254)	0.146*** (0.0294)	0.145*** (0.0309)
β_k	0.0722*** (0.0160)	0.0750*** (0.0151)	0.0795*** (0.0175)	0.0815*** (0.0172)
β_n	0.583*** (0.0479)	0.520*** (0.0441)	0.436*** (0.0975)	0.344*** (0.0925)
β_{chem}			0.291*** (0.100)	0.350*** (0.0985)
CRS	0.000	0.000	0.427	0.186

Note: All estimates use systems GMM with the estimations using instruments dated t-3 lagged levels and on. P-values are reported for the Wald test for CRS which tests the null hypothesis that there are constant returns to scale.
***significant at 1%, **significant at 5%, *significant at 10%.

Another statistic included in the results in Table 10 is the Wald test for Constant Returns to Scale (CRS). For the model specification which does not include chemicals, CRS are rejected, but they are not rejected for the model which includes chemicals. The benefit of using SYS-GMM in estimating the production function is that there is no imposed assumption made on the functional form (Biagini *et al*., 2023). Therefore CRS = 1 is not imposed on the model. Therefore, if the true econometric model is closer to the estimation using the chemical inputs, then perhaps the Cobb Douglas assumes that CRS = 1 does not hold and other functional forms should also be tested, although as discussed earlier, the difference in changing functional form may not be significant.

3.4.2 Total Factor Productivity Estimation

Table 11: TFP Estimates of specifications with and without chemical input

	Without Chemicals			With Chemicals		
Year	Mean	St. dev.	% Change	Mean	St. dev.	% Change
2004	1.085	(0.006)		1.051	(0.005)	
2005	1.091	(0.006)	0.488	1.055	(0.005)	0.351
2006	1.090	(0.006)	-0.037	1.055	(0.005)	0.037
2007	1.082	(0.005)	-0.755	1.051	(0.004)	-0.420
2008	1.069	(0.004)	-1.257	1.043	(0.003)	-0.769
2009	1.072	(0.005)	0.319	1.043	(0.004)	0.073
2010	1.073	(0.005)	0.067	1.045	(0.003)	0.120
2011	1.067	(0.004)	-0.544	1.041	(0.003)	-0.341
2012	1.066	(0.004)	-0.069	1.040	(0.003)	-0.102
2013	1.063	(0.004)	-0.304	1.038	(0.003)	-0.223
2014	1.072	(0.005)	0.892	1.043	(0.003)	0.545
2015	1.080	(0.005)	0.705	1.048	(0.004)	0.459
2016	1.080	(0.005)	-0.015	1.048	(0.004)	-0.031
2017	1.073	(0.005)	-0.604	1.044	(0.004)	-0.356
2018	1.073	(0.005)	0.027	1.045	(0.004)	0.059

Figure 8: Average TFP

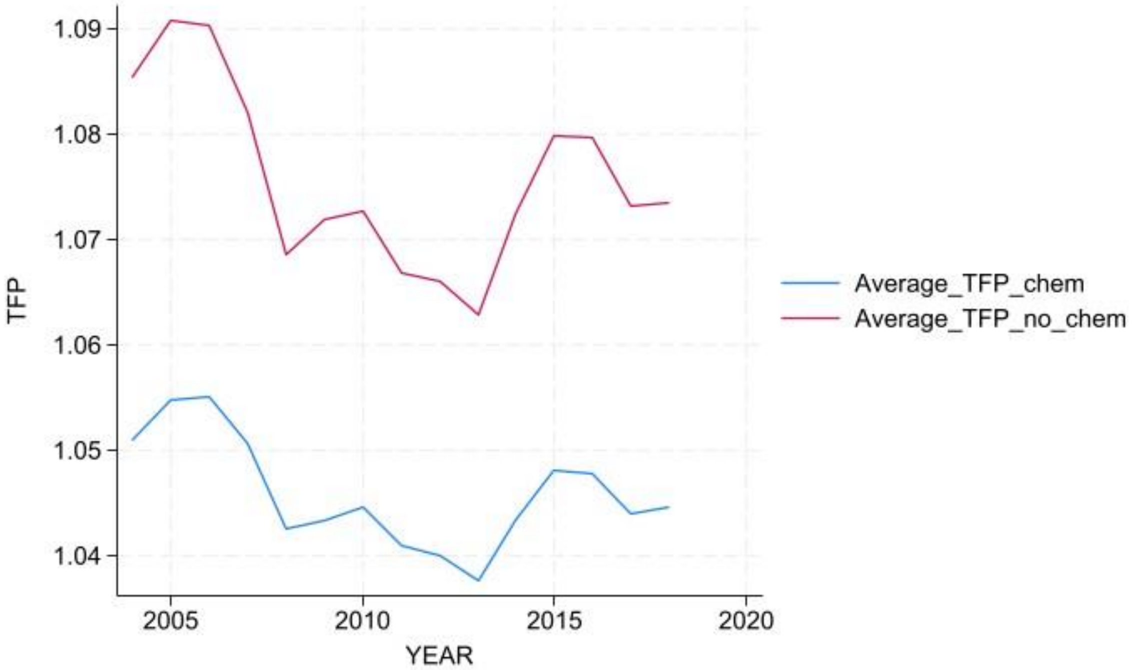


Table 11 and Figure 8 present the average results of the TFP estimation of equation 5 per year of the sample. The mean TFP is slightly smaller than reported in (Biagini *et al*., 2023) but these differences may be due to differences in the implementation of the GMM as well as their incorporation of materials in the estimation. Table 11 also presents the percentage changes year by year in TFP. Figure 8 clearly shows that the TFP with chemicals follows the same pattern as the TFP without the difference is that the TFP is higher without the chemical input as this would be contained within the residual. The trends in these TFPs follow a similar pattern as well to the results in the UK sample for (Biagini *et al*., 2023) where TFP is lower over time, but this change in TFP has been relatively flat.

3.5 Conclusions

This is to the author's knowledge the first estimation of a systems GMM for a Cobb-Douglas production function using chemical inputs as a factor of production. In addition to the estimation of elasticities of output with respect to these factors of production, TFP is also estimated.

Systems GMM is used in order to combat possible issues relating to endogeneity if the production function were to be estimated through another method, for example OLS, within estimators and even frontier approaches such as DEA and SFA.

A limitation in the estimations is that the Hansen test fails to reject the null hypothesis suggesting a model misspecification.

The results in Table 9 suggest that an increase in chemical inputs result in the biggest increase in output by 0.35% with an increase in chemical expenditure by 1%. This might support an argument behind there being some farms which are more intensive and may benefit from the returns to higher chemical input use and other farms which are more extensive and thereby maximise benefits to the environment.

Appendix

Additional Results

Table 12: Production function estimates without chemical input variable – alternative estimation

	One-step		Two-step	
	(1)	(2)	(3)	(4)
y_t	SYS-GMM $t-2$	SYS-GMM $t-3$	SYS-GMM $t-2$	SYS-GMM $t-3$
l_t	0.274* (0.142)	0.419** (0.171)	0.320** (0.131)	0.372** (0.156)
l_{t-1}	0.0757 (0.137)	0.103 (0.168)	4.59e-05 (0.138)	0.0299 (0.154)
k_t	0.301*** (0.0871)	0.316*** (0.115)	0.227*** (0.0863)	0.270*** (0.104)
k_{t-1}	0.159* (0.0850)	0.0935 (0.113)	0.106 (0.0695)	0.117 (0.0919)
n_t	0.623** (0.267)	0.439 (0.321)	0.657** (0.276)	0.412 (0.327)
n_{t-1}	-0.400 (0.290)	-0.430 (0.345)	-0.384 (0.302)	-0.275 (0.353)
y_{t-1}	0.118* (0.0658)	0.133 (0.159)	0.188*** (0.0631)	0.128 (0.169)
m1 (P-value)	-5.39 (0.000)	-2.38 (0.017)	-6.79 (0.000)	-2.50 (0.012)
m2 (P-value)	-1.29 (0.196)	-0.36 (0.717)	-0.26 (0.795)	-0.44 (0.661)
Sargan, p-value (d.f.)	1.000 (97)	1.000 (83)	1.000 (97)	1.000 (83)
Hansen, p-value (d.f.)	0.334 (97)	0.558 (83)	0.334 (97)	0.558 (83)
Instruments in the first-differenced equations	Lagged levels t-2	Lagged levels t-3	Lagged levels t-2	Lagged levels t-3
Instruments in the levels equations	Lagged first differences	Lagged first differences	Lagged first differences	Lagged first differences
Number of instruments	118	104	118	104
Number of observations	8,219	8,219	8,219	8,219

Notes: Parentheses contain asymptotic standard errors. Standard errors have had the Windmeijer correction applied in all the GMM estimations. All models include year dummies.
***significant at 1%, **significant at 5%, *significant at 10%.
The Arellano-Bond tests for serial correlation for first-order and second-order serial correlation, respectively m1 and m2, are reported, asymptotically N(0, 1).

Table 13: Production function estimates without chemical input variable – alternative estimation

	One-step		Two-step	
	(1)	(2)	(3)	(4)
y_t	SYS-GMM $t-2$	SYS-GMM $t-3$	SYS-GMM $t-2$	SYS-GMM $t-3$
l_t	0.274* (0.141)	0.453** (0.184)	0.309*** (0.115)	0.426*** (0.162)
l_{t-1}	0.140 (0.129)	0.239 (0.159)	0.0371 (0.115)	0.116 (0.143)
k_t	0.299*** (0.0848)	0.279** (0.122)	0.267*** (0.0836)	0.272*** (0.100)
k_{t-1}	0.107 (0.0796)	0.0667 (0.118)	0.0727 (0.0671)	0.0770 (0.0886)
n_t	0.463* (0.264)	0.250 (0.312)	0.481* (0.277)	0.239 (0.316)
n_{t-1}	-0.307 (0.282)	-0.333 (0.338)	-0.376 (0.298)	-0.212 (0.353)
$chem_t$	0.255*** (0.0909)	0.195* (0.102)	0.278*** (0.0726)	0.216** (0.0859)
$chem_{t-1}$	-0.102 (0.0755)	-0.0116 (0.0873)	-0.123* (0.0639)	-0.0540 (0.0826)
y_{t-1}	0.0796 (0.0771)	-0.0467 (0.198)	0.155** (0.0674)	-0.0163 (0.211)
m1 (P-value)	-4.60 (0.000)	-1.39 (0.165)	-5.94 (0.000)	-1.60 (0.110)
m2 (P-value)	-1.06 (0.288)	-1.03 (0.302)	-0.20 (0.842)	-0.86 (0.391)
Sargan, p-value (d.f.)	1.000 (95)	1.000 (81)	1.000 (95)	1.000 (81)
Hansen, p-value (d.f.)	0.637 (95)	0.655 (81)	0.637 (95)	0.655 (81)
Instruments in the first-differenced equations	Lagged levels t-2	Lagged levels t-3	Lagged levels t-2	Lagged levels t-3
Instruments in the levels equations	Lagged first differences	Lagged first differences	Lagged first differences	Lagged first differences
Number of instruments	118	104	118	104
Number of observations	8,096	8,096	8,096	8,096

Notes: Parentheses contain asymptotic standard errors. Standard errors have had the Windmeijer correction applied in all the GMM estimations. All models include year dummies.
***significant at 1%, **significant at 5%, *significant at 10%.
The Arellano-Bond tests for serial correlation for first-order and second-order serial correlation, respectively m1 and m2, are reported, asymptotically N(0, 1).

Table 14: Production Function Estimates with Chemicals Separated

	One-step		Two-step	
	(1)	(2)	(3)	(4)
y_t	SYS-GMM $t-2$	SYS-GMM $t-3$	SYS-GMM $t-2$	SYS-GMM $t-3$
l_t	0.131*** (0.0338)	0.126*** (0.0343)	0.155*** (0.0332)	0.142*** (0.0363)
l_{t-1}	-0.0318 (0.024)	-0.0394 (0.0287)	-0.0483* (0.0259)	-0.0650* (0.0349)
k_t	0.0879*** (0.0202)	0.0843*** (0.0221)	0.109*** (0.0214)	0.0950*** (0.0216)
k_{t-1}	-0.0336** (0.0158)	-0.0354** (0.0162)	-0.0289* (0.0168)	-0.0372** (0.0174)
n_t	0.508*** (0.123)	0.487*** (0.128)	0.405*** (0.14)	0.411** (0.164)
n_{t-1}	-0.00821 (0.0495)	-0.0183 (0.0881)	-0.0499 (0.0526)	-0.0788 (0.096)
ln_fert_adj	0.232*** (0.0822)	0.281*** (0.0838)	0.184** (0.0811)	0.207** (0.0892)
L.ln_fert_adj	-0.0331* (0.0194)	0.0257 (0.108)	-0.0376** (0.0179)	0.00116 (0.0991)
ln_CP_adj	0.123 (0.0905)	0.104 (0.0868)	0.173 (0.165)	0.155 (0.194)
L.ln_CP_adj	-0.0151 (0.026)	-0.106 (0.0781)	-0.0127 (0.0335)	-0.0782 (0.0968)
y_{t-1}	0.187*** (0.04)	0.254** (0.122)	0.231*** (0.0422)	0.348** (0.155)
m1 (P-value)	-14.03 (0.000)	-3.64 (0.000)	-12.09 (0.000)	-3.83 (0.000)
m2 (P-value)	0.68 (0.496)	0.28 (0.782)	1.05 (0.295)	0.76 (0.449)
Sargan, p-value (d.f.)	0.985 (40)	0.964 (37)	0.985 (40)	0.964 (37)
Hansen, p-value (d.f.)	0.006 (40)	0.782 (37)	0.006 (40)	0.006 (37)
Instruments in the first-differenced equations	Lagged levels t-2	Lagged levels t-3	Lagged levels t-2	Lagged levels t-3
Instruments in the levels equations	Lagged first differences	Lagged first differences	Lagged first differences	Lagged first differences
Number of instruments	65	62	65	62
Number of observations	7,917	7,917	7,917	7,917

Notes: Parentheses contain asymptotic standard errors. Standard errors have had the Windmeijer correction applied in all the GMM estimations. All models include year dummies.
***significant at 1%, **significant at 5%, *significant at 10%.
The Arellano-Bond tests for serial correlation for first-order and second-order serial correlation, respectively m1 and m2, are reported, asymptotically N(0, 1).

Table 15: Production Function Estimates with Materials

	One-step		Two-step	
	(1)	(2)	(3)	(4)
y_t	SYS-GMM $t-2$	SYS-GMM $t-3$	SYS-GMM $t-2$	SYS-GMM $t-3$
l_t	0.0803*** (0.0279)	0.0779*** (0.0255)	0.0841*** (0.0272)	0.0811*** (0.0248)
l_{t-1}	-0.0348* (0.0198)	-0.0433* (0.0261)	-0.0436** (0.0202)	-0.0651** (0.0261)
k_t	0.0638*** (0.0176)	0.0527*** (0.0169)	0.0860*** (0.0173)	0.0665*** (0.0176)
k_{t-1}	-0.0351** (0.0140)	-0.0383** (0.0154)	-0.0301** (0.0140)	-0.0419*** (0.0148)
n_t	0.466*** (0.0780)	0.433*** (0.0754)	0.369*** (0.0621)	0.354*** (0.0583)
n_{t-1}	0.00125 (0.0390)	-0.0258 (0.0580)	-0.0286 (0.0408)	-0.0896 (0.0616)
m_t	0.552*** (0.0461)	0.566*** (0.0495)	0.569*** (0.0409)	0.524*** (0.0534)
m_{t-1}	-0.0528 (0.0324)	-0.0914 (0.0966)	-0.0512 (0.0318)	-0.190** (0.0968)
y_{t-1}	0.149*** (0.0326)	0.260 (0.169)	0.186*** (0.0318)	0.462*** (0.169)
m1 (P-value)	-15.71 (0.000)	-3.64 (0.000)	-15.41 (0.000)	-4.48 (0.000)
m2 (P-value)	0.03 (0.980)	0.48 (0.631)	0.52 (0.603)	1.31 (0.189)
Sargan, p-value (d.f)	0.939 (17)	0.800 (16)	0.939 (17)	0.800 (16)
Hansen, p-value	0.009 (17)	0.009 (16)	0.009 (33.85)	0.009 (16)
Instruments in the first-differenced equations	Lagged levels t-2	Lagged levels t-3	Lagged levels t-2	Lagged levels t-3
Instruments in the levels equations	Lagged first differences	Lagged first differences	Lagged first differences	Lagged first differences
Number of instruments	40	39	40	39
Number of observations	1,168	1,168	1,168	1,168

Notes: Parentheses contain asymptotic standard errors. Standard errors have had the Windmeijer correction applied in all the GMM estimations. All models include year dummies.
***significant at 1%, **significant at 5%, *significant at 10%.
The Arellano-Bond tests for serial correlation for first-order and second-order serial correlation, respectively m1 and m2, are reported, asymptotically N(0, 1).

Table 16: Technology parameter estimates with materials

	One-step		Two-step	
	t-2	t-3	t-2	t-3
β_l	0.0928*** (0.0260)	0.0910*** (0.0235)	0.103*** (0.0254)	0.0988*** (0.0215)
β_k	0.0699*** (0.0160)	0.0529*** (0.0159)	0.0866*** (0.0160)	0.0642*** (0.0151)
β_n	0.403*** (0.0638)	0.359*** (0.0546)	0.358*** (0.0539)	0.313*** (0.0442)
β_m	0.534*** (0.0350)	0.544*** (0.0315)	0.527*** (0.0330)	0.496*** (0.0273)
CRS	0.0591	0.3308	0.1285	0.5381

Note: All estimates use systems GMM with the estimations using instruments dated t-3 lagged levels and on. P-values are reported for the Wald test for CRS which tests the null hypothesis that there are constant returns to scale.
***significant at 1%, **significant at 5%, *significant at 10%.

Chapter 3 Code

*Estimations made in Stata/MP 18.0

*Data in panel structure

xtset id_new year

*Production function estimates without chemical input variable

*One-step No Chem t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

*One-step No Chem t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

*Two-step No Chem t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

*Two-step No Chem t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

****

```
*Introducing Chem Inputs

*One-step Chem t-2

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y ln_chem_inputs, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

*One-step Chem t-3

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y ln_chem_inputs, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

*Two-step Chem t-2

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y ln_chem_inputs, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

*Two-step Chem t-3

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y ln_chem_inputs, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two


*****************************************************************************

*Appendix Estimates

*****************************************************************************

*One-step No Chem t-2

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(2 .)) iv(i.year,equation(level)) r h(1)

*One-step No Chem t-3

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(3 .)) iv(i.year,equation(level)) r h(1)
```

*Two-step No Chem t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(2 .)) iv(i.year,equation(level)) r h(1) two

*Two-step No Chem t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(3 .)) iv(i.year,equation(level)) r h(1) two

****

*Introducing Chem Inputs

*One-step Chem t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y, lag(2 .)) iv(i.year,equation(level)) r h(1)

*One-step Chem t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y, lag(3 .)) iv(i.year,equation(level)) r h(1)

*Two-step Chem t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y, lag(2 .)) iv(i.year,equation(level)) r h(1) two

*Two-step Chem t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K_current l.ln_K_current ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y, lag(3 .)) iv(i.year,equation(level)) r h(1) two

****

*Introducing Split Chem Inputs

*One-step Split Chem t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_fert_adj l.ln_fert_adj ln_CP_adj l.ln_CP_adj l.ln_y i.year, gmm(ln_y ln_fert_adj ln_CP_adj, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_fert_adj l.ln_fert_adj ln_CP_adj l.ln_CP_adj l.ln_y i.year, gmm(ln_y ln_fert_adj ln_CP_adj, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_fert_adj l.ln_fert_adj ln_CP_adj l.ln_CP_adj l.ln_y i.year, gmm(ln_y ln_fert_adj ln_CP_adj, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_fert_adj l.ln_fert_adj ln_CP_adj l.ln_CP_adj l.ln_y i.year, gmm(ln_y ln_fert_adj ln_CP_adj, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

****

*Estimations with Materials

*One-step Mat t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_mat l.ln_mat l.ln_y i.year, gmm(ln_y, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land ln_mat, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

*One-step Mat t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_mat l.ln_mat l.ln_y i.year, gmm(ln_y, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land ln_mat, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)

*Two-step Mat t-2

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_mat l.ln_mat l.ln_y i.year, gmm(ln_y, lag(2 .) collapse) gmm(ln_K ln_total_L ln_land ln_mat, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

*Two-step Mat t-3

xi: xtabond2 ln_y ln_total_L l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_mat l.ln_mat l.ln_y i.year, gmm(ln_y, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land ln_mat, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two

```
******************************************************************************
*Recovering Technological Parameters
******************************************************************************
**Re-estimating production function estimates - No chems
*One-step t-3
xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)
**Two-step t-3
xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land l.ln_y i.year, gmm(ln_y, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1)   two

*Constructing the Technological Parameters - below is shown without chems
*Minimum distance
matrix B = e(b)'
matrix F = e(V)
matlist B[1. .7,1]
matlist F[1. .7,1. .7]
matrix B1 = B[1. .7,1]
matrix F1 = F[1. .7,1. .7]
matrix H =(I(1),0,0,0\-_b[l.ln_y],0,0,0\0,I(1),0,0\0,-_b[l.ln_y],0,0\0,0,I(1),0\0,0,-_b[l.ln_y],0\0,0,0,I(1))
```

```
matrix H1 = H'

matrix list H

matrix list H1

matrix list F1

matrix list B1

matrix delta = invsym(H1*invsym(F1)*H)*(H1*invsym(F1)*B1)

matrix delta = delta'

matrix H2= invsym(H1*invsym(F1)*H)

ereturn  post delta H2

ereturn display

**** test CRS******

testnl (_b[c1]+_b[c2]+_b[c3]=1)


*6. Implied shock

gen z0_no_chem=(ln_y-_b[c1]*ln_total_L-_b[c2]*ln_K-_b[c3]*ln_land)

gen z_no_chem=exp(z0/total_y_adj100_coef)

sort year

by year: sum z_no_chem


*** calculus productivity olley and pakes 1996 - Table 9 TFP Estimates without chems
```

```
sort year

by year: egen sum=total(SE131)

xtset id_new year

gen share2=SE131/sum

gen z_no_chem_def=z*share2

sort year

by year: egen sectTFP1_no_chem=total(z_no_chem_def)

by year: su sectTFP1


***************************************************************************

est clear

drop z0 z sum share2 zdef sectTFP1


*Data in panel structure

xtset id_new year


**Re-estimating production function estimates - Chems

*One-step t-3

xi: xtabond2 ln_y ln_total_L  l.ln_total_L ln_K l.ln_K ln_land l.ln_land ln_chem_inputs l.ln_chem_inputs l.ln_y i.year, gmm(ln_y ln_chem_inputs, lag(3 .) collapse) gmm(ln_K ln_total_L ln_land, lag(1 2) collapse) iv(i.year,equation(level)) r h(1) two
```

```
*Matrix code adapted to include chem inputs

*Minimum distance

matrix B = e(b)'

matrix F = e(V)

matlist B[1. .9,1]

matlist F[1. .9,1. .9]

matrix B1 = B[1. .9,1]

matrix F1 = F[1. .9,1. .9]

matrix H =(I(1),0,0,0,0\-_b[l.ln_y],0,0,0,0\0,I(1),0,0,0\0,-_b[l.ln_y],0,0,0\0,0,I(1),0,0\0,0,-_b[l.ln_y],0,0\0,0,0,I(1),0\0,0,0,-_b[l.ln_y],0\0,0,0,0,I(1))

matrix H1 = H'

matrix delta = invsym(H1*invsym(F1)*H)*(H1*invsym(F1)*B1)


matrix list B


matrix delta = delta'

matrix H2= invsym(H1*invsym(F1)*H)


ereturn  post delta H2

ereturn display
```

```
**** test CRS******

testnl (_b[c1]+_b[c2]+_b[c3]+_b[c4]=1)


*Implied shock for chems

gen z0_chem=(ln_y-_b[c1]*ln_total_L-_b[c2]*ln_K-_b[c3]*ln_land-_b[c4]*ln_chem_inputs)

gen z_chem=exp(z0_chem/total_y_adj100_coef)

sort year

by year: sum z_chem


*** calculus productivity olley and pakes 1996 - Table 9 TFP estimates with chems

sort year

by year: egen sum=total(SE131)

xtset id_new year

gen share2=SE131/sum

gen z_chem_def=z_chem_*share2

sort year

by year: egen sectTFP1=total(z_chem_def)

by year: su sectTFP1
```

Chapter 4: Does organic farming lead to higher returns to education?

Using the raising of the school leaving age as a quasi-experiment

Abstract

This chapter examines the farmer's return to education differentiating between organic and conventional farming. By using the 1972 Raising of the School Leaving Age as a quasi-experiment with a Regression Discontinuity Design, we identify a causal relationship for the farmer's return to education on farm economic performance. Using data from a sample of English farms between 2011 and 2018 from the Farm Business Survey, we show: (i) a positive return to education on farm performance (ii) a higher education return in organic farming in comparison with conventional farming.

4.1 Introduction

The adoption of new techniques or production technologies and their effective employment requires human capital – skills and knowledge in the selection of the most appropriate technologies, in the adaptation, interpretation and implementation of the technologies into the wider systems of production in a given context and ultimately to employ these skills for economic gain. Education, training and experience enhance our skills, ability, knowledge and human capital. We expect that the complexity of farm systems, relying, as they do, on unreliable nature, which produce a wide range of outputs and operate in environments that are difficult to monitor in real time, would require broad skill sets. Human capital theory in the context of production efficiency has been a longstanding proposition suggesting that education could foster farmers' ability to understand and interpret market information, enabling them to respond more effectively to economic imbalances (Schultz, 1975). Specifically, education may enhance the decision-making process in farm resource allocation and contribute to the development of farmers' production skills (Welch, 1970). Moreover, a large body of literature emphasises that education positively influences the adoption of promising new technologies

(Feder *et al*., 1985); (Lin, 1991), adopting new farm inputs, having a preference for risky production technologies and displaying better management skills (Asadullah and Rahman, 2009).

The objective of this paper is to analyse returns to education in agriculture In England. More precisely, we compare returns to education between conventional farming and organic farming from the 1972 Raising of the School Leaving Age (ROSLA). We suppose that education is not only required for the adoption of these techniques, but also for their adaptation to specific agro-ecosystems, to specific soil types and climatic conditions.

Little research has been carried out on the returns from a higher educated workforce in organic farming, a type of farming approach that reduces the farms requirement for chemical fertilisers and pesticides. Research so far has mainly focused on differences in the quantity of labour in organic and conventional farming. Analyses in these studies tried to reveal the effects on productivity and output risk as the organic and conventional farms reduce their use of chemical inputs. In particular, these studies consider crop protection chemicals and consequent changes in labour demand and capital, *e.g.* whether organic farming, or using fewer chemical inputs, requires more labour (*e.g.* Gardebroek *et al*., (2010); Kumbhakar *et al*., (2009); Zhengfei *et al*., (2005)). However, not only the quantity of labour demand in different farming techniques is important, but also the requirements toward the quality of labour.

Previous literature considering the impact of education on the determinants of agricultural productivity presents mixed findings. First, macroeconomic level studies predominantly indicated a significant and positive effect of education on the agricultural productivity of states (Nguyen, 1979). However, contrasting results have emerged from more recent investigations, where studies highlight non-significant (Vollrath, 2007) or even negative effects of education on agricultural productivity (Craig *et al*., 1997). An exception is Reimers and Klasen (2013). Second and in contrast, microeconomic studies consistently emphasize a positive role for education (Phillips, 1994), revealing a disparity in the conclusions drawn at different analytical scales. This divergence in findings emphasises the complexity of the relationship between education and agricultural productivity, warranting a nuanced examination that considers contextual factors and methodological approaches.

Thus, our work's contribution to the literature is twofold. First, to the best of our knowledge, this is the first work which exploits a quasi-experiment to identify a causal return to education in agriculture. Second, our empirical strategy allows us to identify heterogeneous returns to education between conventional farming and organic farming.

Our identification strategy relies on a Regression Discontinuity Design (RDD) methodology to exploit, as a quasi-experiment, the ROSLA which occurred in England and Wales in 1972. The quasi-experiment is undertaken in two stages using 8 years of Farm Business Survey data to estimate the returns to education. The first stage estimates the number of years of schooling depending on the birth year of the farmer. In the second stage, RDD estimates farm output using Two Stage Least Squares where a dummy variable for being born before or after 1957 is used as an instrument for years of schooling. The model is extended through using a Correlated Random Effect model and in estimating the difference between conventional and organics farms a heterogeneous local average treatment effect (HLATE) approach is used.

The results show first that the ROSLA resulted in an average increase in education by 0.40 years for our sample of farmers. Second, that with an additional year of education there is a higher increase for farmers on organic farms by an average of 5.5% to total output compared with a 1.3% increase for conventional farmers. These results hold when expanding the model to use covariates and in robustness checks.

The paper is structured as follows. A literature review presents evidence in the literature documenting the link between farming by reducing, particularly chemical, farm inputs and returns to education. The following section explains the data and methodology used in this chapter. Next is a presentation of the results and finally this chapter concludes.

4.2 Literature Review

4.2.1 Education, skills and environmental farm practices

One of the problems of the empirical analysis of the effects of techniques that lead toward farming for food production as well as considering the environment on returns to education is that it is a very broad concept, incorporating a mix of more traditional and more recent environmentally friendly farm practices. Also, internationally, there is not a common definition or a standard certification process as, for example, the one that is in place for organic products and, as a consequence, there is a lack of relevant statistical information. As a result, the bulk of studies on ecological farming include mainly broad discourse and do not attempt more rigorous quantitative analyses.

Therefore, it is not surprising that there is little previous research to inform the analysis in the present paper. Mills (2012) looked at the social benefits of agri-environmental schemes (AESs) beyond the targeted environmental gains. The data for the analysis was collected through 360 interviews with environment schemes agreement holders out of which 288 were telephone interviews and the remaining face-to-face. The study compared the effect on workload and development of human capital by two AESs implemented in England, the Entry Level Stewardship Scheme and Higher-Level Stewardship Scheme, the latter being a more challenging one. Human capital here including education. The results indicated that the participation in AESs contributed to developing human capital, *i.e.*, increasing farmers' skills to farm more sustainably. There is some possible reverse causality here in that farmers who have more 'ecocentric attitudes' and farm organically tend to have more educational qualifications (Kings and Ilbery, 2010) – they are therefore more likely to participate in AESs and especially higher tier AESs.

Marinoudi *et al*., (2019) employing a framework of skill biased technological change investigated the effect of automation and robots on skill sets in agriculture. They emphasise that more training and education are required in to increase the cognitive capabilities and meet the requirements for human-skill. Marinoudi *et al*., (2019) underline three major changes: first, whilst in the past labour was basically focused on completing manual tasks, labour and technology were assumed to be perfect substitutes since technology for cognitive tasks was not considered. Currently, most of the jobs are complex since modern work processes require a set of various inputs of different aptitudes and skills, and each one of these labour inputs play an essential and non-replaceable role. Second, concerning automation in agriculture, there is a complementarity between labour and machines, *e.g.*, a human operator is required to offset the shortcomings of the robot's intelligence to cope with unpredictable events. Third, on the other hand, modern technology can have the opposite effect, *i.e.*, it often reduces the requirements for human skills, *e.g*., the implementation of autosteering and navigation-aiding systems for agricultural machinery. Overall, the authors argue that new technologies may lead to polarisation of skill requirements and thus wages. When the automation level increases there are increased requirements in terms of skills and education from the workers who complement the introduction of new technologies, and on the other hand, there is still a demand for low-skilled labour for the execution of the residual activities in routine tasks. This narrows down the demand for and use of middle-skilled labour.

Concerning organic farming, Navarrete *et al*., (2015) looked at organic horticulture farms divided into four categories: specialised and small; specialised and large; diversified and small; diversified and large. The authors found that diversified farms required more labour per hectare as well as more knowledge and skills as this method is generally more complex due to different crop requirements, crop diversification and plot agronomical constraints that are associated with organic farms.

However, not all the studies supported that different/higher skilled participating farmers were required in AES or organic farming. For example, often farmers participate in AES schemes because of a combination of business interest to capture the attractive agri-environmental payments and because the schemes required very small adaptations of existing farming practices or no change at all (Harrison *et al*., (1998); Wilson and Hart (2001); Schmitzberger *et al*., (2005); Lobley *et al*., (2013)). Burton *et al*., (2008) argue that skills were necessary at the stage of setting the AES, e.g. to decide which land to allocate for AES or how to maximise subsidies. However, after that initial stage, in the implementation process there were not any particular skill requirements since farmers simply had to follow the prescribed practices of a particular scheme, and this often constrains the development of farmers' abilities to develop and implement innovative ideas in conservation agriculture.

Based on the review above, it appears that the effect of adopting environmental farming practices on returns to education is to a great extent an empirical issue since these practices may require additional education and skills or may only involve strict compliance with AES prescriptions.

4.2.2 ROSLA in England

The Education Act 1944 raised the school leaving age from 14 to 15 in 1947 and stated that the school leaving age should further rise to 16 when it would next be possible (West, 2022). Legislation for the next ROSLA was implemented on 1 September 1972. Therefore, the first cohort of students affected by the reform were those who turned 15 years old in the 1972/1973 academic year (Wallace, 2009) and were therefore born in 1957/1958. Prior to the Education Act 1944, unlike in other countries where students can leave school once they reach the compulsory age on their birthday, in England and Wales those born between 1st September and the 31st January needed to remain in school until the following Easter (Garrouste and Godard, 2016). Those born between 1st February and 31st August could leave in the summer (usually May or June) of the year they become 16 years old, in effect meaning that those with birthdays in July and August could leave school when they are 15 years old. The aim of the 1944 education reform was to increase equality of opportunity, remove the advantage given to privileged classes, and instead promote meritocracy (Halsey *et al*., 1980)[8].

Since this second ROSLA, implemented in 1972, there have been two further increases in the age young people are obliged to participate in education or training until - referred to as raising the participation

[8] Halsey *et al.,* (1980) provides an overview studying the effects of post-war school and *'welfare state'* reforms up to the national 1972 Oxford Mobility Study, particularly that of the Education Act of 1944, on educational inequalities.

age (RPA). The first RPA made participation compulsory up to the age of 17 in 2013 and the second raised the age to 18 in 2015 in order to 'upskill' Britain's workforce and better compete with comparable countries (Simmons, 2008).

Following the oil crisis in 1973 each cohort of students leaving school in the years of 1974-1976 began looking for jobs in a recession with increasingly worse job prospects (Garrouste and Godard, 2016). In the same timeframe the proportion of 16 year olds remaining in education barely increased in the 1970s; the proportion being just above 40% and only starting to increase from 1980 (Micklewright *et al.*, 1989). This therefore suggests that students in England and Wales leave at the earliest legal opportunity and irrespective of worsening employment opportunities. This argument is supported by Garrouste and Godard (2016) in that they argue that the 1973 oil crisis was unexpected and students who were about to leave school did not anticipate the impact it may have on them finding a job.

4.2.3 Examples of the use of changes in the compulsory school leaving age in the literature

A number of different papers in the literature exploit changes in the compulsory school leaving age to identify causality between education generated through the reform and an outcome variable (Avendano *et al.*, 2020). One example includes examining the effects of increasing compulsory school leaving ages on income earnings in Canada where different provinces enacted increased leaving ages in different years (Oreopoulos, 2006a). Another example investigates the income and employment effects of the ROSLA in Greece (Psacharopoulos, 1978) where the cohort prior to the reform had 6 years in school and the following cohort 9 years – this is in contrast to separating the ROSLA over a number of years like in Britain. A couple of papers investigate the economic effects of the 1947 ROSLA in Britain (O'Keefe (1975); Oreopoulos (2006b)). Oreopoulos (2006b) uses a regression discontinuity design to estimate returns to education, finding that the benefits from the additional schooling are economically significant.

More papers have explored the effects of the 1972 ROSLA in England and Wales using regression discontinuity design. A couple of examples explore the effects of the reform on health (Jürges, Kruk and Reinhold (2013); Avendano, de Coulon and Nafilyan (2020)). Jürges, Kruk and Reinhold (2013) find a strong correlation but not necessarily a causal effect (due to lacking statistical significance) suggesting an improvement in overall health from an increase in education. Avendano, de Coulon and Nafilyan (2020) find that the ROSLA did not improve mental health. Using the 1972 ROSLA, Bruscha and Dickson (2012) find an increase in the returns to education over 40 years after the reform. Powdthavee (2021) estimate attitudes and behaviours towards climate change using the change of the law and finding a willingness to change attitudes but little change to behaviour. To the author's knowledge this is the first paper to explore the returns to education in agriculture of the 1972 ROSLA in England and Wales and more specifically the differentiated effects on organic and conventional farms.

4.3 Data and Methods

4.3.1 Sample description and data sources

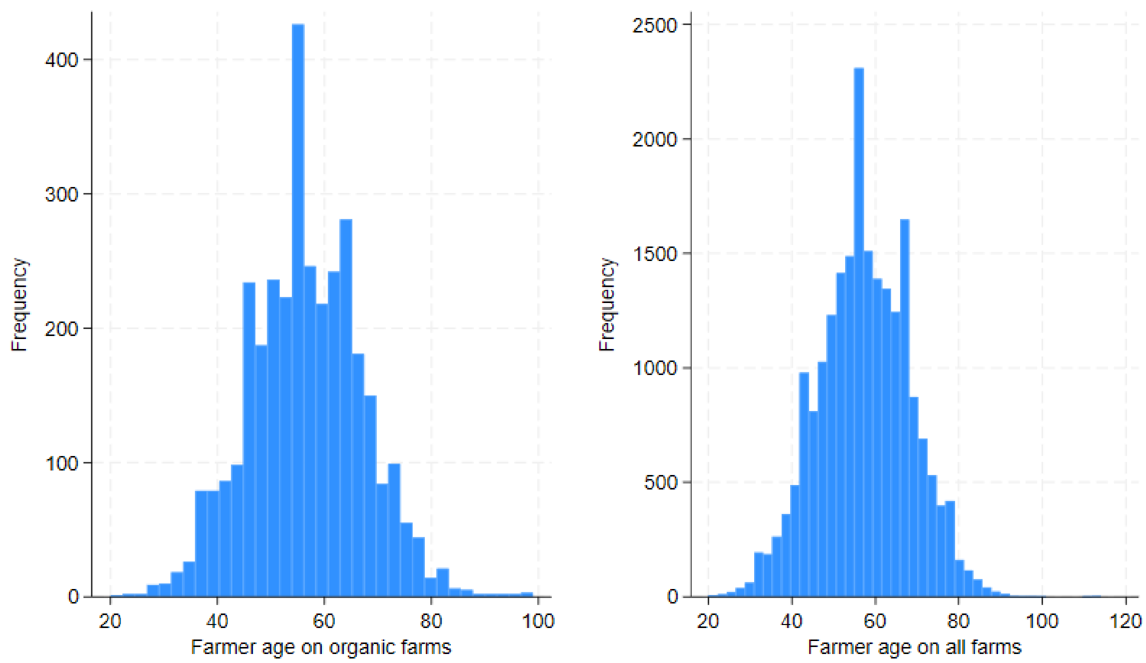
The data used here have been collected through the annual DEFRA FBS for the years 2011-2019 in an unbalanced panel containing 3,835 farms (Duchy College, 2022). FBS provides data on crop, livestock and land use on farms as well as the financial data of the farm businesses (Areal et al., 2018). Data for all farm types were used with controls adjusted for farm type introduced in some model specifications.

Table 17 presents descriptive statistics of the organic farms within the FBS dataset and compares them to all the farms (thereby including organic farms) within the sample. Organic farmers seem to have higher output and gross margin per hectare as well as using more labour and capital but farming fewer hectares (ha). In terms of farmer differences, organic farmers seem to be slightly younger with more time spent in education. The age profile of the farmers in the sample are shown in Figure 9 with little differences in what are normal distributions of the age data. These differences in descriptive statistics between the two farm samples however are not statistically significant.

Table 17: Descriptive statistics comparing organic farms with the entire sample of farms

	Organic farms			All farms		
	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.
Output	12.22	1.10	3,372	12.10	1.07	21,369
Gross margin	11.24	1.29	3,285	11.15	1.31	20,767
TFP	2.25	0.10	3,365	2.24	0.09	21,102
Output per ha	9.60	2.57	3,372	8.04	1.82	21,197
Gross margin per ha	8.58	2.66	3,285	6.99	1.99	20,597
Capital	11.46	1.16	3,366	11.37	1.18	21,277
Labour	8.57	0.84	3,373	8.44	0.87	21,373
Land (UAA)	2.67	2.33	3,373	4.15	1.73	21,201
Farmer age	56.54	10.52	3,373	57.35	10.98	21,373
Farmer gender	1.06	0.23	3,373	1.04	0.20	21,373
Farmer years of education	10.95	3.26	3,349	10.33	3.26	21,143
Note: Apart from age, gender and years of education for the farmer, all variables are in logarithms.						

Figure 9: Age distribution of farmers in the samples of organic farms and all farms



4.3.2 Empirical Strategy

Our estimation strategy relies on using the 1972 ROSLA in England and Wales. We adopt a RDD approach, as is usual in the case of exploiting reforms on school leaving age. In this case, the discontinuity is created by the raising the minimum legal age for cohorts born after a specific threshold date c (*i.e.* 1957, for our study).

Similarly to Oreopoulos (2006b), we estimate a first stage, that involves linking the implementation of the reform to the number of years of schooling, by introducing a polynomial approximation of the running variable:

$$\ln(S_i) = \alpha_0 + \alpha_1 D_i + f(b_i - c) + \epsilon_i \tag{6}$$

where for farmer i, S_i is the number of years of education D_i represents a dummy variable which takes the value 1 for individuals born after the threshold date c, the cutoff point *i.e.* 1957 in our study, and zero for those born before; $f(.)$ is a polynomial function of the farmer's birthdate; b_i is the birth year for farmer i and ϵ_i a disturbance term. Therefore, the group treated with the additional year of education are taken as those born after the 1957 cutoff point, c, and the control group are those born before this cutoff point. The polynomial function allows for different approximations of the polynomial fit regarding the population conditional expectation functions for the treated and control groups. For instance, a first order polynomial fit would be a linear approximation of $b_i - c$, second order becomes $(b_i - c)^2$, and a third order polynomial fit is $(b_i - c)^3$ and so on. Adjusting this polynomial will adjust the 'line of best fit' between the number of years of schooling and when the farmer was born.

Farmer i's return to education is then estimated by Two-Stage Least Squares on the following equation:

$$ln(Y_{it}) = \beta_0 + \beta_1 S_i + f(b_i - c) + \beta_k X_{k,it} + \eta_{it} \tag{7}$$

where for farmer i in year t; $\ln(Y_{it})$ represents the logarithm on a farm economic outcome (respectively total output, gross margin, total factor productivity, total output per hectare, and gross margin per hectare); S_i is farmer's years of education (instrumented by D_i) and η_{it} the error term. The instrument here is the dummy variable of having received additional education as part of the treated group (or not in the case of the control group) with respect to the ROSLA and this instrument replaces the number of years of education for each farmer controlling for endogeneity related to receiving extra education. The vector X_k of k control variables is composed by input variables traditionally included in a farm production function (logarithms of capital, labour and utilized agricultural area)[9], farmer's gender, farm specialisation and altitude dummies. Farm i's total productivity is estimated from a Cobb-Douglas function with capital, labour and land as inputs. Formally, we measure the returns to education for those farmers who were to study for an extra year resulting from the reform (namely the *"compliers"*).

In order to exploit the panel dimension of our sample, we extend our model to estimate a Correlated Random Effect model (Becker *et al*., 2013). Thus, we add the average of the covariates over the time periods, included as $X_{k,it}$, in equation 7 in order to capture the farm specific effect on economic performance (Mundlak (1978); Chamberlain (1978)).

All our specifications are estimated parametrically, which leads to the estimation of a flexible high order polynomial to predict the relationship between farm's economic performance and birthdate. Although this approach uses the whole sample, we restrict our sample to the farmers born between 1949 and 1967. This choice of sample restriction is based on minimizing the mean squared error of Equation (7), inspired by the bandwidth selection in non-parametric RDD studies (Imbens and Kalyanaraman, 2012).

Moreover, we adopt a HLATE approach proposed by Becker *et al*., (2013) to estimate specific farmer's education return for organic farming similarly to Gagliardi and Percoco (2017) where the dimension of the heterogeneity is not continuous. This approach assumes that the choice between conventional and organic farming was not affected directly by the ROSLA, which seems reasonable in our application[10].

[9] Input variables are not included when the farm outcome is total factor productivity.
[10] A test of this assumption is described in the results section.

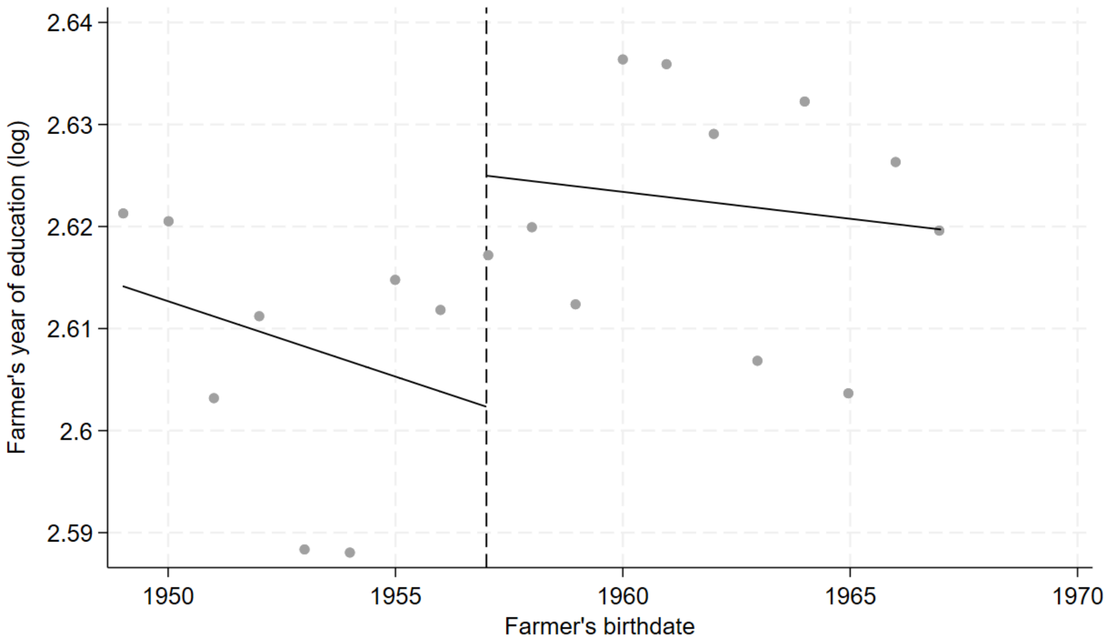
4.4 Results

In this section, we present the results of our estimations. Firstly, we outline the effect of the reform on the average number of years of education for farmers, derived from the estimation of our first-stage regression. We also assess how the reform has influenced the educational attainment level (by degree). Secondly, we detail our main results. Finally, we provide additional results to evaluate the robustness of our analysis. The results in a tabular form are presented for each estimation in the appendix to this chapter. Also shown in the appendix is the Stata code used to estimate the results for this chapter.

4.4.1 Did SLA reform impact the schooling of farmers?

The validity of our natural experiment relies on the fact that the School Leaving Age reform indeed exogenously influenced farmers' education decisions. Graphically depicted in Figure 10 is a clear discontinuity in the number of years of education between farmers unaffected by the reform (born before 1957) and those born after, and consequently, affected by the reform. In regressing the number of years of education over the period from 1947 to 1967 there is a significant and positive relationship between farmer's year of education and farmer's birthdate. However, there is a slightly negative and nonsignificant relationship for both periods from 1947 to 1957 and 1957 to 1967. While the data points appear to be negatively correlated over time, this is not significant within each subperiod, but the discontinuity demonstrates an increase in education over the entire period of data available.

Figure 10: Discontinuity in years of education from ROSLA



The average effect of the reform on the number of years of education is illustrated in Figure 11. In Figure 11, we present the estimation results of equation (1), introducing respectively 1st, 2nd, or 3rd order polynomials for the running variable. The vertical bars correspond to 95% confidence intervals. Our results reveal that the average effect of the reform, around the discontinuity, ranges from 0.41 to 0.36 depending on the polynomial order's choice. In other words, the reform has, on average, increased education by 0.40 years for our sample of farmers. Also shown in Figure 11 is that there is little difference in the choice of order of polynomial. Regarding organic farming, we observe a positive and significant effect on all three economic performance variables.

Figure 11: Effect of ROSLA on number of years of education

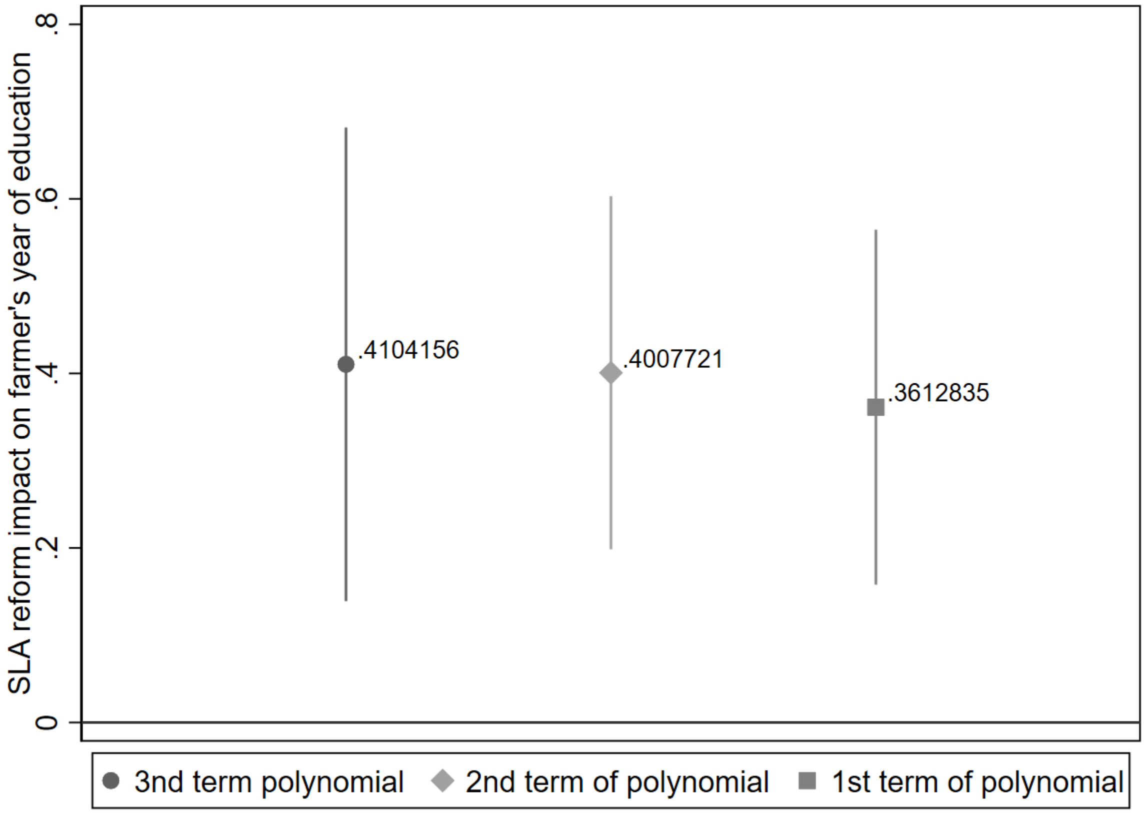
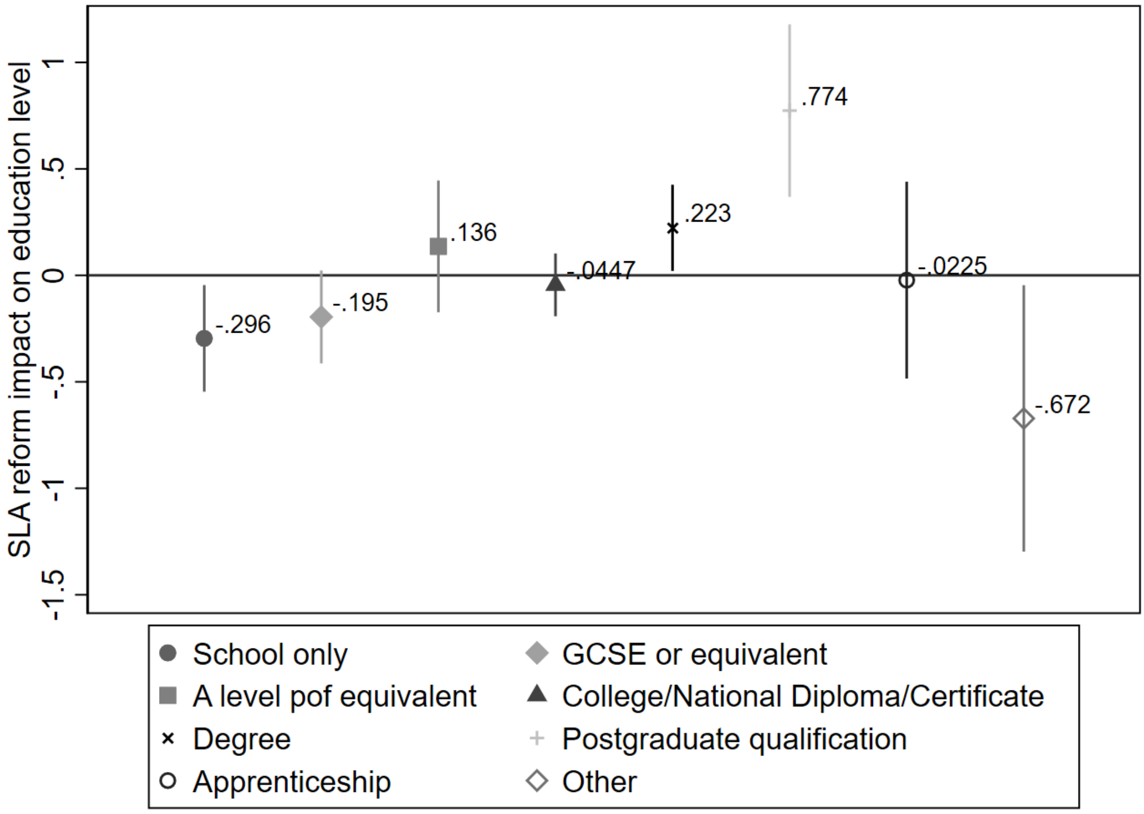


Figure 12 documents the average effect of the reform on education level, by diploma. In this case, we observe a significant decrease for lower education levels (schooling, GCSE, and others) and an increase for higher education levels (A-level or equivalent, degree, and Postgraduate). The effect on education levels such as postgraduate is more surprising, considering that the reform was expected to primarily impact individuals leaving the education system early. Our interpretation is that concurrently with the School Leaving Age reform, access to university was facilitated during the same period (*e.g.*, creation of regional universities).

Figure 12: Impact of ROSLA on farmers' education level



4.4.2 Main Results

After analysing the impact of the reform on the number of years of education for farmers, we will now explore the returns of an additional year of education on the economic performance of their farms. The economic performance of farms is measured as total output, gross margin, and total factor productivity (Figure 13). TFP here is estimated simply as a residual from the production function variables of labour, capital and labour rather than following the same procedure as in chapter 3. Additionally, we have examined the effect on total output per hectare and gross margin per hectare (Figure 15). Finally, control variables have been incorporated into our estimations (see Figure 14 and Figure 16).

Figure 13: Average farmer's education returns on farm performance (RDD estimates)

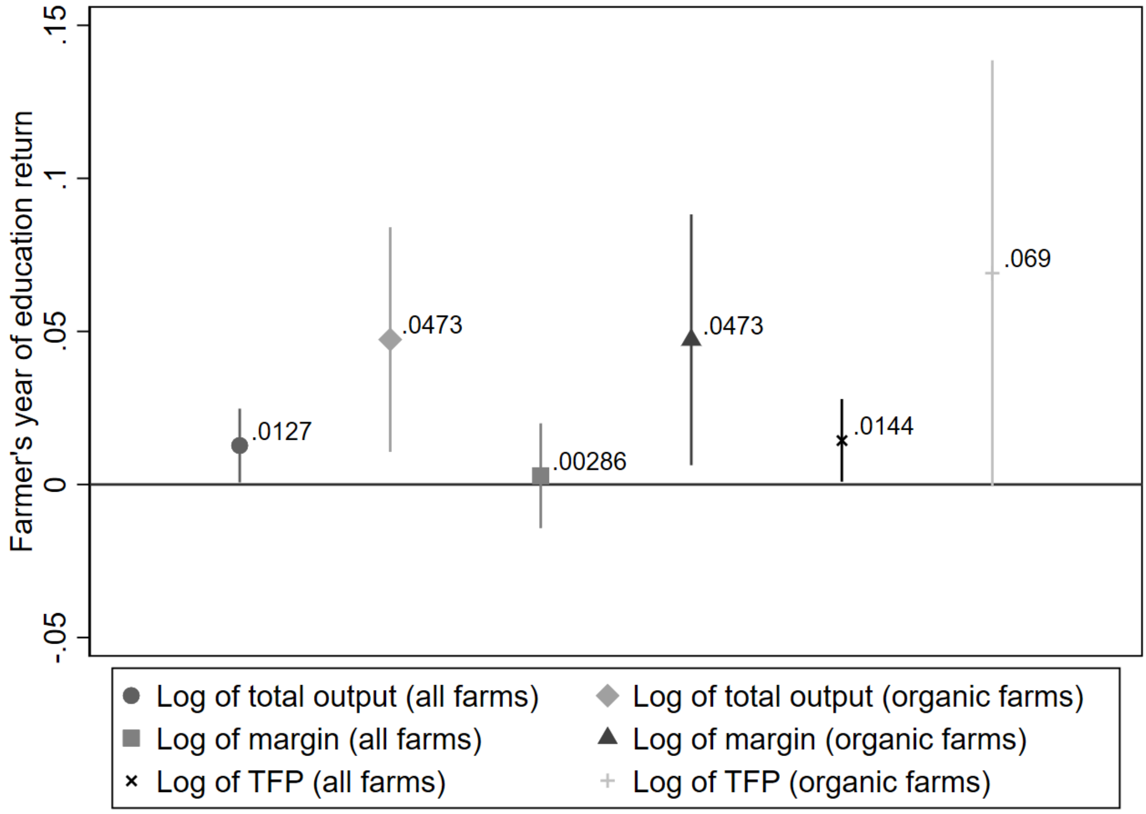
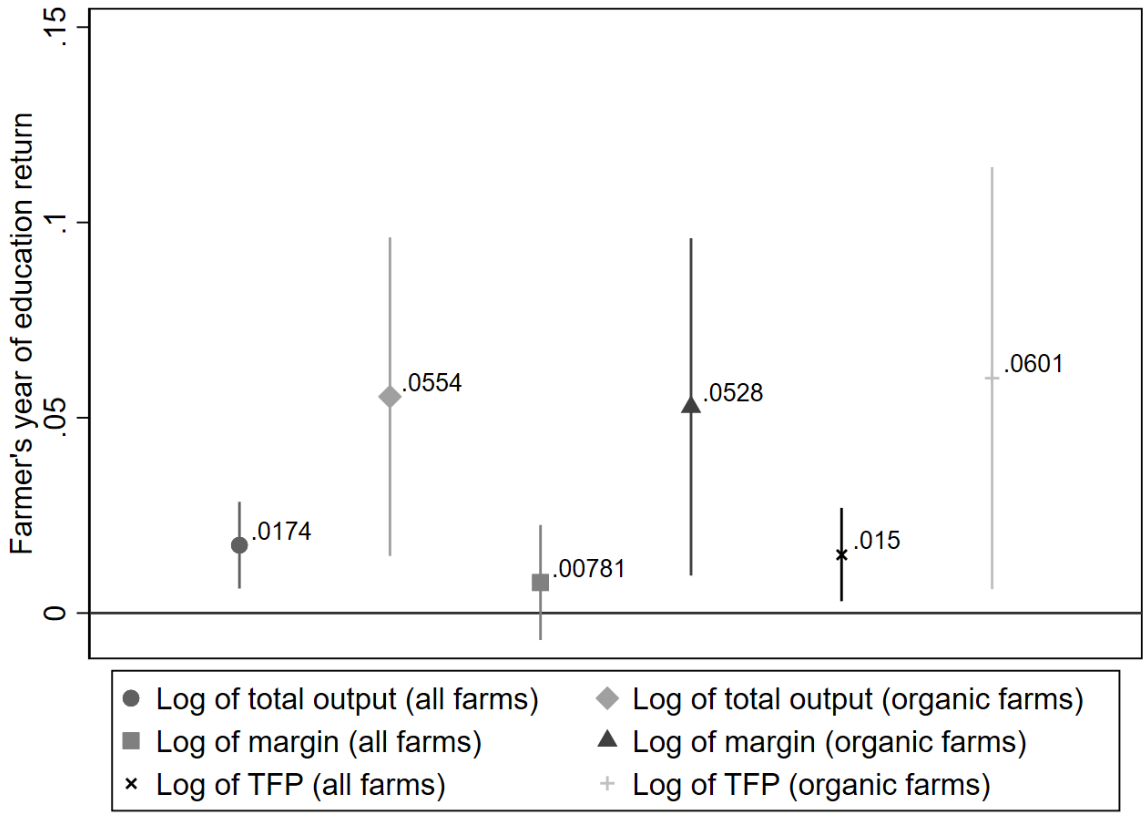


Figure 13 summarises the average return to education on farm economic performance for all farms in our sample, and for the subsample of organic farms. We observe a positive and significant effect of education on the logs of total output and TFP for all farm sample, while the effect on log of gross margin is not significant. As education includes the quantity of schooling received (Huffman, 2001), and more education may result in the earlier adoption of newer technologies so additional economic return should be earned by those with the additional education as found in these results.

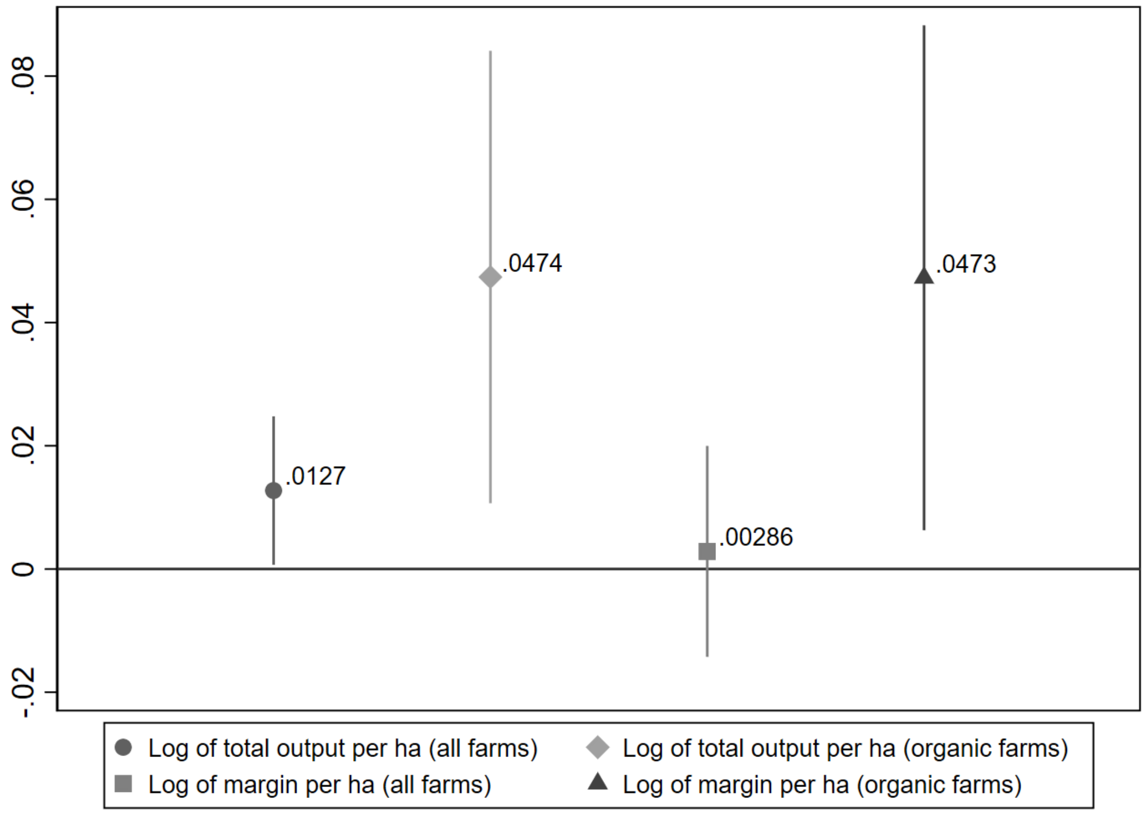
For the sample of all farms, we identify that an increase of one year of education, on average, enhances total output by 1.3% (1.4% for TFP). This return is slightly lower than what we find in the microeconomic literature (Phillips, 1994); (Singh and Santiago, 1997), suggesting that the relationship between education and agricultural performance is generally overestimated. On the other hand, studies in other sectors examining the effect of entrepreneurs' education on productivity show higher returns, around 5% (Queiró, 2022). These results hold when we add individual covariates, farm specialisation and altitude (Figure 14). Moreover, the estimated return to education estimated on all sample farmers seems to be lower than estimated on UK workers, around 7% (Devereux and Fan, 2011).

Figure 14: Average farmer's education returns on farm performance with covariates (RDD estimates)



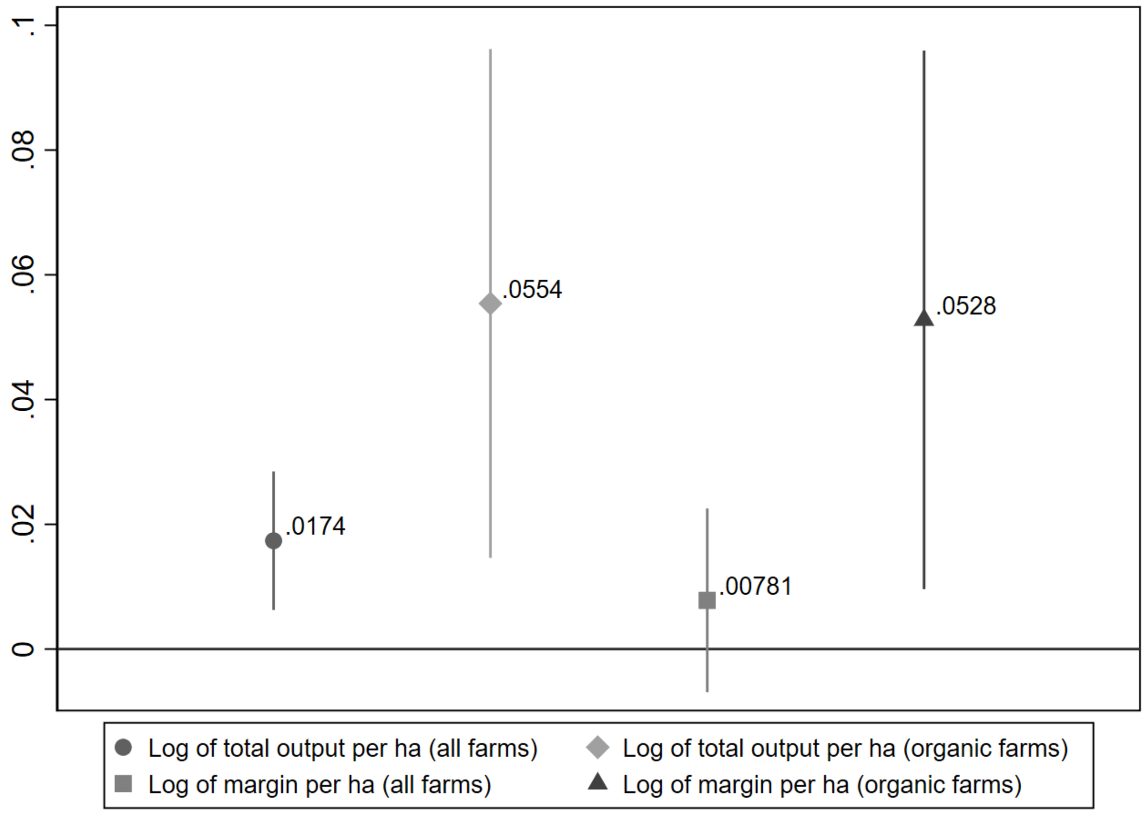
Nevertheless, we observe that the returns to education are higher for farms that have adopted organic agriculture. Indeed, the return to an additional year of education is 5.5% on total output (respectively 5.3% and 6% on gross margin and TFP). The difference between the two samples is statistically significant (z-test with a p-value less than 1%). Taylor and Yunez-Naude (2000) show that returns to education for Mexican farmers is higher in crop production than other activities (after controlling for selection in activity choice). Our results reveal a similar pattern regarding returns to better ecological practices.

Figure 15: Average farmer's education returns on farm performance per ha (RDD estimates)



These results are confirmed when we observe a higher return to education on total output and gross margin per hectare for organic farming operations. For total output, the average return is 1.2%, whereas the estimated return for organic farming operations is 4.7%. Overall, gross margin per hectare is not significantly influenced by education, while the return is consistently close to 5% for organic farms exclusively.

Figure 16: Average farmer's education returns on farm performance per ha with covariates (RDD estimates)



4.4.3 Robustness checks

This section is dedicated to assessing the robustness of our main results. First, we assess whether our results hold when we use different specifications (log-log rather than log-linear) or use a different bandwidth. Second, we show if the reform of school leaving age have influenced the farmer's choice to adopt organic farming, and farm input choices (similar to an exclusion restriction checks).

Figure 17 depicts the result by estimating a log-log relationship between farm economic performance and farmer's year of education, which reinforce our main results. We observe a similar pattern as depicted in Figure 13, *i.e.,* a return to education of around 1.5% for the entire sample concerning total output (1.6% for TFP; not significant for gross margin). We also observe a significantly better return for farmers who have adopted organic farming (5.7% for both total output and gross margin, and 8% for TFP, respectively).

Figure 17: Average farmer's education returns on farm performance in log-log (RDD estimates)

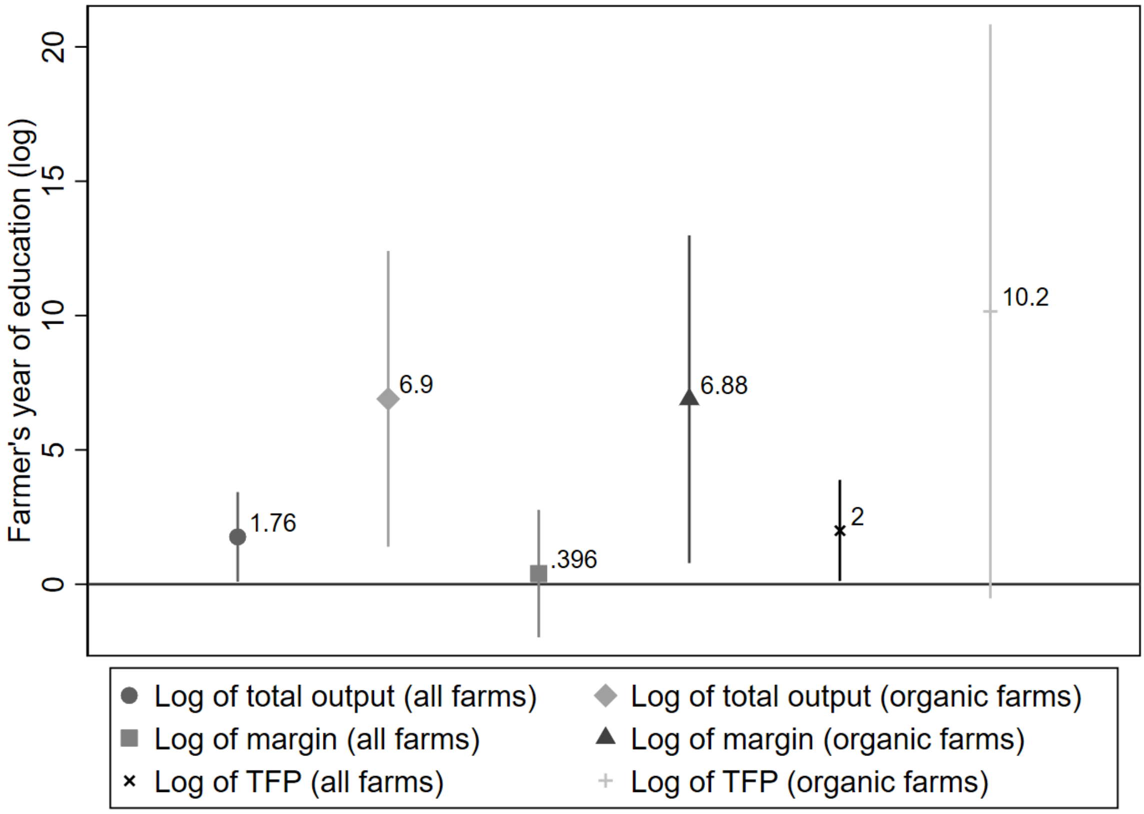
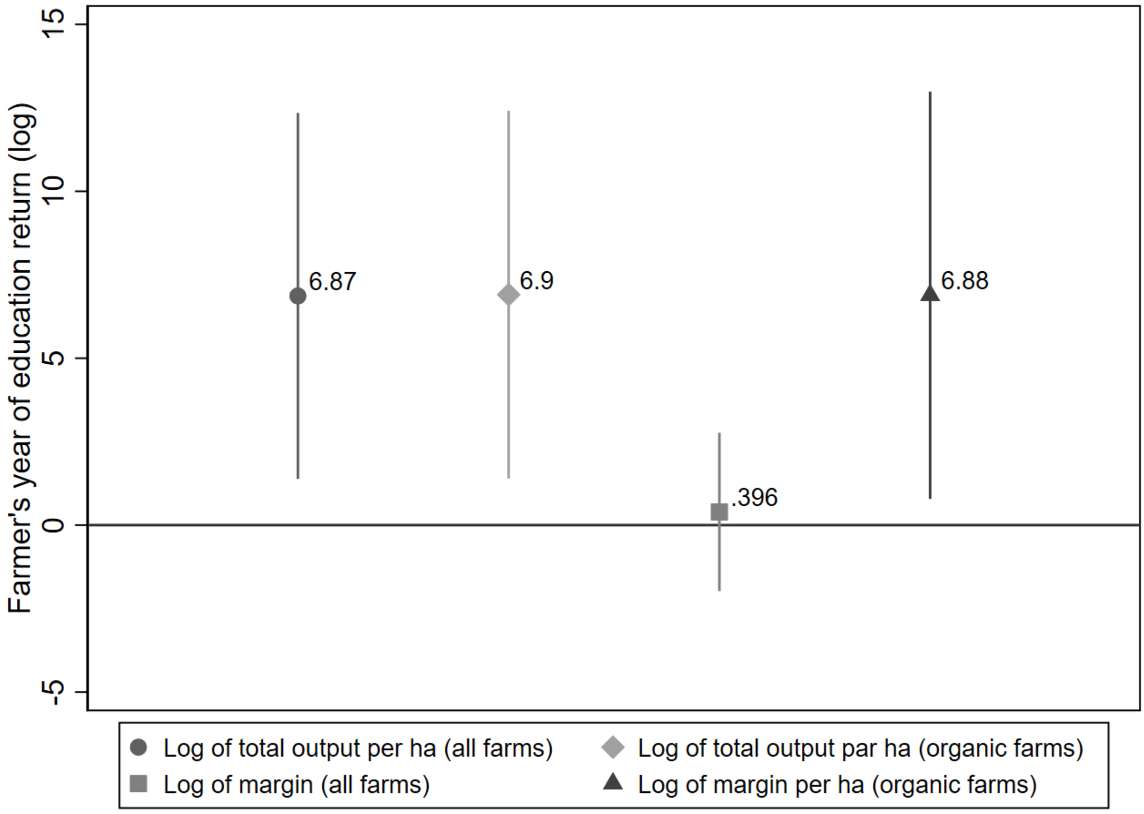


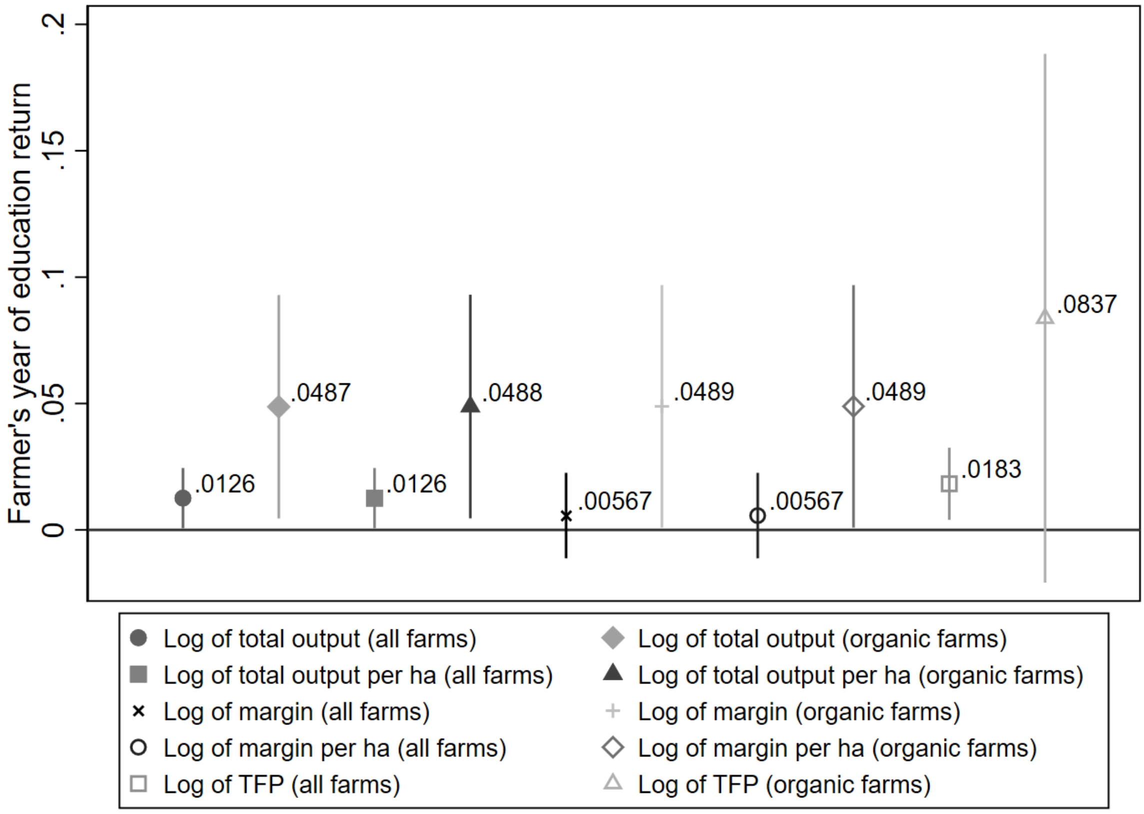
Figure 18: Average farmer's education returns on farm performance per ha in log-log (RDD estimates)



Then, we estimate equation (7) again, but this time by using a smaller cohort bandwidth (1949-1965) to test the sensitivity of our results to this choice. This latter bandwidth was chosen by using a local randomization based regression proposed by (Cattaneo *et al*., 2015) as a robustness check[11].

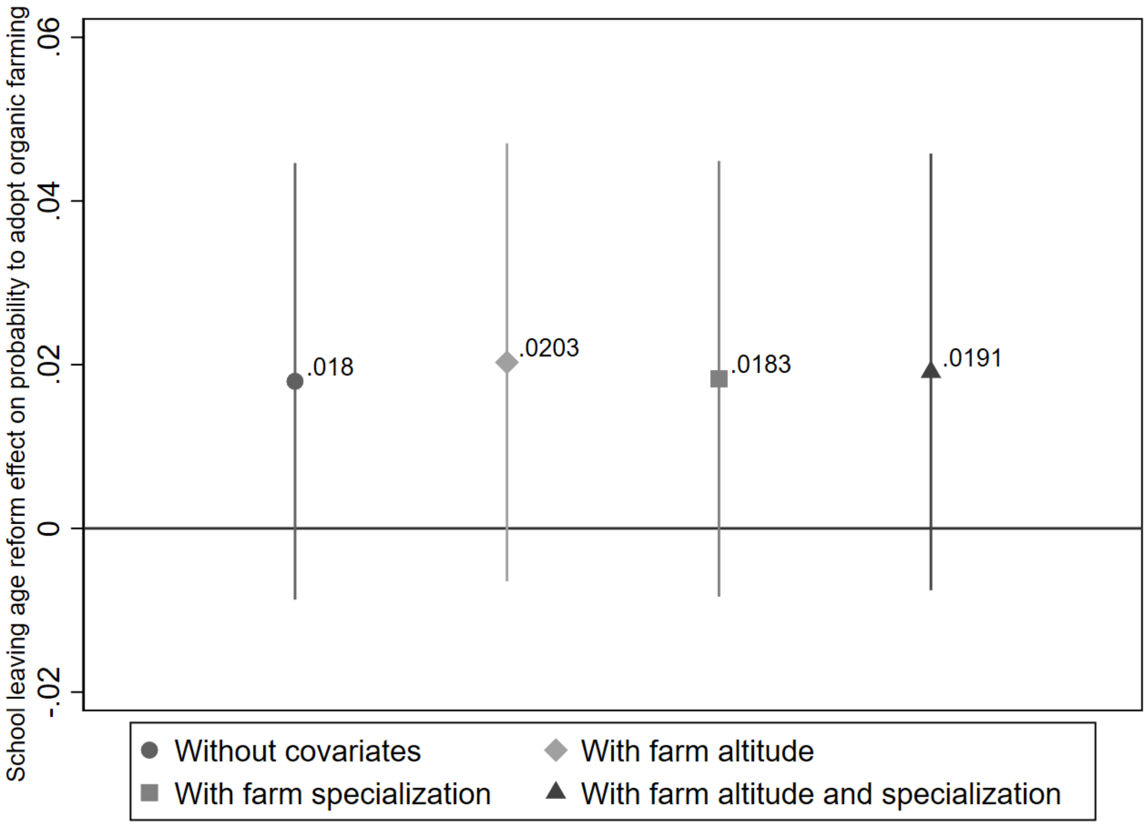
[11] To do so, we use farmer's gender, farmer has a spouse, farm specialization and farm altitude as covariates to compute local randomisation.

Figure 19: Average farmer's education returns with smaller bandwidth (1949-1965)



Our main results generally hold, although the precision of our estimations is affected by a reduction in the size of our sample. The return to education remains higher for farmers who have adopted organic farming (4.87% for organic farming compared to 1.26% for the all sample on total output).

Figure 20: Continuity assumption between ROSLA and farmers' propensity to adopt organic farming



In order to test the continuity assumption between the school leaving age reform and the farmer's propensity to adopt organic farming, we estimate a reduced form model linking directly the eligibility dummy D and the adoption of organic farming T (Figure 20). Since we observe a positive direct effect of the reform on organic farming, the latter is non-significant, which confirms the validity of our approach to identify heterogeneous returns to education along this dimension (Becker *et al.*, 2013).

4.5 Conclusion

To the best of our knowledge, this is the first work which exploits a quasi-experiment to identify a causal return to education in agriculture. Second and more specifically, this chapter explores the heterogeneous effects on organic and conventional farming which are shown in the literature to require different levels of labour as well as education. The quasi-experiment exploited the 1972 ROSLA in England and Wales whereby the students turning 15 years old in the 1972/1973 academic year, therefore born in 1957/1958, had an extra year of compulsory schooling from the cohort in the previous academic year. At the time, only about 40% of students continued studying after it was no longer required to stay in school so there was an associated increase in school buildings and teaching staff.

Farm Business Survey data taken from the years 2011 to 2019 was used in a regression discontinuity design methodology in two stages to estimate the returns to education. The first stage estimates the number of years of schooling depending on the birth year of the farm year whereby there is a clear discontinuity for those born after the ROSLA in 1972 as we would expect. Then, the second stage of the RDD estimates farm output using Two Stage Least Squares where the number of years of schooling is instrumented by their year of birth being before or after 1957. The model is extended through using a Correlated Random Effect model. In order to assess the specific farmer's education return for organic farming a HLATE approach is employed.

In the first stage estimation we find an average increase in education by 0.40 years for our sample of farmers**.** In the second stage, for the sample with all farms an increase of one year of education is estimated to result on average, in an increase in total output by 1.3% (1.4% for TFP). Organic farming on the other hand has a much higher increase in returns: an additional year of education increases total output by 5.5% (respectively 5.3% and 6% for gross margin and TFP). These results hold when expanding the model to use covariates and in robustness checks.

An important limitation in this chapter is that the ROSLA in 1972 was over 40 years ago and therefore how plausible is it that an impact on this policy was so significant as to both be economically and statistically significant. It is possible that an extra year of education resulted in a greater desire for students to partake in further education, for example postgraduate education or even just taking up more training opportunities than those who did not need to stay in school until they were 16. In addition, at the same time there was a reform in the type of schools available for students and a move away from private/grammar schools towards more comprehensive schooling. This would open opportunities for more students and possibly help them engage more with schools and receive a better-quality education. This makes it challenging to distinguish between this quality improvement and an increase in quantity of education.

It is important to first note that an additional year of education results, on average in an increase in total output and productivity for both conventional and organic farms. This suggests that production could be made more efficient through greater learning and farmers should be encouraged to undertake additional and relevant courses and training to increase their productivity on farms. The greater complexity and requirement to use fewer chemical inputs on organic farms also shows that the farmers who would gain most from additional education opportunities are organic farmers. Indeed, farmers with more education are also more likely to farm organically and with the environment in mind.

Appendix

Chapter 4 Results Tables

Table 18: Average farmer's education returns on farm performance (RDD estimates)

	LATE_ALL_output	LATE_org_output	LATE_ALL_margin	LATE_org_margin	LATE_ALL_TFP	LATE_org_TFP
farmer_ed_bis	0.013**	0.047**	0.003	0.047**	0.014**	0.069*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.04)
log_K	0.359***	0.381***	0.453***	0.426***		
	(0.01)	(0.03)	(0.01)	(0.04)		
log_L	0.664***	0.546***	0.758***	0.612***		
	(0.03)	(0.09)	(0.04)	(0.10)		
log_UAA	0.052***	0.118***	-0.030***	0.017		
	(0.01)	(0.03)	(0.01)	(0.03)		
forcing_cohort	0.002	0.012**	-0.003*	-0.004	-0.000	0.016*
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
sq_forcing_cohort	0.001***	0.001	0.001*	-0.000	0.000	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
m__farmer_ed_bis	0.077	-0.109	0.055	0.215	-0.036	-0.110***
	(0.09)	(0.12)	(0.12)	(0.14)	(0.04)	(0.04)
m__log_K	-0.536***	-0.106	-0.524**	1.262		
	(0.17)	(1.48)	(0.24)	(1.74)		
m__log_L	-4.170	-1.175	-6.741	-2.363		
	(3.37)	(2.11)	(4.70)	(2.49)		
m__log_UAA	-0.080***	-0.197	-0.004	-0.489**		
	(0.01)	(0.18)	(0.02)	(0.21)		
m__forcing_cohort	-0.125*	-0.027	0.040	0.263	0.016	-0.036
	(0.06)	(0.15)	(0.09)	(0.18)	(0.05)	(0.15)
m__sq_forcing_cohort	-0.063**	-0.051	-0.227***	-0.169	0.003	-0.014
	(0.03)	(0.10)	(0.04)	(0.12)	(0.02)	(0.04)
_cons	34.988	23.722	62.375	-19.017	2.470	5.305*
	(35.78)	(18.74)	(50.00)	(22.08)	(5.33)	(2.87)
r2_a	0.719	0.303	0.627	0.263	-0.213	-5.73
N	9274	1667	9045	1636	9274	1667

Table 19: Average farmer's education returns on farm performance per ha (RDD estimates)

	LATE_ALL_output_ha	LATE_org_output_ha	LATE_ALL_margin_ha	LATE_org_margin_ha
farmer_ed_bis	0.013**	0.047**	0.003	0.047**
	(0.01)	(0.02)	(0.01)	(0.02)
log_K	0.359***	0.381***	0.453***	0.426***
	(0.01)	(0.03)	(0.01)	(0.04)
log_L	0.664***	0.546***	0.758***	0.612***
	(0.03)	(0.09)	(0.04)	(0.10)
log_UAA	-0.948***	-0.882***	-1.030***	-0.983***
	(0.01)	(0.03)	(0.01)	(0.03)
forcing_cohort	0.002	0.012**	-0.003*	-0.004
	(0.00)	(0.01)	(0.00)	(0.01)
sq_forcing_cohort	0.001***	0.001	0.001*	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
m__farmer_ed_bis	0.076	-0.024	0.055	0.215
	(0.09)	(0.12)	(0.12)	(0.14)
m__log_K	-0.061	0.472	-0.524**	1.262
	(0.17)	(1.48)	(0.24)	(1.74)
m__log_L	-5.656*	-0.667	-6.741	-2.363
	(3.36)	(2.12)	(4.70)	(2.49)
m__log_UAA	-0.083***	-0.227	-0.004	-0.489**
	(0.01)	(0.18)	(0.02)	(0.21)
m__forcing_cohort	0.016	0.116	0.040	0.263
	(0.06)	(0.15)	(0.09)	(0.18)
m__sq_forcing_cohort	-0.166***	-0.064	-0.227***	-0.169
	(0.03)	(0.10)	(0.04)	(0.12)
_cons	45.390	2.948	62.375	-19.017
	(35.77)	(18.76)	(50.00)	(22.08)
r2_a	0.909	0.878	0.852	0.845
N	9274	1667	9045	1636

Table 20: Average farmer's education returns on farm performance with covariates (RDD estimates)

	LATE_ALL_output_COV	LATE_org_output_COV	LATE_ALL_margin_COV	LATE_org_margin_COV	LATE_ALL_TFP_COV	LATE_org_TFP_COV
farmer_ed_bis	0.017***	0.055***	0.008	0.053**	0.015**	0.060**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
log_K	0.279***	0.380***	0.363***	0.443***		
	(0.01)	(0.05)	(0.01)	(0.05)		
log_L	0.592***	0.456***	0.620***	0.443***		
	(0.02)	(0.10)	(0.03)	(0.11)		
log_UAA	0.136***	0.139***	0.114***	0.076**		
	(0.02)	(0.03)	(0.02)	(0.04)		
forcing_cohort	0.003*	0.018**	-0.004*	0.004	0.002	0.018*
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
sq_forcing_cohort	0.000**	0.002	0.000	-0.000	0.000**	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
m__farmer_ed_bis	-0.003	0.036	-0.027	0.282	-0.038	-0.130***
	(0.09)	(0.33)	(0.13)	(0.36)	(0.04)	(0.04)
m__log_K	-0.577***	-2.012	-0.479**	-0.056		
	(0.18)	(3.61)	(0.24)	(3.97)		
m__log_L	-3.605	3.860	-7.151*	0.927		
	(3.15)	(9.46)	(4.20)	(10.41)		
m__log_UAA	-0.148***	-0.182	-0.135***	-0.494**		
	(0.02)	(0.20)	(0.03)	(0.23)		
m__forcing_cohort	-0.156**	0.046	0.016	0.286	0.008	-0.118
	(0.06)	(0.28)	(0.09)	(0.31)	(0.05)	(0.14)
m__sq_forcing_cohort	-0.041	0.059	-0.203***	-0.092	0.005	-0.019
	(0.03)	(0.22)	(0.04)	(0.24)	(0.02)	(0.04)
m__farmer_gender	10.818*	-7.867	8.285	-4.588	3.245	
	(5.86)	(17.11)	(7.84)	(18.78)	(3.38)	
farmer_gender	-0.150***	-0.160	-0.162***	-0.242	-0.148***	-0.259
	(0.05)	(0.15)	(0.05)	(0.16)	(0.05)	(0.17)
1.altitude	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
2.altitude	-0.014	0.172	-0.133***	0.089	-0.024	0.195
	(0.02)	(0.11)	(0.03)	(0.12)	(0.02)	(0.12)
3.altitude	-0.234***	-0.184	-0.376***	-0.217	-0.245***	-0.138
	(0.08)	(0.32)	(0.11)	(0.35)	(0.08)	(0.35)
4.altitude	0.293	1.163	0.099	1.273	0.234	1.382
	(0.20)	(1.18)	(0.25)	(1.26)	(0.19)	(1.36)
11.ePub_farm_type	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
12.ePub_farm_type	0.030	0.230*	0.146***	0.349**	0.051**	0.240*
	(0.03)	(0.13)	(0.03)	(0.15)	(0.02)	(0.14)
21.ePub_farm_type	0.128***	0.422**	0.148***	0.511**	0.149***	0.352**
	(0.04)	(0.18)	(0.06)	(0.20)	(0.04)	(0.18)
22.ePub_farm_type	-0.383***	0.032	-0.478***	-0.048	0.175***	0.558**
	(0.04)	(0.20)	(0.05)	(0.21)	(0.04)	(0.25)
31.ePub_farm_type	0.287***	0.568**	0.284***	0.690***	0.099***	0.250

	(0.04)	(0.24)	(0.05)	(0.26)	(0.03)	(0.24)
32.ePub_farm_type	0.639***	1.140***	0.534***	1.067***	0.130***	0.494**
	(0.04)	(0.23)	(0.05)	(0.25)	(0.04)	(0.23)
33.ePub_farm_type	-0.189***	0.183	-0.305***	0.189	0.117***	0.475**
	(0.03)	(0.20)	(0.04)	(0.21)	(0.03)	(0.23)
131.ePub_farm_type	-0.396***	-0.701***	-0.477***	-0.996***	-0.059	-0.678*
	(0.08)	(0.23)	(0.10)	(0.25)	(0.08)	(0.35)
132.ePub_farm_type	0.085	0.091	0.437***	0.482**	0.005	-0.419***
	(0.06)	(0.21)	(0.08)	(0.23)	(0.03)	(0.16)
133.ePub_farm_type	0.266***	0.389	0.707***	0.911***	0.071	-0.316
	(0.07)	(0.30)	(0.10)	(0.33)	(0.05)	(0.26)
134.ePub_farm_type	-0.356***	0.276	-0.170***	0.481	0.000	0.358
	(0.05)	(0.31)	(0.06)	(0.34)	(0.04)	(0.27)
231.ePub_farm_type	-0.393***	0.209	-0.465***	0.344	0.240***	0.830***
	(0.05)	(0.25)	(0.08)	(0.28)	(0.06)	(0.31)
232.ePub_farm_type	-0.528***	-0.101	-0.857***	-0.409	0.251***	0.671**
	(0.06)	(0.25)	(0.09)	(0.27)	(0.06)	(0.30)
233.ePub_farm_type	-0.419***	0.237	-0.657***	0.188	0.282***	0.931**
	(0.07)	(0.30)	(0.09)	(0.32)	(0.07)	(0.37)
_cons	29.436	-10.589	67.721	-37.322	2.636	5.406**
	(33.48)	(69.43)	(44.60)	(76.42)	(5.29)	(2.45)
r2_a	0.754	0.172	0.703	0.232	-0.196	-3.765
N	9274	1667	9045	1636	9274	1667

Table 21: Average farmer's education returns on farm performance per ha with covariates (RDD estimates)

	LATE_ALL_output_ ha_COV	LATE_org_output_ ha_COV	LATE_ALL_margin_ ha_COV	LATE_org_margin_ ha_COV
farmer_ed_bis	0.017***	0.055***	0.008	0.053**
	(0.01)	(0.02)	(0.01)	(0.02)
log_K	0.279***	0.380***	0.363***	0.443***
	(0.01)	(0.05)	(0.01)	(0.05)
log_L	0.592***	0.456***	0.620***	0.443***
	(0.02)	(0.10)	(0.03)	(0.11)
log_UAA	-0.864***	0.862***	0.886***	-0.924***
	(0.02)	(0.03)	(0.02)	(0.04)
forcing_cohort	0.003*	0.018**	-0.004*	0.004
	(0.00)	(0.01)	(0.00)	(0.01)
sq_forcing_cohort	0.000**	0.002	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
m__farmer_ed_bis	-0.007	0.025	-0.027	0.282
	(0.09)	(0.33)	(0.13)	(0.36)
m_log_K	-0.109	-0.409	-0.479**	-0.056
	(0.18)	(3.61)	(0.24)	(3.97)
m_log_L	-5.098	1.453	-7.151*	0.927
	(3.15)	(9.47)	(4.20)	(10.41)
m_log_UAA	-0.151***	-0.229	-0.135***	-0.494**
	(0.02)	(0.20)	(0.03)	(0.23)
m_forcing_cohort	-0.016	0.117	0.016	0.286
	(0.06)	(0.28)	(0.09)	(0.31)
m__sq_forcing_cohort	-0.144***	-0.014	-0.203***	-0.092
	(0.03)	(0.22)	(0.04)	(0.24)
m__farmer_gender	11.302*	-2.443	8.285	-4.588
	(5.86)	(17.11)	(7.84)	(18.78)
farmer_gender	-0.150***	-0.160	-0.162***	-0.242
	(0.05)	(0.15)	(0.05)	(0.16)
1.altitude	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
2.altitude	-0.014	0.172	-0.133***	0.089
	(0.02)	(0.11)	(0.03)	(0.12)
3.altitude	-0.234***	-0.186	-0.376***	-0.217
	(0.08)	(0.32)	(0.11)	(0.35)
4.altitude	0.293	1.164	0.099	1.273
	(0.20)	(1.18)	(0.25)	(1.26)
11.ePub_farm_type	0	0	0	0
	(.)	(.)	(.)	(.)
12.ePub_farm_type	0.030	0.229*	0.146***	0.349**
	(0.03)	(0.13)	(0.03)	(0.15)
21.ePub_farm_type	0.128***	0.421**	0.148***	0.511**
	(0.04)	(0.18)	(0.06)	(0.20)
22.ePub_farm_type	-0.383***	0.032	-0.478***	-0.048
	(0.04)	(0.20)	(0.05)	(0.21)
31.ePub_farm_type	0.287***	0.567**	0.284***	0.690***
	(0.04)	(0.24)	(0.05)	(0.26)

32.ePub_farm_type	0.639***	1.139***	0.534***	1.067***
	(0.04)	(0.23)	(0.05)	(0.25)
33.ePub_farm_type	-0.189***	0.183	-0.305***	0.189
	(0.03)	(0.20)	(0.04)	(0.21)
131.ePub_farm_type	-0.396***	-0.702***	-0.477***	-0.996***
	(0.08)	(0.23)	(0.10)	(0.25)
132.ePub_farm_type	0.085	0.089	0.437***	0.482**
	(0.06)	(0.21)	(0.08)	(0.23)
133.ePub_farm_type	0.266***	0.389	0.707***	0.911***
	(0.07)	(0.30)	(0.10)	(0.33)
134.ePub_farm_type	-0.356***	0.275	-0.170***	0.481
	(0.05)	(0.31)	(0.06)	(0.34)
231.ePub_farm_type	-0.393***	0.209	-0.465***	0.344
	(0.05)	(0.25)	(0.08)	(0.28)
232.ePub_farm_type	-0.528***	-0.101	-0.857***	-0.409
	(0.06)	(0.25)	(0.09)	(0.27)
233.ePub_farm_type	-0.419***	0.238	-0.657***	0.188
	(0.07)	(0.30)	(0.09)	(0.32)
_cons	39.922	-10.291	67.721	-37.322
	(33.48)	(69.45)	(44.60)	(76.42)
r2_a	0.920	0.855	0.883	0.838
N	9274	1667	9045	1636

Table 22: Average farmer's education returns on farm performance in log-log (RDD estimates)

	LATE_ALL_output_log_log	LATE_org_output_log_log	LATE_ALL_margin_log_log	LATE_org_margin_log_log	LATE_ALL_TFP_log_log	LATE_org_TFP_log_log
log_farmer_yr_educ	1.764**	6.913**	0.396	6.898**	2.005**	10.193*
	(0.85)	(2.81)	(1.21)	(3.12)	(0.96)	(5.47)
log_K	0.357***	0.379***	0.453***	0.423***		
	(0.01)	(0.03)	(0.01)	(0.04)		
log_L	0.665***	0.541***	0.758***	0.606***		
	(0.03)	(0.09)	(0.04)	(0.11)		
log_UAA	0.053***	0.120***	-0.030***	0.022		
	(0.01)	(0.03)	(0.01)	(0.03)		
forcing_cohort	0.002	0.012**	-0.003*	-0.004	-0.000	0.017*
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
sq_forcing_cohort	0.001**	0.001	0.001	-0.001	0.000	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
m__log_K	-0.472***	-0.385	-0.478**	-0.206	-0.059	0.119
	(0.16)	(0.82)	(0.22)	(0.96)	(0.15)	(1.16)
m_log_L	-6.317***	-12.571	-8.298**	-14.270	0.841	-9.582
	(2.32)	(11.81)	(3.23)	(13.87)	(2.13)	(16.81)
m_log_UAA	-0.083***	-0.272***	-0.006	-0.155**	-0.003	-0.155*
	(0.01)	(0.06)	(0.02)	(0.08)	(0.01)	(0.08)
m_forcing_cohort	-0.165***	-0.137	0.011	0.217	0.031	0.016
	(0.05)	(0.24)	(0.06)	(0.27)	(0.04)	(0.34)
m__sq_forcing_cohort	-0.075***	-0.048	-0.235***	-0.026	-0.004	-0.052
	(0.03)	(0.13)	(0.04)	(0.16)	(0.02)	(0.19)
_cons	58.781***	97.461	81.133***	107.588	-11.551	54.621
	(18.98)	(93.94)	(26.34)	(109.94)	(17.58)	(133.16)
r2_a	0.718	0.259	0.627	0.229	-0.224	-6.395
N	9274	1667	9045	1636	9274	1667

Table 23: Average farmer's education returns on farm performance per ha in log-log (RDD estimates)

	LATE_ALL_ output_ha_log_log	LATE_org_ output_ha_log_log	LATE_ALL _margin_ha_log_log	LATE_org _margin_ha_log_log
log_farmer_yr_educ	1.764**	6.912**	0.396	6.898**
	(0.85)	(2.81)	(1.21)	(3.12)
log_K	0.357***	0.379***	0.453***	0.423***
	(0.01)	(0.03)	(0.01)	(0.04)
log_L	0.665***	0.541***	0.758***	0.606***
	(0.03)	(0.09)	(0.04)	(0.11)
log_UAA	-0.947***	-0.880***	-1.030***	-0.978***
	(0.01)	(0.03)	(0.01)	(0.03)
forcing_cohort	0.002	0.012**	-0.003*	-0.004
	(0.00)	(0.01)	(0.00)	(0.01)
sq_forcing_cohort	0.001**	0.001	0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
m__log_K	0.003	0.091	-0.478**	-0.206
	(0.16)	(0.82)	(0.22)	(0.96)
m_log_L	-7.791***	-14.064	-8.298**	-14.270
	(2.32)	(11.81)	(3.23)	(13.87)
m_log_UAA	-0.086***	-0.275***	-0.00	-0.155**
	(0.01)	(0.06)	(0.02)	(0.08)
m_forcing_cohort	-0.023	0.005	0.011	0.217
	(0.05)	(0.24)	(0.06)	(0.27)
m__sq _forcing_cohort	-0.178***	-0.152	-0.235***	-0.026
	(0.03)	(0.13)	(0.04)	(0.16)
_cons	69.050***	107.863	81.133***	107.588
	(18.98)	(93.93)	(26.34)	(109.94)
r2_a	0.909	0.871	0.853	0.838
N	9274	1667	9045	1636

Table 24: Average farmer's education returns with smaller bandwidth (1949-1965)

	LATE_ALL_output_band	LATE_org_output_band	LATE_ALL_output_ha_band	LATE_org_output_ha_band	LATE_ALL_margin_band	LATE_org_margin_band	LATE_ALL_margin_ha_band	LATE_org_margin_ha_band	LATE_ALL_TFP_band	LATE_org_TFP_band
farmer _ed_bis	0.013**	0.049**	0.013**	0.049**	0.006	0.049**	0.006	0.049**	0.018**	0.084
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.05)
log_K	0.370***	0.394***	0.370***	0.394***	0.474***	0.427***	0.474***	0.427***		
	(0.01)	(0.04)	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)		
log_L	0.653***	0.527***	0.653***	0.527***	0.727***	0.597***	0.727***	0.587***		
	(0.03)	(0.11)	(0.03)	(0.11)	(0.05)	(0.12)	(0.05)	(0.12)		

log_UAA	0.048***	0.104***	-0.952***	-0.896***	-0.037***	0.010	-1.037***	-0.990***		
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)		
forcing_cohort	0.002	0.013*	0.002	0.013*	-0.002	-0.003	-0.002	-0.003	0.001	0.024
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)
sq_forcing_cohort	0.001**	0.001	0.001**	0.001	0.000	-0.001	0.000	-0.001	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
m_log_K	-0.460***	-0.420	0.015	0.055	-0.437*	-0.372	-0.437*	-0.372	-0.048	0.148
	(0.17)	(0.85)	(0.17)	(0.85)	(0.24)	(1.00)	(0.24)	(1.00)	(0.16)	(1.38)
m_log_L	-6.611***	-11.265	-8.089***	-12.753	-9.288***	-12.443	-9.288***	-12.443	0.828	-8.674
	(2.46)	(12.21)	(2.46)	(12.21)	(3.42)	(14.37)	(3.42)	(14.37)	(2.39)	(19.88)
m_log_UAA	-0.079***	-0.252***	-0.082***	-0.256***	-0.001	-0.141*	-0.001	-0.141*	-0.003	-0.171
	(0.01)	(0.07)	(0.01)	(0.07)	(0.02)	(0.08)	(0.02)	(0.08)	(0.01)	(0.11)
m_forcing_cohort	-0.163***	-0.138	-0.021	0.005	0.027	0.158	0.027	0.158	0.035	0.011
	(0.05)	(0.24)	(0.05)	(0.24)	(0.07)	(0.29)	(0.07)	(0.29)	(0.05)	(0.40)
m__sq_forcing_cohort	-0.076***	-0.041	-0.179***	-0.145	-0.240***	-0.058	-0,240***	-0.058	-0.003	-0.040
	(0.03)	(0.14)	(0.03)	(0.14)	(0.04)	(0.16)	(0.04)	(0.16)	(0.03)	(0.22)
_cons	64.252***	98.849	74.547***	109.219	89.600***	107.117	89.600***	107.117	-8.490	63.113
	(19.84)	(97.64)	(19.84)	(97.62)	(27.59)	(114.74)	(27.59)	(114.74)	(19.32)	(158.46)
r2_a	0.718	0.251	0.907	0.868	0.626	0.208	0.850	0.832	-0.366	-8.755
N	8487	1544	8487	1544	8272	1514	8272	1514	8487	1544

Chapter 4 Code

```
***** Results
*** Did SLA reform impact the schooling of farmers?
**** Plot discontinuity on Farmer's education - Figure 6
rdplot log_farmer_yr_educ birthdate if birthdate>=1949 & birthdate<=1967, c(1957) p(1)

*** Effect of ROSLA on number of years of education - Figure 7
generate  forcing_cohort=1957-birthdate
generate  sq_forcing_cohort=forcing_cohort*forcing_cohort
generate cb_forcing_cohort=forcing_cohort*forcing_cohort*forcing_cohort

reg farmer_yr_educ dummy__after_reform forcing_cohort sq_forcing_cohort cb_forcing_cohort if birthdate>=1949 & birthdate<=1967 & diff==0
estimates store p3
reg farmer_yr_educ dummy__after_reform forcing_cohort i.altitude  if birthdate>=1949 & birthdate<=1967 & diff==0
estimates store p2
reg farmer_yr_educ dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0
estimates store p1
```

```
coefplot (p3, label("3rd term polynomial")) (p2, label("2nd term polynomial")) (p1, label("1st term polynomial")), vertical keep(dummy__after_reform) yline(0) ytitle(SLA reform impact on farmer's year of education) legend(pos(6) row(1)) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))

*** Impact of ROSLA on farmers' education level - Figure 8

estimates clear

logit missing_farm_educ dummy__after_reform forcing_cohort    if birthdate>=1950 & birthdate<=1965 & diff==0

estimates store code0

logit farm_educ_code_1 dummy__after_reform forcing_cohort    if birthdate>=1949 & birthdate<=1967 & diff==0

estimates store code1

logit farm_educ_code_2 dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0

estimates store code2

logit farm_educ_code_3 dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0

estimates store code3

logit farm_educ_code_4 dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0

estimates store code4

logit farm_educ_code_5 dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0

estimates store code5

logit farm_educ_code_6 dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0

estimates store code6

logit farm_educ_code_9 dummy__after_reform forcing_cohort  if birthdate>=1949 & birthdate<=1967 & diff==0
```

estimates store code9

coefplot *, format(%9.3g) vertical keep(dummy__after_reform) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))

****Main Results

*** Average farmer's education returns on farm performance (total and per ha) (RDD estimates) - Figure 9 and Figure 11

estimates clear

drop m__* d__*

by year, sort: center farmer_ed_bis log_K log_L log_UAA forcing_cohort sq_forcing_cohort if birthdate>=1949 & birthdate<=1967 & diff==0, prefix(d__) mean(m__)

*Log of total output (all farms)

ivreg2 log_output (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_output

ivreg2 log_output_ha (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_output_ha

*Log of margin (all farms)

ivreg2 log_gross_margin (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_margin

```
ivreg2 log_gross_margin_ha ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967  ,

estimates store LATE_ALL_margin_ha

drop m__* d__*

by year, sort: center farmer_ed_bis  forcing_cohort sq_forcing_cohort if birthdate>=1949 & birthdate<=1967 & diff==0, prefix(d__) mean(m__)

*Log of TFP (all farms)

ivreg2 log_TFP_6_12 ( farmer_ed_bis=dummy__after_reform) forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967,

estimates store LATE_ALL_TFP

drop m__* d__*

by year, sort: center farmer_ed_bis  log_K log_L log_UAA  forcing_cohort sq_forcing_cohort if birthdate>=1949 & birthdate<=1967 & diff==0 & dummy_organic_fully==1, prefix(d__) mean(m__)

*Log of total output (organic farms)

ivreg2 log_output ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_output

ivreg2 log_output_ha ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_output_ha

*Log of margin (organic farms)

ivreg2 log_gross_margin ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_margin
```

```
ivreg2 log_gross_margin_ha ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_ha

drop m__* d__*

by year, sort: center farmer_ed_bis  forcing_cohort sq_forcing_cohort if birthdate>=1949 & birthdate<=1967 & diff==0 & dummy_organic_fully==1, prefix(d__) mean(m__)

*Log of TFP (organic farms)

ivreg2 log_TFP_6_12 ( farmer_ed_bis=dummy__after_reform) forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_TFP


estout LATE_ALL_output LATE_org_output LATE_ALL_margin LATE_org_margin LATE_ALL_TFP LATE_org_TFP, style(tab) cells(b(star fmt(3)) se(par fmt(2))) stats(r2_a N, fmt(%9.3f %9.0g)) starlevels(* 0.10 ** 0.05 *** 0.01) replace

coefplot LATE_ALL_output LATE_org_output LATE_ALL_margin LATE_org_margin LATE_ALL_TFP LATE_org_TFP , format(%9.3g) vertical keep(farmer_ed_bis) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))

estout LATE_ALL_output_ha LATE_org_output_ha LATE_ALL_margin_ha LATE_org_margin_ha, style(tab) cells(b(star fmt(3)) se(par fmt(2))) stats(r2_a N, fmt(%9.3f %9.0g)) starlevels(* 0.10 ** 0.05 *** 0.01) replace

coefplot LATE_ALL_output_ha LATE_org_output_ha LATE_ALL_margin_ha LATE_org_margin_ha , format(%9.3g) vertical keep(farmer_ed_bis) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))


***** Adding covariates such as gender dummy farm type altitude spouse

**Figure 10 and Figure 12 - Average farmer's education on farm performance including covariates in the model specification
```

```
**All

drop m__* d__*

by year, sort: center farmer_ed_bis  log_K log_L log_UAA  forcing_cohort sq_forcing_cohort farmer_gender if birthdate>=1949 & birthdate<=1967 & diff==0, prefix(d__) mean(m__)

*Log of total output (all farms)

ivreg2 log_output ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__*  farmer_gender i.altitude i.ePub_farm_type if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_output_COV

ivreg2 log_output_ha ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* farmer_gender i.altitude i.ePub_farm_type if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_output_ha_COV

ivreg2 log_gross_margin ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* farmer_gender i.altitude i.ePub_farm_type if birthdate>=1949 & birthdate<=1967  ,

estimates store LATE_ALL_margin_COV

ivreg2 log_gross_margin_ha ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* farmer_gender i.altitude i.ePub_farm_type if birthdate>=1949 & birthdate<=1967  ,

estimates store LATE_ALL_margin_ha_COV

drop m__* d__*

by year, sort: center farmer_ed_bis  forcing_cohort sq_forcing_cohort if birthdate>=1949 & birthdate<=1967 & diff==0, prefix(d__) mean(m__)

ivreg2 log_TFP_6_12 ( farmer_ed_bis=dummy__after_reform) forcing_cohort sq_forcing_cohort  m__* farmer_gender i.altitude i.ePub_farm_type if birthdate>=1949 & birthdate<=1967,

estimates store LATE_ALL_TFP_COV
```

*** organic

drop m__* d__*

by year, sort: center farmer_ed_bis log_K log_L log_UAA forcing_cohort sq_forcing_cohort farmer_gender if birthdate>=1949 & birthdate<=1967 & diff==0 & dummy_organic_fully==1, prefix(d__) mean(m__)

ivreg2 log_output (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort farmer_gender i.altitude i.ePub_farm_type m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_output_COV

ivreg2 log_output_ha (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort farmer_gender i.altitude i.ePub_farm_type m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_output_ha_COV

ivreg2 log_gross_margin (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort farmer_gender i.altitude i.ePub_farm_type m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_COV

ivreg2 log_gross_margin_ha (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort farmer_gender i.altitude i.ePub_farm_type m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_ha_COV

drop m__* d__*

by year, sort: center farmer_ed_bis forcing_cohort sq_forcing_cohort farmer_gender if birthdate>=1949 & birthdate<=1967 & diff==0 & dummy_organic_fully==1, prefix(d__) mean(m__)

****Figure 10 - Log of TFP (org farms)

ivreg2 log_TFP_6_12 (farmer_ed_bis=dummy__after_reform) forcing_cohort sq_forcing_cohort m__* farmer_gender i.altitude i.ePub_farm_type if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1,

estimates store LATE_org_TFP_COV

drop m__* d__*

estout LATE_ALL_output_COV LATE_org_output_COV LATE_ALL_margin_COV LATE_org_margin_COV LATE_ALL_TFP_COV LATE_org_TFP_COV, style(tex) cells(b(star fmt(3)) se(par fmt(2))) stats(r2_a N, fmt(%9.3f %9.0g)) replace

coefplot LATE_ALL_output_COV LATE_org_output_COV LATE_ALL_margin_COV LATE_org_margin_COV LATE_ALL_TFP_COV LATE_org_TFP_COV , format(%9.3g) vertical keep(farmer_ed_bis) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))

coefplot LATE_ALL_output_ha_COV LATE_org_output_ha_COV LATE_ALL_margin_ha_COV LATE_org_margin_ha_COV , format(%9.3g) vertical keep(farmer_ed_bis) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))

****Robustness checks

*Figure 13 and Figure 14 - log-log estimates

*Log-Log of total output (all farms)

ivreg2 log_output (log_farmer_yr_educ =dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_output_log_log

ivreg2 log_output_ha (log_farmer_yr_educ =dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_output_ha_log_log

```
*Log-Log of margin (all farms)

ivreg2 log_gross_margin ( log_farmer_yr_educ=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 ,

estimates store LATE_ALL_margin_log_log

ivreg2 log_gross_margin_ha ( log_farmer_yr_educ=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967  ,

estimates store LATE_ALL_margin_ha_log_log

*Log-Log of TFP (all farms)

ivreg2 log_TFP_6_12 ( log_farmer_yr_educ=dummy__after_reform) forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967,

estimates store LATE_ALL_TFP_log_log

*Log-Log of total output (organic farms)

ivreg2 log_output ( log_farmer_yr_educ=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_output_log_log

ivreg2 log_output_ha ( log_farmer_yr_educ=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_output_ha_log_log


*Log-Log of margin (organic farms)

ivreg2 log_gross_margin ( log_farmer_yr_educ=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_log_log
```

ivreg2 log_gross_margin_ha (log_farmer_yr_educ=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_ha_log_log

*Log-Log of TFP (organic farms)

ivreg2 log_TFP_6_12 (log_farmer_yr_educ=dummy__after_reform) forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1967 & dummy_organic_fully==1 ,

estimates store LATE_org_TFP_log_log

estout LATE_ALL_output_log_log LATE_org_output_log_log LATE_ALL_margin_log_log LATE_org_margin_log_log LATE_ALL_TFP_log_log LATE_org_TFP_log_log, style(tab) cells(b(star fmt(3)) se(par fmt(2))) stats(r2_a N, fmt(%9.3f %9.0g)) starlevels(* 0.10 ** 0.05 *** 0.01) replace

estout LATE_ALL_output_ha_log_log LATE_org_output_ha_log_log LATE_ALL_margin_ha_log_log LATE_org_margin_ha_log_log, style(tab) cells(b(star fmt(3)) se(par fmt(2))) stats(r2_a N, fmt(%9.3f %9.0g)) starlevels(* 0.10 ** 0.05 *** 0.01) replace

coefplot LATE_ALL_output_ha_log_log LATE_org_output_ha_log_log LATE_ALL_margin_ha_log_log LATE_org_margin_ha_log_log , format(%9.3g) vertical keep(farmer_ed_bis) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))

*** Smaller bandwidth - Figure 15

estimates clear

*Log of total output (all farms)

ivreg2 log_output (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965 ,

estimates store LATE_ALL_output_band

ivreg2 log_output_ha (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965 ,

estimates store LATE_ALL_output_ha_band

*Log of margin (all farms)

ivreg2 log_gross_margin (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965 ,

estimates store LATE_ALL_margin_band

ivreg2 log_gross_margin_ha (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965 ,

estimates store LATE_ALL_margin_ha_band

*Log of TFP (all farms)

ivreg2 log_TFP_6_12 (farmer_ed_bis=dummy__after_reform) forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965,

estimates store LATE_ALL_TFP_band

*Log of total output (organic farms)

ivreg2 log_output (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965 & dummy_organic_fully==1 ,

estimates store LATE_org_output_band

ivreg2 log_output_ha (farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort m__* if birthdate>=1949 & birthdate<=1965 & dummy_organic_fully==1 ,

estimates store LATE_org_output_ha_band

*Log of margin (organic farms)

```
ivreg2 log_gross_margin ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1965 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_band

ivreg2 log_gross_margin_ha ( farmer_ed_bis=dummy__after_reform) log_K log_L log_UAA forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1965 & dummy_organic_fully==1 ,

estimates store LATE_org_margin_ha_band

*Log of TFP (organic farms)

ivreg2 log_TFP_6_12 ( farmer_ed_bis=dummy__after_reform) forcing_cohort sq_forcing_cohort  m__* if birthdate>=1949 & birthdate<=1965 & dummy_organic_fully==1 ,

estimates store LATE_org_TFP_band


coefplot LATE_ALL_output_band LATE_org_output_band LATE_ALL_output_ha_band LATE_org_output_ha_band LATE_ALL_margin_band LATE_org_margin_band LATE_ALL_margin_ha_band LATE_org_margin_ha_band LATE_ALL_TFP_band LATE_org_TFP_band, format(%9.3g) vertical keep(farmer_ed_bis) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))


***Figure 16 - Continuity Assumption

estimates clear

reg dummy_organic_fully dummy__after_reform forcing_cohort sq_forcing_cohort   if  birthdate>=1949 & birthdate<=1967 , robust

estimates store continuity_org1

reg dummy_organic_fully dummy__after_reform forcing_cohort sq_forcing_cohort i.altitude   if  birthdate>=1949 & birthdate<=1967, robust

estimates store continuity_org2

reg dummy_organic_fully dummy__after_reform  forcing_cohort sq_forcing_cohort i.ePub_farm_type if  birthdate>=1949 & birthdate<=1967, robust
```

```
estimates store continuity_org3

reg dummy_organic_fully dummy__after_reform forcing_cohort sq_forcing_cohort i.altitude  i.ePub_farm_type if  birthdate>=1949 & birthdate<=1967, robust

estimates store continuity_org


estout continuity_org1 continuity_org2 continuity_org3 continuity_org, style(tex) cells(b(star fmt(3)) se(par fmt(2))) stats(r2_a N, fmt(%9.3f %9.0g))  replace

coefplot *, vertical keep(dummy__after_reform) yline(0) addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(2) mlabcolor(black))
```

Chapter 5 – Conclusion

Background and Research Objectives

The main objective of this thesis was to explore how outputs and inputs, in particular labour, change in response to a change of farming practices towards a reduction in chemical input use. Chapter 2 investigated using stakeholder perceptions what are the possible socioeconomic effects of certain scenarios of adopting ecological approaches to farming. Chapter 3 considered how production function and TFP estimates would change considering the inclusion of chemical inputs and thereby exploring the relationship between factors of production where chemical inputs are one of them. Chapter 4 then explored what are the returns to education from organic and conventional farming.

Main findings

Chapter 2 considered as a whole the socioeconomic effects of farms adopting ecological approaches to farming. Ecological approaches to farming here include organic and low-input approaches to agriculture as a couple examples. This chapter used stakeholder-based approaches to imagine future scenarios of ecological agriculture adoption. These approaches are both Delphi exercises and Q-methodology.

Chapter 3 estimated Total Factor Productivity using a systems-GMM approach of a Cobb-Douglas production function. This chapter included the use of chemical inputs which is absent in previous GMM estimations of TFP in the literature. Data was used from the Farm Accountancy Data Network for cereal crop farms from 2004-2018. Including chemical inputs in the specification makes little difference to labour productivity, but it has a large effect in reducing the coefficient on land productivity. It also has a significant effect on increasing output when it is increased and therefore this may encourage farms to specialise in those that farm more intensively to support food production and others that may farm more for environmental goals.

Chapter 4 considered the heterogenous returns to education for organic and conventional farming. The chapter addressed the shortfall of a lack of studies on the returns to education in agriculture and in particular in the context of organic farming. This chapter exploited the 1972 Raising of the School Leaving Age (ROSLA) in a regression discontinuity design (RDD) setting in two stages. First, it estimated the number of years of schooling depending on the birth year of the farmer. Second, an RDD estimation for farm output using Two Stage Least Squares was applied to estimate returns to agriculture across all farms in the sample as well as the organic farms. The RDD model was extended through using a Correlated Random Effect model and in estimating the organic farming a heterogeneous local average treatment effect (HLATE) approach is used.

It is important to first note that an additional year of education results, on average in an increase in total output and productivity for both conventional and organic farms. This suggests that production could be made more efficient through greater learning and farmers should be encouraged to undertake additional and relevant courses and training to increase their productivity on farms. The greater complexity and requirement to use fewer chemical inputs on organic farms also shows that the farmers who would gain most from additional education opportunities are organic farmers. Indeed, farmers with more education are also more likely to farm organically and with the environment in mind.

Further research could extend the analysis on using ecological agriculture or even farming through using a lower intensity of chemical inputs, especially fertilisers and crop protection chemicals. Principal Component Analysis could construct an index of farm intensity to compare the returns of education on different levels of farm chemical input intensity and exploiting the above 1972 ROSLA. In addition, a quantile regression could attempt to explore if higher levels of education would increase output inequalities further. Another potential further extension is to use a more precise estimation method for output *e.g.* estimating technical and allocative efficiency. A limitation to the study in this chapter would explore the returns to training for which we do not have the data.

References

Ackerberg, D.A., Frazer, G., Kim, K. il, Luo, Y., Su, Y., 2023. Under-identification of structural models based on timing and information set assumptions. Journal of Econometrics 237, 105463. https://doi.org/10.1016/j.jeconom.2023.04.007

Akune, Y., Hosoe, N., 2021. Microdata analysis of Japanese farmers' productivity: Estimating farm heterogeneity and elasticity of substitution among varieties. Agricultural Economics 52, 633–644. https://doi.org/10.1111/agec.12639

Alexander, K.S., Parry, L., Thammavong, P., Sacklokham, S., Pasouvang, S., Connell, J.G., Jovanovic, T., Moglia, M., Larson, S., Case, P., 2018. Rice farming systems in Southern Lao PDR: Interpreting farmers' agricultural production decisions using Q methodology. Agricultural Systems 160, 1–10. https://doi.org/10.1016/j.agsy.2017.10.018

Areal, F.J., Jones, P.J., Mortimer, S.R., Wilson, P., 2018. Measuring sustainable intensification: Combining composite indicators and efficiency analysis to account for positive externalities in cereal production. Land Use Policy 75, 314–326. https://doi.org/10.1016/j.landusepol.2018.04.001

Arellano, M., Bond, S., 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. The Review of Economic Studies 58, 277–297. https://doi.org/10.2307/2297968

Asadullah, M.N., Rahman, S., 2009. Farm productivity and efficiency in rural Bangladesh: the role of education revisited. Applied Economics 41, 17–33. https://doi.org/10.1080/00036840601019125

Avendano, M., de Coulon, A., Nafilyan, V., 2020. Does longer compulsory schooling affect mental health? Evidence from a British reform. Journal of Public Economics 183, 104137. https://doi.org/10.1016/j.jpubeco.2020.104137

Bailey, A., Davidova, S., Henderson, S., Ayouba, K., Bakucs, Z., Benedek, Z., Billaudet, L., Bruma, S., Chitea, M., Dobos, S., Eckart, L., Gerner, L., Fereira, J., Florian, V., Gouta, P., Hansson, H., Jeanneaux, P., Jendrzejewski, B., Kantelhardt, J., Konstantidelli, V., Lascano Galarza, M.X., Latruffe, L., Legras, S., Lepicier, D., Manevska-Tasevska, G., Niedermayr, A., Polge, E., Rusu, M., Schaller, L., Simion, G., Tanasa, L., Tzouramani, I., Vasiliu, C.D., Walder, P., Zavalloni, M., Zawalinska, K., 2021. Socio-economic impact of ecological agriculture at the territorial level.

Baráth, L., Fertő, I., 2023. The relationship between the ecologisation of farms and total factor productivity: A continuous treatment analysis. Journal of Agricultural Economics n/a. https://doi.org/10.1111/1477-9552.12563

Barnes, A.P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., Gómez-Barbero, M., 2019. Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. Land Use Policy 80, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004

Barnes, A.P., Thompson, B., Toma, L., 2022. Finding the ecological farmer: A farmer typology to understand ecological practice adoption within Europe. Current Research in Environmental Sustainability 4, 100125. https://doi.org/10.1016/j.crsust.2022.100125

Barry, J., Proops, J., 1999. Seeking sustainability discourses with Q methodology. Ecological Economics 28, 337–345. https://doi.org/10.1016/S0921-8009(98)00053-6

Bayles, B., 2010. Perceptions of childhood obesity on the Texas-Mexico border. Public Health Nurs 27, 320–328. https://doi.org/10.1111/j.1525-1446.2010.00861.x

Becker, S.O., Egger, P.H., Von Ehrlich, M., 2013. Absorptive capacity and the growth and investment effects of regional transfers: A regression discontinuity design with heterogeneous treatment effects. American Economic Journal: Economic Policy 5, 29–77.

Biagini, L., Antonioli, F., Severini, S., 2023. The impact of CAP subsidies on the productivity of cereal farms in six European countries: A historical perspective (2008–2018). Food Policy 119, 102473. https://doi.org/10.1016/j.foodpol.2023.102473

Blundell, R., Bond, S., 2000. GMM Estimation with Persistent Panel Data: An Application to Production Functions. Econometric Reviews 19.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., Finnveden, G., 2006. Scenario types and techniques: Towards a user's guide. Futures 38, 723–739. https://doi.org/10.1016/j.futures.2005.12.002

Brown, W.M., Ferguson, S.M., Viju-Miljusevic, C., 2020. Farm Size, Technology Adoption and Agricultural Trade Reform: Evidence from Canada. Journal of Agricultural Economics 71, 676–697. https://doi.org/10.1111/1477-9552.12372

Burton, Rob.J.F., Kuczera, C., Schwarz, G., 2008. Exploring Farmers' Cultural Resistance to Voluntary Agri-environmental Schemes. Sociologia Ruralis 48, 16–37. https://doi.org/10.1111/j.1467-9523.2008.00452.x

Buscha, F., Dickson, M., 2012. The raising of the school leaving age: Returns in later life. Economics Letters 117, 389–393. https://doi.org/10.1016/j.econlet.2012.06.018

Cattaneo, M.D., Frandsen, B.R., Titiunik, R., 2015. Randomization inference in the regression discontinuity design: An application to party advantages in the US Senate. Journal of Causal Inference 3, 1–24.

Chamberlain, G., 1978. Omitted variable bias in panel data: estimating the returns to schooling, in: Annales de l'INSEE. JSTOR, pp. 49–82.

Chambers, R.G., Lichtenberg, E., 1994. Simple Econometrics of Pesticide Productivity. American Journal of Agricultural Economics 76, 407–417. https://doi.org/10.2307/1243653

Chavas, J.-P., Nauges, C., 2020. Uncertainty, Learning, and Technology Adoption in Agriculture. Applied Economic Perspectives and Policy 42, 42–53. https://doi.org/10.1002/aepp.13003

Craig, B.J., Pardey, P.G., Roseboom, J., 1997. International productivity patterns: Accounting for input quality, infrastructure, and research. American Journal of Agricultural Economics 79, 1064–1076.

Cross, R.M., 2005. Exploring attitudes: the case for Q methodology. Health Education Research 20, 206–213. https://doi.org/10.1093/her/cyg121

Cuppen, E., Breukers, S., Hisschemöller, M., Bergsma, E., 2010. Q methodology to select participants for a stakeholder dialogue on energy options from biomass in the Netherlands. Ecological Economics 69, 579–591. https://doi.org/10.1016/j.ecolecon.2009.09.005

DEFRA, 2024. Structure of the agricultural industry in England and the UK at June [WWW Document]. GOV.UK. URL https://www.gov.uk/government/statistical-data-sets/structure-of-the-agricultural-industry-in-england-and-the-uk-at-june (accessed 6.20.24).

DEFRA, 2023. Environmental Land Management (ELM) update: how government will pay for land-based environment and climate goods and services [WWW Document]. GOV.UK. URL https://www.gov.uk/government/publications/environmental-land-management-update-how-government-will-pay-for-land-based-environment-and-climate-goods-and-services/environmental-land-management-elm-update-how-government-will-pay-for-land-based-environment-and-climate-goods-and-services (accessed 12.29.23).

Devereux, P.J., Fan, W., 2011. Earnings returns to the British education expansion. Economics of Education Review 30, 1153–1166.

Dries, L., Ciaian, P., Kancs, d'Artis, 2012. Job creation and job destruction in EU agriculture. Food Policy 37, 600–608. https://doi.org/10.1016/j.foodpol.2012.07.007

Duchy College, 2022. Farm Business Survey, 2019-2020: Special Licence Access. https://doi.org/10.5255/UKDA-SN-8816-2

Duenckmann, F., 2010. The village in the mind: Applying Q-methodology to re-constructing constructions of rurality. Journal of Rural Studies 26, 284–295. https://doi.org/10.1016/j.jrurstud.2010.01.003

Feder, G., Just, R.E., Zilberman, D., 1985. Adoption of agricultural innovations in developing countries: A survey. Economic development and cultural change 33, 255–298.

Firbank, L.G., Elliott, J., Drake, B., Cao, Y., Gooday, R., 2013. Evidence of sustainable intensification among British farms. Agriculture, Ecosystems & Environment 173, 58–65. https://doi.org/10.1016/j.agee.2013.04.010

Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Evaluating the Sustainable Intensification of arable farms. Journal of Environmental Management 150, 288–298. https://doi.org/10.1016/j.jenvman.2014.10.005

Gagliardi, L., Percoco, M., 2017. The impact of European Cohesion Policy in urban and rural regions. Regional Studies 51, 857–868.

Gallego, D., Bueno, S., 2014. Exploring the application of the Delphi method as a forecasting tool in Information Systems and Technologies research. Technology Analysis & Strategic Management 26, 987–999. https://doi.org/10.1080/09537325.2014.941348

Gardebroek, C., Chavez, M.D., Lansink, A.O., 2010. Analysing Production Technology and Risk in Organic and Conventional Dutch Arable Farming using Panel Data. Journal of Agricultural Economics 61, 60–75. https://doi.org/10.1111/j.1477-9552.2009.00222.x

Garrone, M., Emmers, D., Lee, H., Olper, A., Swinnen, J., 2019b. Subsidies and agricultural productivity in the EU. Agricultural Economics 50, 803–817. https://doi.org/10.1111/agec.12526

Garrone, M., Emmers, D., Olper, A., Swinnen, J., 2019a. Jobs and agricultural policy: Impact of the common agricultural policy on EU agricultural employment. Food Policy 87, 101744. https://doi.org/10.1016/j.foodpol.2019.101744

Garrouste, C., Godard, M., 2016. The Lasting Health Impact of Leaving School in a Bad Economy: Britons in the 1970s Recession. Health Economics 25, 70–92. https://doi.org/10.1002/hec.3391

Giannoulis, C., Botetzagias, I., Skanavis, C., 2010. Newspaper Reporters' Priorities and Beliefs About Environmental Journalism: An Application of Q-Methodology. Science Communication 32, 425–466. https://doi.org/10.1177/1075547010364927

Graymore, M.L.M., Sipe, N.G., Rickson, R.E., 2008. Regional sustainability: How useful are current tools of sustainability assessment at the regional scale? Ecological Economics 67, 362–372. https://doi.org/10.1016/j.ecolecon.2008.06.002

Green, M., Maynard, R., 2006. The employment benefits of organic farming, in: Atkinson, C., Ball, B., Davies, D.H.K., Rees, R., Russell, G., Stockdale, E.A., Watson, C.A., Walker, R., Younie, D. (Eds.), Aspects of Applied Biology 79, What Will Organic Farming Deliver? COR 2006. Association of Applied Biologists, pp. 51–55.

Grimsrud, K., Graesse, M., Lindhjem, H., 2020. Using the generalised Q method in ecological economics: A better way to capture representative values and perspectives in ecosystem service management. Ecological Economics 170, 106588. https://doi.org/10.1016/j.ecolecon.2019.106588

Halsey, A.H. (Albert H., Heath, A.F., Heath, A.F. (Anthony F., Ridge, J.M. (John M., 1980. Origins and destinations : family, class, and education in modern Britain.

Harrison, C.M., Burgess, J., Clark, J., 1998. Discounted knowledges: farmers» and residents» understandings of nature conservation goals and policies. Journal of Environmental Management 54, 305–320. https://doi.org/10.1006/jema.1998.0242

Headley, J.C., 1968. Estimating the Productivity of Agricultural Pesticides [WWW Document]. https://doi.org/10.2307/1237868

Helm, D., 2022. Agriculture after Brexit. Oxford Review of Economic Policy 38, 112–126. https://doi.org/10.1093/oxrep/grab042

Huffman, W.E., 2001. Chapter 7 Human capital: Education and agriculture, in: Handbook of Agricultural Economics, Agricultural Production. Elsevier, pp. 333–381. https://doi.org/10.1016/S1574-0072(01)10010-1

Imbens, G., Kalyanaraman, K., 2012. Optimal bandwidth choice for the regression discontinuity estimator. The Review of economic studies 79, 933–959.

Iofrida, N., De Luca, A.I., Gulisano, G., Strano, A., 2018. An application of Q-methodology to Mediterranean olive production – stakeholders' understanding of sustainability issues. Agricultural Systems 162, 46–55. https://doi.org/10.1016/j.agsy.2018.01.020

Jürges, H., Kruk, E., Reinhold, S., 2013. The effect of compulsory schooling on health—evidence from biomarkers. J Popul Econ 26, 645–672. https://doi.org/10.1007/s00148-012-0409-9

Kampen, J.K., Tamás, P., 2014. Overly ambitious: contributions and current status of Q methodology. Qual Quant 48, 3109–3126. https://doi.org/10.1007/s11135-013-9944-z

Kazukauskas, A., Newman, C., Sauer, J., 2014. The impact of decoupled subsidies on productivity in agriculture: a cross-country analysis using microdata. Agricultural Economics 45, 327–336. https://doi.org/10.1111/agec.12068

Kazukauskas, A., Newman, C.F., Thorne, F.S., 2010. Analysing the Effect of Decoupling on Agricultural Production: Evidence from Irish Dairy Farms using the Olley and Pakes Approach. German Journal of Agricultural Economics, GJAE (59) 3. https://doi.org/10.22004/ag.econ.145290

Khafagy, A., Vigani, M., 2022. Technical change and the Common Agricultural Policy. Food Policy 109, 102267. https://doi.org/10.1016/j.foodpol.2022.102267

Kings, D., Ilbery, B., 2010. The environmental belief systems of organic and conventional farmers: Evidence from central-southern England. Journal of Rural Studies 26, 437–448. https://doi.org/10.1016/j.jrurstud.2010.05.003

Kumbhakar, S.C., Tsionas, E.G., Sipiläinen, T., 2009. Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. J Prod Anal 31, 151–161. https://doi.org/10.1007/s11123-008-0081-y

Latruffe, L., Bravo-Ureta, B.E., Carpentier, A., Desjeux, Y., Moreira, V.H., 2017. Subsidies and Technical Efficiency in Agriculture: Evidence from European Dairy Farms. American Journal of Agricultural Economics 99, 783–799.

Latruffe, L., Nauges, C., 2014. Technical efficiency and conversion to organic farming: the case of France. European Review of Agricultural Economics 41, 227–253. https://doi.org/10.1093/erae/jbt024

Lauwers, L., 2009. Justifying the incorporation of the materials balance principle into frontier-based eco-efficiency models. Ecological Economics, Eco-efficiency: From technical optimisation to reflective sustainability analysis 68, 1605–1614. https://doi.org/10.1016/j.ecolecon.2008.08.022

Lawton, J.H., Brotherton, P.N.M., Brown, V.K, Elphick, C., Fitter, A.H., Forshaw, J., Haddow, R.W., Hilborne, S., Leafe, R.N., Mace, G.M., Southgate, M.P, Sutherland, W.J., Tew, T.E., Varley, J., & Wynne, G.R., 2010. Making Space for Nature: A review of England's Wildlife Sites and Ecological Network. Report to Defra.

Lehrer, N., Sneegas, G., 2018. Beyond polarization: using Q methodology to explore stakeholders' views on pesticide use, and related risks for agricultural workers, in Washington State's tree fruit industry. Agric Hum Values 35, 131–147. https://doi.org/10.1007/s10460-017-9810-z

Levinsohn, J., Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. The Review of Economic Studies 70, 317–341. https://doi.org/10.1111/1467-937X.00246

Lichtenberg, E., Zilberman, D., 1986. The Econometrics of Damage Control: Why Specification Matters. American Journal of Agricultural Economics 68, 261–273. https://doi.org/10.2307/1241427

Lin, J.Y., 1991. Education and innovation adoption in agriculture: evidence from hybrid rice in China. American Journal of Agricultural Economics 73, 713–723.

Lobley, M., Saratsi, E., Winter, M., Bullock, J. (Eds.), 2013. Training farmers in agri-environmental management: the case of Environmental Stewardship in lowland England. International Journal of Agricultural Management. https://doi.org/10.22004/ag.econ.199356

Mahlalela, L.S., Jourdain, D., Mungatana, E.D., Lundhede, T.H., 2022. Diverse stakeholder perspectives and ecosystem services ranking: Application of the Q-methodology to Hawane Dam and Nature Reserve in Eswatini. Ecological Economics 197, 107439. https://doi.org/10.1016/j.ecolecon.2022.107439

Marinoudi, V., Sørensen, C.G., Pearson, S., Bochtis, D., 2019. Robotics and labour in agriculture. A context consideration. Biosystems Engineering 184, 111–121. https://doi.org/10.1016/j.biosystemseng.2019.06.013

Mary, S., 2013. Assessing the Impacts of Pillar 1 and 2 Subsidies on TFP in French Crop Farms. Journal of Agricultural Economics 64, 133–144. https://doi.org/10.1111/j.1477-9552.2012.00365.x

McKeown, B., Thomas, D.B., 2013. Q Methodology. SAGE Publications.

Micklewright, J., Pearson, M., Smith, S., 1989. Has Britain an Early School-leaving Problem? Fiscal Studies 10, 1–16.

Mills, J., 2012. Exploring the social benefits of agri-environment schemes in England. Journal of Rural Studies, Growing Old in Rural Places 28, 612–621. https://doi.org/10.1016/j.jrurstud.2012.08.001

Moakes, S., Lampkin, N., Gerrard, C.L., 2015. Organic farm incomes in England and Wales 2013/14 (Report). Aberystwyth University and Organic Research Centre, Aberystwyth and Newbury.

Morison, J., Hine, R., Pretty, J., 2005. Survey and Analysis of Labour on Organic Farms in the UK and Republic of Ireland. International Journal of Agricultural Sustainability 3, 24–43. https://doi.org/10.1080/14735903.2005.9684742

Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica: journal of the Econometric Society 69–85.

Natural England, 2024. Natural England Access to Evidence - National Character Areas [WWW Document]. URL https://publications.naturalengland.org.uk/category/587130 (accessed 7.1.24).

Navarrete, M., Dupré, L., Lamine, C., 2015. Crop management, labour organization, and marketing: three key issues for improving sustainability in organic vegetable farming. International Journal of Agricultural Sustainability 13, 257–274. https://doi.org/10.1080/14735903.2014.959341

Nguyen, D., 1979. On agricultural productivity differences among countries. American Journal of Agricultural Economics 61, 565–570.

Offermann, F., Nieberg, H., 2000. Economic Performance of Organic Farms in Europe. Organic Farming in Europe: Economics and Policy 5.

O’Keeffe, D.J., 1975. Some Economic Aspects of Raising the School Leaving Age in England and Wales in 1947. The Economic History Review 28, 500–516. https://doi.org/10.2307/2593596

Olley, G.S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64, 1263–1297. https://doi.org/10.2307/2171831

Omer, A., Pascual, U., Russell, N.P., 2007. Biodiversity Conservation and Productivity in Intensive Agricultural Systems. Journal of Agricultural Economics 58, 308–329. https://doi.org/10.1111/j.1477-9552.2007.00091.x

ONS, 2024. Estimates of the population for the UK, England, Wales, Scotland, and Northern Ireland - Office for National Statistics [WWW Document]. URL https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland (accessed 7.1.24).

Oreopoulos, P., 2006a. The compelling effects of compulsory schooling: Evidence from Canada. Canadian Journal of Economics/Revue canadienne d’économique 39, 22–52.

Oreopoulos, P., 2006b. Estimating Average and Local Average Treatment Effects of Education When Compulsory Schooling Laws Really Matter. The American Economic Review 96, 152–175.

Petrick, M., Kloss, M., 2018. Identifying Factor Productivity from Micro-Data: The Case of EU Agriculture.

Phillips, J.M., 1994. Farmer education and farmer efficiency: A meta-analysis. Economic development and cultural change 43, 149–165.

Powdthavee, N., 2021. Education and pro-environmental attitudes and behaviours: A nonparametric regression discontinuity analysis of a major schooling reform in England and Wales. Ecological Economics 181, 106931. https://doi.org/10.1016/j.ecolecon.2020.106931

Provision of environmental output within a multi-output distance function approach, 2012. . Ecological Economics 78, 47–54. https://doi.org/10.1016/j.ecolecon.2012.03.011

Psacharopoulos, G., 1978. Economic Implications of Raising the School Leaving Age. Comparative Education Review 22, 71–79.

Queiró, F., 2022. Entrepreneurial human capital and firm dynamics. The Review of Economic Studies 89, 2061–2100.

Reimers, M., Klasen, S., 2013. Revisiting the role of education for agricultural productivity. American Journal of Agricultural Economics 95, 131–152.

Rizov, M., Davidova, S., Bailey, A., 2018. Employment effects of CAP payments in the UK non-farm economy. European Review of Agricultural Economics 45, 723–748. https://doi.org/10.1093/erae/jby008

Rizov, M., Pokrivcak, J., Ciaian, P., 2013. CAP Subsidies and Productivity of the EU Farms. Journal of Agricultural Economics 64, 537–557. https://doi.org/10.1111/1477-9552.12030

Roodman, D., 2009. How to do Xtabond2: An Introduction to Difference and System GMM in Stata. The Stata Journal 9, 86–136. https://doi.org/10.1177/1536867X0900900106

Schmitzberger, I., Wrbka, Th., Steurer, B., Aschenbrenner, G., Peterseil, J., Zechmeister, H.G., 2005. How farming styles influence biodiversity maintenance in Austrian agricultural landscapes. Agriculture, Ecosystems & Environment, Agri-Environmental Schemes as Landscape Experiments 108, 274–290. https://doi.org/10.1016/j.agee.2005.02.009

Schmolck, P., 2024. The QMethod page. http://schmolck.org/qmethod/

Schultz, T.W., 1975. The Value of the Ability to Deal with Disequilibria. Journal of Economic Literature 13, 827–846.

Simmons, R., 2008. Raising the Age of Compulsory Education in England: A Neet Solution? British Journal of Educational Studies 56, 420–439.

Singh, R.D., Santiago, M., 1997. Farm earnings, educational attainment, and role of public policy: some evidence from Mexico. World development 25, 2143–2154.

Stephenson, W., 1953. The study of behavior; Q-technique and its methodology, The study of behavior; Q-technique and its methodology. University of Chicago Press, Chicago, IL, US.

Stephenson, W., 1935. Technique of Factor Analysis. Nature 136, 297–297. https://doi.org/10.1038/136297b0

Taylor, J.E., Yunez-Naude, A., 2000. The returns from schooling in a diversified rural economy. American Journal of Agricultural Economics 82, 287–297.

Vecchio, Y., Di Pasquale, J., Del Giudice, T., Pauselli, G., Masi, M., Adinolfi, F., 2022. Precision farming: what do Italian farmers really think? An application of the Q methodology. Agricultural Systems 201, 103466. https://doi.org/10.1016/j.agsy.2022.103466

Vollrath, D., 2007. Land distribution and international agricultural productivity. American Journal of Agricultural Economics 89, 202–216.

Wallace, S., 2009. Raising of the school-leaving age, in: Wallace, S. (Ed.), A Dictionary of Education. Oxford University Press.

Watts, S., Stenner, P., 2012. Doing Q Methodological Research: Theory, Method and Interpretation. SAGE Publications Ltd. https://doi.org/10.4135/9781446251911

Webler, T., Danielson, S., Tuler, S., 2009. Using Q method to reveal social perspectives in environmental research. Greenfield MA: Social and Environmental Research Institute. http://www.seri-us.org/sites/default/files/Qprimer.pdf

Welch, F., 1970. Education in Production. Journal of Political Economy 78, 35–59. https://doi.org/10.1086/259599

West, A., 2022. Education and ignorance in the UK 80 years after Beveridge: The role of government and equality of opportunity. Social Policy & Administration 56, 299–314. https://doi.org/10.1111/spol.12781

Wilson, G.A., Hart, K., 2001. Farmer Participation in Agri-Environmental Schemes: Towards Conservation-Oriented Thinking? Sociologia Ruralis 41, 254–274. https://doi.org/10.1111/1467-9523.00181

Zepharovich, E., Ceddia, M.G., Rist, S., 2020. Perceptions of deforestation in the Argentinean Chaco: Combining Q-method and environmental justice. Ecological Economics 171, 106598. https://doi.org/10.1016/j.ecolecon.2020.106598

Zhengfei, G., Lansink, A.O., Wossink, A., Huirne, R., 2005. Damage control inputs: a comparison of conventional and organic farming systems. European Review of Agricultural Economics 32, 167–189. https://doi.org/10.1093/eurrag/jbi015