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On the Empirics of Agri-Environmental Policies and Agricultural Support – A Microeconomic Perspective

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List of Abbreviations

AES	Agri-environment schemes
ATE	Average treatment effect
ATT	Average treatment effect on the treated
CAP	Common Agricultural Policy
CSA	Climate-smart agriculture
DCE	Discrete choice experiment
DEA	Data Envelopment Analysis
DiD	Difference-in-difference
EC	European Commission
EEA	European Environment Agency
EU	European Union
FADN	Farm Accountancy Data Network
FAO	Food and Agriculture Organization of the United Nations
FE	Fixed effects model
GDP	Gross domestic product
GHG	Greenhouse gas
IDP	Input distance function
LCM	Latent class model
MFA	Multifunctional agriculture
ODP	Output distance function
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PES	Payments for ecosystem services
PSM	Propensity Score Matching
RTS	Returns to scale
SEC	Scale efficiency change
SFA	Stochastic Frontier Analysis
SI	Sustainable intensification
TC	Technical change
TE	Technical efficiency

TEC Technical efficiency change

TFP Total factor productivity

WTO World Trade Organization

Summary

Like arguably no other sector, agriculture is affected by the 21st century's global challenges. Its special role stems from its position at the intersection of the core issues of population growth, climate change and natural resource scarcity/protection. None of these three challenges can be viewed in isolation and none can be solved without affecting the other dimensions. For example, the constant increase of a world population that requires food, fibre, energy and infrastructure as well as climate change reduce the amount of land available for agricultural purposes and thus increase the pressure on natural resources. Needed are therefore multifunctional and at the same time productive agricultural systems that make goods and services available to a society that gradually transforms to a bio-based one. At the same time, such production systems may neither ignore the special features of agricultural production (e.g. immobile production factors, dependence on weather conditions) nor the requirements of world trade and changing needs and attitudes of society. Further, there is a need for agricultural policy to be designed in a way that promotes the production systems just described.

Looking at the development of the European Union's Common Agricultural Policy (CAP) since its introduction in 1962, a tendency towards the creation of structures that take account of the multifunctionality of modern agriculture and that attempt to meet current and future challenges can be observed. Examples are the shift from a price support to a market-oriented agricultural policy that gradually promotes environmentally friendly production processes. The recent reform of the CAP confirmed this trend. In order to further adjust agricultural policy measures, policymakers rely on empirical evidence of the impacts of different measures. In many cases, however, there is a lack of such studies, in particular when it comes to farm-level effects. This thesis shall narrow this research gap. In four embedded studies, it addresses four core questions of current agricultural and environmental policy debates: (1) How can the effectiveness of agri-environment schemes (AES) be increased? (2) Which effect does the participation in agri-environment schemes have on farm productivity keeping in mind rules for agricultural support of the World Trade Organization? (3) Which measures are effective when it comes to promoting organic farming? (4) How does the decoupling of direct payments from production affect farm performance?

The first study deals with the current design and (rather low) effectiveness of agri-environment schemes in Europe. Based on economic theory, it is shown that a poor implementation of the economic principles on which the measures are grounded can be assumed to be a reason for the lack of effectiveness. Study two combines the econometric methods of Stochastic Frontier Analysis, Propensity Score Matching and Difference-in-Difference to investigate microeconomic effects of participating in agri-environment schemes. It could be shown that AES do not meet the requirements of the World Trade Organization as concerns production neutrality and compensation for income losses and costs incurred and thus potentially have a trade-distorting effect. In the third study, an innovative German agricultural policy instrument was analysed, namely the organic flagship region programme. Following the policy goal of a steady increase in the production of organic food, farmers shall be motivated to switch to organic farming by appointing municipal associations as organic flagship regions. These regions are allocated support that is used to organise events and connect stakeholders with the aim of promoting organic production. Using a Choice Experiment and a Difference-in-Difference approach, we could show that the programme fails to motivate farmers to switch to organic production and that there is a need to more effectively target decision-influencing factors. The last study is dedicated to decoupling, i.e. the agricultural policy trend of cutting

the link between direct payments and production. Addressing major shortcomings of previous studies by combining quasi-experimental empirical methods with a latent-class production function, we show that farms operate with distinct production technologies and that decoupling has positive and significant effects on productivity. Our results further show that under decoupling, farmers tend to diversify their businesses while keeping environmental pressure at a similar level as with coupled support.

Zusammenfassung

Wie kaum ein anderer Sektor ist die Landwirtschaft im 21. Jahrhundert von globalen Herausforderungen betroffen. Ihre Sonderstellung rührt von ihrer Positionierung an der Schnittstelle der Problematiken Bevölkerungswachstum, Klimawandel und Ressourcenknappheit/-schutz her. Keine dieser drei wesentlichen Herausforderungen kann isoliert betrachtet, keine für sich gelöst werden. So verknappen etwa die stetige Zunahme einer zu ernährenden und Infrastruktur benötigenden Weltbevölkerung sowie der Klimawandel das für landwirtschaftliche Zwecke zur Verfügung stehende Flächenangebot und erhöhen auf diese Weise den Druck auf natürliche Ressourcen. Gefragt sind deshalb multifunktionale und gleichzeitig produktive landwirtschaftliche Produktionssysteme, die für eine zunehmend bioökonomisch ausgerichtete Gesellschaft Güter und Dienstleistungen nachhaltig zur Verfügung stellen und dabei die Besonderheiten der Agrarproduktion (z.B. immobile Produktionsfaktoren, wetter- und witterungsbedingte Unwägbarkeiten), aber auch Erfordernisse des Welthandels sowie sich wandelnde gesellschaftliche Rahmenbedingungen im Blick behalten. Gefragt sind in gleichem Maße agrarpolitische Maßnahmen, die solche Produktionssysteme fördern.

Betrachtet man die Entwicklung der für Europa maßgebenden Agrarpolitik, der Gemeinsamen Europäischen Agrarpolitik (GAP), seit ihrer Einführung 1962, so ist eine Tendenz zur Schaffung von Strukturen erkennbar, die der Multifunktionalität moderner Landwirtschaft Rechnung tragen und aktuellen wie zukünftigen Herausforderungen zu begegnen versuchen. Diese reichen von der Abkehr einer einkommensorientierten Preispolitik zugunsten einer am Markt orientierten Agrarpolitik zur Förderung umweltgerechter Produktionsverfahren. Die jüngste Reform der GAP bestätigte den erwähnten Trend. Vielfach mangelt es jedoch an empirischen Untersuchungen zur Wirkung agrarpolitischer Maßnahmen auf einzelbetrieblicher Ebene, welche Rückschlüsse auf die Vorteilhaftigkeit der Weichenstellungen zuließen. Diese Forschungslücke soll durch die vorliegende Arbeit verkleinert werden. Sie widmet sich in vier eingebundenen Studien vier Kernfragen aktueller agrar- und umweltpolitischer Diskussionen: (1) Wie kann die Effektivität von Agrarumweltmaßnahmen erhöht werden? (2) Welchen Einfluss hat die Teilnahme an Agrarumweltmaßnahmen auf die betriebliche Produktivität vor dem Hintergrund der Subventionsbestimmungen der Welthandelsorganisation? (3) Mit welchen Maßnahmen kann der Ökologische Landbau gefördert werden? (4) Wie wirkt sich die Entkopplung von Direktzahlungen von der Produktion auf betriebliche Leistungsmerkmale aus?

Die erste Studie befasst sich mit der derzeitigen Ausgestaltung und (eher geringen) Effektivität von Agrarumweltmaßnahmen in Europa. Ausgehend von (umwelt)ökonomischer Theorie wird dargelegt, dass eine mangelhafte Umsetzung der den Maßnahmen zugrunde liegenden ökonomischen Prinzipien als mögliche Ursache für die belegte mangelnde Effektivität vermutet werden kann. Studie zwei untersucht unter Zuhilfenahme der ökonometrischen Methoden Stochastic Frontier Analysis, Propensity Score Matching und Difference-in-Difference, welche mikroökonomischen landwirtschaftlichen Produktionswirkungen von der Teilnahme an Agrarumweltmaßnahmen ausgehen. Es ließ sich nachweisen, dass Agrarumweltmaßnahmen die von der Welthandelsorganisation entwickelten Vorgaben der Produktionsneutralität und der Kompensation von Einkommensverlusten und entstandenen Kosten nicht erfüllen und somit potentiell handelsverzerrend wirken. In der dritten Studie wurde das innovative Förderinstrument der Ökomodellregionen näher beleuchtet. Dem Ziel einer stetigen Steigerung der Erzeugung von Bio-Lebensmitteln folgend, wird mit der Ernennung von Gemeindeverbünden zu Ökomodellregionen in Deutschland versucht,

Landwirte zur Umstellung auf Ökologischen Landbau zu bewegen. Mittels eines Choice Experiments und eines Difference-in-Difference-Ansatzes konnten wir belegen, dass die Maßnahme den gewünschten Erfolg (noch) nicht erzielen konnte. Zudem konnten Gründe hierfür identifiziert werden. Die letzte Studie widmet sich dem agrarpolitischen Trend der Deregulierung. Untersucht wurde, welche Produktionsentscheidungen Landwirte beim Wegfall gekoppelter Direktzahlungen treffen. Die durch ein Latent Class Modell sowie ein kontrafaktisches Szenario ermittelten Ergebnisse deuten darauf hin, dass sowohl die landwirtschaftliche Produktivität als auch die Diversifizierungsbereitschaft durch eine stärkere Marktorientierung als Folge entkoppelter Zahlungen steigen.

Part 1: Introduction and Methodology

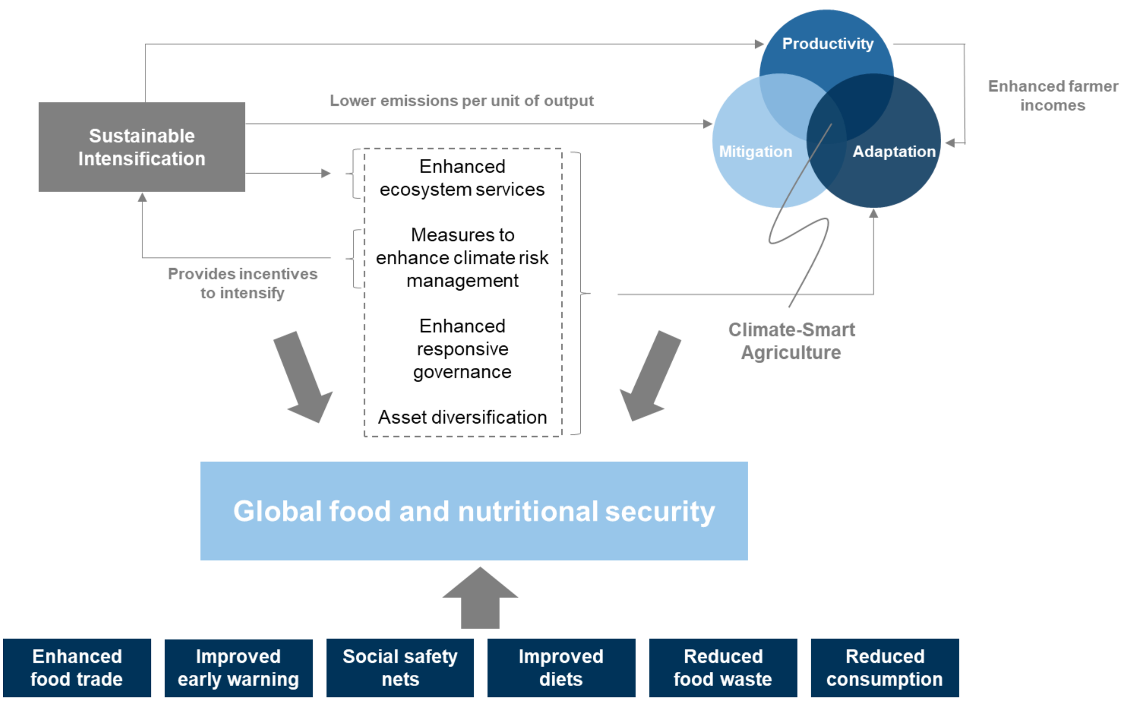
I Introduction

Since the Neolithic Revolution, agriculture has played a vital role in human development by providing enough food and fibre for large communities, allowing forms of administration and political structures to develop, the accumulation of goods as well as specialization, division of labour and trade. In this role, it has also shaped (rural) landscapes all over the globe. Today, agriculture is the world's largest user of land. Around 37% of the global land area is used for agricultural purposes (numbers for 2018, World Bank, 2021). For the European Union (EU), the respective number amounts to around 41% (ibid.). Both numbers illustrate that the agricultural sector bears responsibility that exceeds its economic contribution of food and fibre production. Agricultural practices influence the functioning of ecosystems in various ways and affect biodiversity (Foley *et al.*, 2005; Power, 2010). In this context, the multifunctional agriculture (MFA) concept has emerged as an important notion in public, scientific and political discourse about the future of farming and rural development (Renting *et al.*, 2009). It refers to societal expectations about the multifunctional role that modern agriculture should play. Beyond its role of producing food and raw material for energetic and industrial purposes, agricultural activity is assigned several other functions such as renewable natural resources and landscape management, biodiversity protection and social care and the upkeep of cohesion in rural areas. This MFA concept was first addressed in the Agenda 21 documents of the Rio Earth Summit in 1992 (UNCED, 1992). Despite varying interpretations of the term 'multifunctionality' in different settings, the concept quickly gained popularity. Its use in scientific debates was quickened by two publications of the Organisation for Economic Co-operation and Development (OECD) from the early 2000s, in which neo-classical theory provided the basis to explain jointness of production of commodities in agriculture and market failures with respect to externalities and public goods (OECD, 2003, 2001b). At around the same time, the Food and Agriculture Organization (FAO) used the concept with a focus on developing countries and the multiple roles of agriculture as regards livelihood strategies and development pathways of households and rural development (Bresciani, Dévé and Stringer, 2004). Their approach considered multifunctionality in agriculture as the sector's contribution to challenges such as guaranteeing food security, overcoming poverty and preserving identity and cultural heritage. A third influential angle on the concept was provided by the EU in the context of reforms of the Common Agricultural Policy (CAP). Beginning with the 1992 MacSharry Reform, the EU began to adopt multifunctionality as an essential aspect of its agricultural model, not least driven by growing pressure from the World Trade Organization (WTO), which insisted on the implementation of agricultural policies that do not or only minimally distort trade (Renting *et al.*, 2009). In order to go along with WTO rules, the CAP was slowly transformed from a protectionist system (guaranteed producer prices, intervention prices, export subsidies) to a system justifying income support with production standards and multifunctionality. In recent years, various other approaches to multifunctionality in agriculture have emerged, the most prominent arguably being the ecosystem services concept. Coined by Ehrlich and Ehrlich in 1981 following a half-century history of global research on environmental pollution and resource scarcity, it has gained a sound political profile in the course of the last 15 years and is for example embedded in today's CAP (Bouwma *et al.*, 2018). One reason for its integration in agricultural policies might be its bridging character with natural and social sciences notions. This feature is in accordance with the need for sustainable development of the agricultural sector. It is especially the ecological branch of the sustainability concept that represents a challenge for agriculturalists. While the benefits of agriculture, mainly as a consequence of the ‘Green Revolution’, have been immense – modern agriculture now feeds almost eight billion people, cereal yields tripled between 1961 and 2019 (FAO, 2021) – the sector has become a major force behind many environmental threats on its way of increasing global per capita food supply and improving nutrition (Foley *et al.*, 2011; Pingali, 2012). Food systems are responsible for around 60% of global terrestrial biodiversity loss (UNEP, 2016), they have a detrimental impact on water quality (FAO, 2017b; Galloway *et al.*, 2003) and soils (FAO, 2015; Amundson *et al.*, 2015) and contribute with 20% to global CO_2eq emissions (FAO, 2020). Remarkably, the four Earth system processes/features that according to the planetary boundary concept (introduced by Rockström *et al.*, 2009) exceed boundaries, which represent the environmental limits within which humanity can safely operate, are to a great extent linked to agriculture: climate change, biosphere integrity, biogeochemical flows, and land-system change (Steffen *et al.*, 2015). It is thus vital to ease the environmental pressure of agriculture. However, certain trade-off relations between ecosystem services levels, for example between provisioning and regulating services, complicate the development of proper strategies in light of additional challenges. These challenges are diverse. First, increasing population and changing consumption patterns imply that food production must grow substantially to guarantee future food security and meet future food demands. It is commonly assumed that production would need to increase by 50% to feed a projected global population of over nine billion by 2050 without, as it is the case today, leaving millions chronically undernourished (FAO, 2017a). Second, production needs to keep pace with increasing demands for natural resources of economies that are transforming from fossil-fuel based systems to bioeconomic ones. Considering this aspect, production would even need to roughly double unless consumption of animal products, harvest losses and food waste are not reduced drastically (Tilman *et al.*, 2011). Third, food prices are more likely to experience shocks as a result of deregulation and from market speculation and bioenergy/biomaterial crop expansion (Godfray *et al.*, 2010). Fourth, climate change will negatively affect food production, directly through rising temperatures, changing precipitation patterns, extreme weather events and pests as well as indirectly through migration and conflict (Mbow *et al.*, 2019).

A number of concepts have been developed to address the umbrella challenge covering the four points mentioned above, namely that of the need to increase food and fibre production substantially under changing climatic conditions while, at the same time, reducing agriculture’s environmental footprint dramatically. The most prominent ones might be *sustainable intensification* (SI) and *climate smart agriculture* (CSA). SI, a term first used by Pretty (1997) in a paper about the status and future of African agriculture, can be defined as a process or system that seeks to increase crop and livestock yields and linked economic returns per unit time and land without causing adverse environmental impacts and without converting additional non-agricultural land (Pretty and Bharucha, 2014). The desire to produce more food with a lower environmental footprint has indeed been associated with various terms and concepts, ranging from *alternative agriculture* (NRC, 1989) to *green food systems* (DEFRA, 2012). However, arguably none of them has been backed with a conceptual framework comparable to the one for SI. It has evolved considerably over time, overcoming criticism of putting too much of a focus on production or being contradictory (Collins and Chandrasekaran, 2012). Today, it encompasses notions of productivity and efficiency growth, innovation, technology, resilience, dietary changes, environmental sustainability, conservation agriculture, animal welfare, rural development, zero expansion of agriculture into remaining natural ecosystems, value chains or multifunctional landscapes (Cassman and Grassini, 2020; Garnett *et al.*, 2013). Similar ideas are captured by the CSA concept. The first articulation of it was given by the FAO in 2009 in its report entitled “Food Security and

Agricultural Mitigation in Developing Countries: Options for Capturing Synergies". One year later, the FAO released another influential work on the topic, the paper "'Climate-Smart Agriculture', Policies, Practices and Financing for Food Security, Adaptation and Mitigation". Since then, the CSA concept has been widely adopted and a formal conceptual frame was developed (Lipper and Zilberman, 2018). The most commonly used CSA definition is provided by the FAO. It defines CSA as "agriculture that sustainably increases productivity, [enhances] resilience (adaptation), reduces/removes greenhouse gases (mitigation) [where possible], and enhances achievement of national food security and development goals" (FAO, 2013: 548). The principal goal of CSA is thus to guarantee food security and development, while productivity, adaptation and mitigation can be considered as three pillars that help to reach this aim (Lipper *et al.*, 2014). They represent a foundation that addresses the need for transforming agricultural systems under the new realities of climate change. The focus on outcomes linked to climate change adaptation and mitigation constitutes a main difference between CSA and SI (Figure I-1). Changes in rainfall and temperature patterns in combination with extreme weather events will hamper agricultural growth in almost all parts of the world. Given that developing countries, especially regions in South Asia and sub-Saharan Africa, where agriculture currently is a key economic sector and major employment source, but 80% of people live on less than $1.90 per day, will be hit particularly hard by climate change (Mbow *et al.*, 2019), CSA tends to be used in a development economics context. Just as SI, however, it guides policy makers all over the globe. In Europe, the ideas both concepts share – a need for productivity growth and environmental improvement – make their way into the Common Agricultural Policy.

Figure I-1: Interlinkage between the concepts of Sustainable Intensification and Climate-Smart Agriculture



Source: Adopted from Campbell *et al.* (2014)

Under an ongoing debate about the farming approach that will safely feed the planet (Muller *et al.*, 2017; Reganold and Wachter, 2016; Seufert and Ramankutty, 2017), the CAP tries to provide a framework that opens development paths for various agricultural systems. This framework affects around 10.5 million European farms (figure for 2016, Eurostat, 2021). It needs to bring together current and future societal demands, environmental necessities and economic requirements of farmers, i.e. aspects of SI and CSA, with regulations of the World Trade Organization (WTO). And it should be underpinned by scientific findings and theory. This also means that policy outcomes need to be measured and evaluated against policy goals. In the case of agricultural policy, it is crucial to assess micro-level effects as different farms are likely to respond differently to new regulations. Since agricultural policy, especially in Europe, has been related to fields that will gain in importance in the future – multifunctionality, market deregulation, productivity and innovation – in the past three decades already, empirical evidence on farm production responses of past political actions can help to improve future agricultural policy frameworks. To this end, this dissertation presents four studies that shall contribute to the understanding of micro-level production behaviour with respect to agricultural policy trends and challenges the sector faces. It focuses on agricultural policy within the European Union, which is why the following section provides an overview of the development of the CAP before a section concluding the first chapter will summarise the empirical literature on farm-level effects of respective policies.

I.1 The Common Agricultural Policy – a brief introduction[1]

The CAP, since its beginnings one of the EU's most communitised policy fields, has its origins in the situation Europe faced after the Second World War. In large parts of the continent the population suffered from hunger and malnutrition. As a consequence of destructions and the chaos of war, the agricultural sector was not able to provide enough food for everyone. Food prices were high and spending on food took a large share of people's household expenditures. Despite this situation, the income of farmers was low, mainly as a result of low productivity. Against this background, rapidly increasing food production was a major concern of European policy makers. Consequently, the aims of the future Common Agricultural Policy (it was launched in 1962) were already formulated in the 1957 Treaty of Rome, which established the European Economic Community (EEC). They can be found in Article 39 (EU, 2021b) and read as follows:

(1) To increase agricultural productivity by promoting technical progress and ensuring the optimum use of the factors of production, in particular labour;
(2) To ensure a fair standard of living for farmers;
(3) To stabilise markets;
(4) To ensure the availability of supplies;
(5) To ensure reasonable prices for consumers.

These objectives have remained unchanged since 1957, i.e. still today they are centred around the interests of producers and consumers. Alongside the aforementioned specific CAP goals, several provisions and amendments of the Treaty of Rome, which also accommodate reforms seen over time, lay down additional goals and have gradually become CAP goals without being mentioned in Article 39. Among these are environmental protection to promote sustainable development (Article 11) or animal welfare requirements (Article 13) (ibid.).

These additional goals have gained in importance through the years as a consequence of undesirable developments resulting from early CAP design. In the 1960s, the CAP concentrated on food security and productivity growth. Policymakers regulated agricultural

[1] The content of this section is mainly taken from Thünen-Institut (2021).

markets in order to achieve these goals. They introduced tariffs, which prevented target prices set for EEC farm products from being undercut, guaranteed minimum prices (which were higher than world market prices), set up an intervention system that purchased all produce if a commodity's market price within the Community fell below a predefined threshold and granted export subsidies in order to be able to sell surplus produce on the world market. The measures indeed helped to overcome the delicate post-war situation. In fact, the support system assisted farms in a way that they became so productive that they grew more food than needed. Overproduction of the late 1970s and 1980s caused the famous ”milk lakes”, ”butter mountains” and ”grain mountains”. Furthermore, the CAP budget grew dramatically and export subsidies led to (world) market distortions. In a first reaction to surplus production, a milk quota was introduced in 1984. However, it did not solve the CAP's main problems, which further included negative environmental effects of an increasingly specialised and intensive agriculture.

The first big reform to tackle these issues was the 1992 MacSharry Reform. As a response to the crisis years the European Commissioner for Agriculture at the time, Ray MacSharry, pushed through a major reform, which represented a first step away from income-oriented price policy and towards market-oriented agricultural policy. Intervention prices for grain were cut by 35%. The measure was accompanied by the introduction of area payments and compulsory set-aside for arable farms. Additionally, agri-environment schemes (AES) became integral components of the CAP.

Seven years later, the next CAP reform, which was also used to prepare European agriculture to the EU's eastward enlargement, carried the reform path of market orientation forward. Intervention prices were cut further and income support was granted via direct payments. The CAP's rural development component was strengthened by making it the second pillar, which from then on encompassed agri-environment schemes and rural development measures.

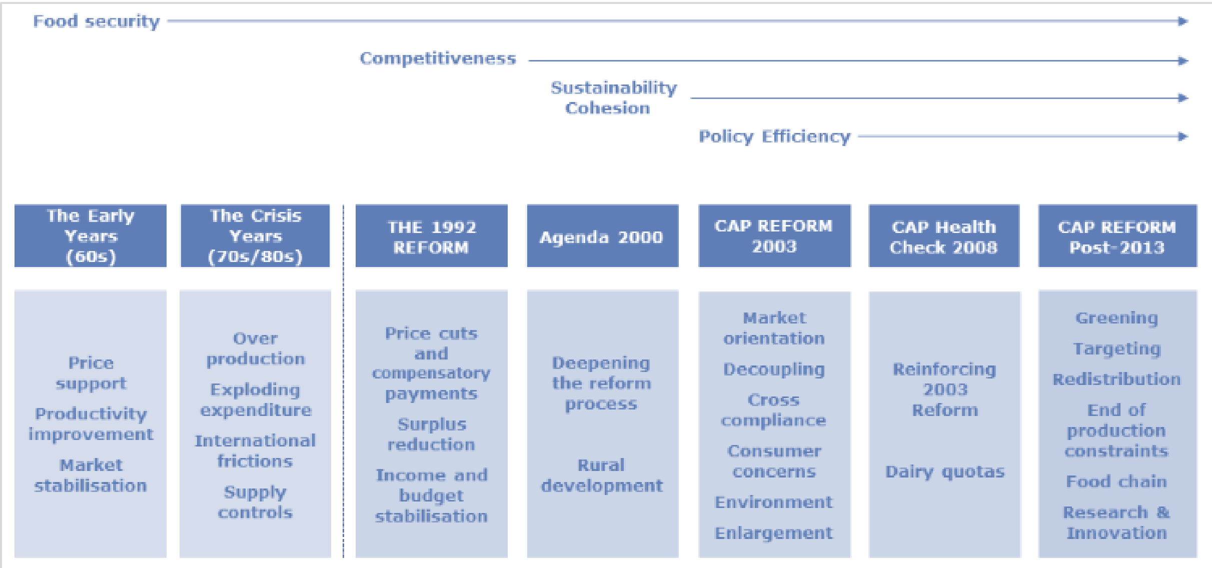
The next CAP reform, agreed upon in 2003, marked a milestone in the evolution of the income support system. Important elements of the reform included further cuts of intervention prices and the decoupling of direct payments. Until then, such payments were linked to the production of certain goods. Since 2005, when the reform was implemented, direct payments are not linked to certain products anymore, but to the condition that farmers look after the farmland and fulfil food safety, environmental, animal health and welfare standards (cross-compliance).

In 2008, the so called „health check” of the CAP resulted in measures for the dairy sector that were supposed to assist dairy farmers in light of the abolition of the European Union milk quota planned for 2015. It also strengthened modulation possibilities, i.e. the option to shift first pillar funds to the second pillar and introduced disproportionate direct payment cuts for large farms.

The system of direct payments remained the central component of the CAP also in the 2014-2020 funding period. Though, as criticism against lump sum transfers for a whole sector got bigger, the 2013 CAP reform attempted to better legitimate direct payments by introducing “greening”. It governed that farmers would only receive full direct payments if they kept certain minimum standards as regards crop rotation and the maintenance of permanent grassland and if they dedicated 5% of their arable land to areas beneficial for biodiversity (ecological focus areas). The “green direct payment” was developed as a measure that would lower the environmental footprint of farming and contribute to EU environmental and climate goals. It is debatable, though, whether this aim was reached. While positive environmental effects of greening were predicted or have been found, they seem to be rather low or farm-group dependent (Bertoni *et al.*, 2021; Cortignani and Dono, 2018; Gocht *et al.*, 2017).

Consequently, ongoing debates about the future design of the CAP centre around agriculture and the environment. The new focus on payments for ecosystem services provision is a reaction to undesirable developments related to earlier CAP designs. These designs can only be assessed against the background of the necessities of the respective time. Figure I-2 depicts how the CAP's focus shifted in the course of the years. What remained constant was the central role that the CAP plays in the big basket of European policy fields. This role is not least explained by the expenditure of the Common Agricultural Policy as a share of the EU budget, which amounted to 74% in 1985 and still reached 37.4% in 2019 (roughly 50 billion euros, 2011 constant prices) (EU, 2021a).

Figure I-2: Historical development of the Common Agricultural Policy



Source: Adopted from the European Commission by Sterly *et al.* (2018: 21)

I.2 The Common Agricultural Policy as a response to characteristics of the agricultural sector

The CAP's importance is further explained by certain economic peculiarities of agriculture, which cause market imperfections. First, farms are geographically spread and exist in large numbers. Collecting and treating agricultural products on the other hand is organised by few processers. Market power is thus unevenly distributed if a price or production coordination among farmers does not exist. Such a coordination, however, involves high transaction costs (Nedergaard, 2006: 400). Furthermore, agriculture is characterised by largely immobile production factors, which reduces flexibility in response to changing market conditions. Second, farmers produce on risk markets. They lack vital information concerning future weather conditions, future prices, exchange rates and other farmers' production (Runge and Myers, 1985). This, together with the biological nature of agricultural products limiting durability, leads to unstable supply (Nedergaard, 2006: 399). Third, the great number of farms means that individual producers have no influence on the price of the product. Individual farmers face a situation of perfect competition. In industry, for example, such a situation rarely exists. Oligopolistic competition dominates there. Nedergaard (2006: 400) states that the competitive situation in agriculture might explain the structural income problem of the sector to some extent. It also forces farmers to constantly introduce new technology in order to keep their income position. Fourth, agricultural production is based on land. Olson (1985) found that production based on land complicates coordination and management and lets diseconomies of scale to be reached at comparatively low levels of turnover, which in turn explains the large number of farms. Fifth, costs of moving resources from farming to non-agricultural sectors are internalised, i.e. paid by the farmer, advantages of structural change are externalised (Hagedorn, 1983). Sixth, agriculture as an activity bound to land is subject to market failures regarding both positive and negative externalities. Agricultural policies therefore make use of welfare economics theory to correct market imperfections through public regulations and expenditures. Political instruments are also used to maximise welfare when markets relevant to agriculture might fail due to the public or common good character of many (environmental) goods and information shortcomings of consumers.

The CAP can be considered as a toolkit that tries to address the aforementioned peculiarities of the primary sector. However, its design is not only influenced by the sector's peculiarities and the aim to correct market failure. It is also the result of political rent-seeking of farmers' interest groups (Krueger, 1989). Permanent income problems of many farmers encourage producers to view it as legitimate to reach economic goals through lobbying for protectionism and direct financial support (Nedergaard, 2006: 402). And agricultural interest groups are typically well-organised and characterised by high affiliation percentages, not least due to the fact that transaction costs for coordination are partly financed over by public funds (ibid., p. 403). Furthermore, a counterweight to homogeneous interest groups representing farmers is missing. Taxpayers and consumers are seldom organised at all. They further are only rarely aware of the functioning of agricultural policy and of the connection between taxes paid in their respective country and CAP expenditures.

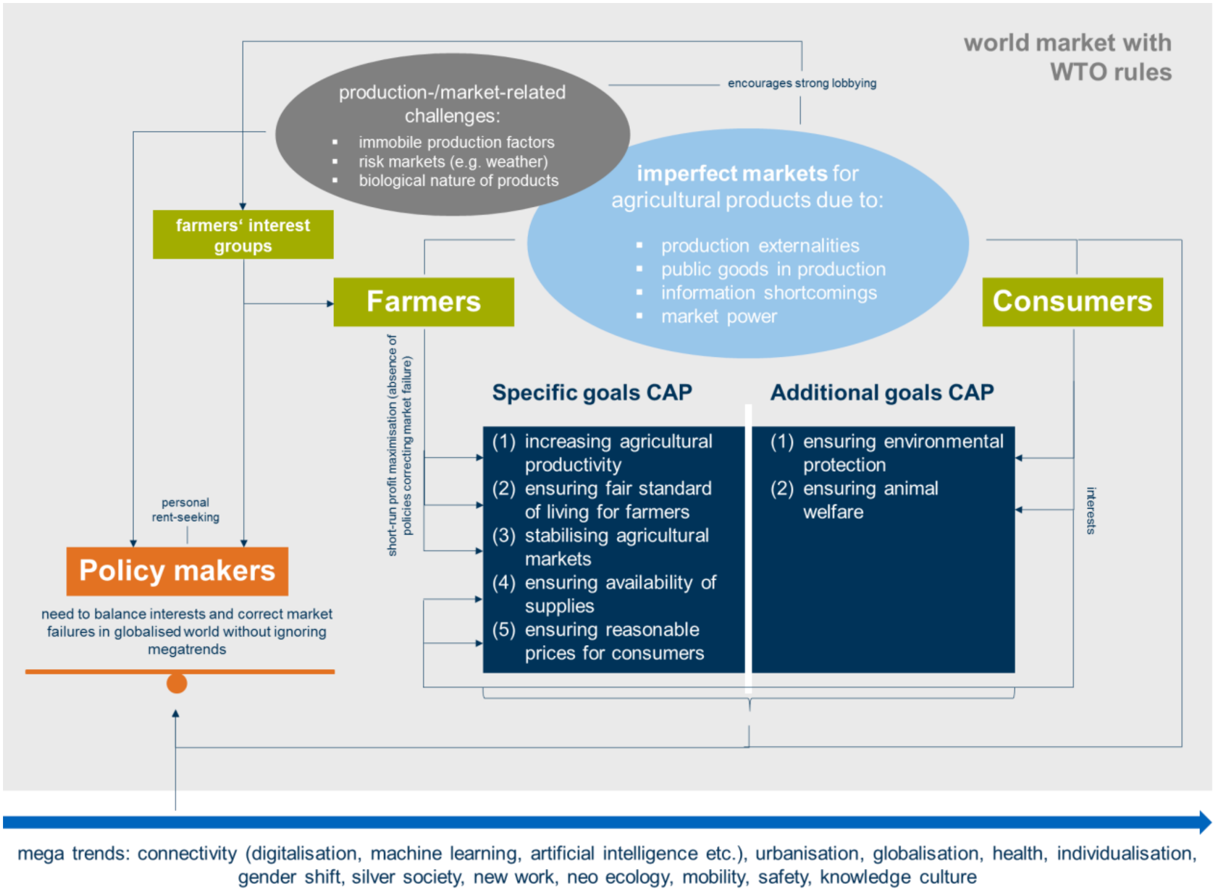
Nedergaard (2006) argues that the design of the CAP is also the result of what he calls an "institutional bias towards agricultural interests within the political system" (p. 407). In addition, and making use of rational choice theory, he reasons that bureaucrats involved in the decision making process concerning agricultural policy act in their own interest (career possibilities, increasing power bases etc.) and therefore prefer an agricultural policy system that is complex, technical, includes bureaucratic interventions and strong governance. He concludes that the CAP shows a certain asymmetry which is sharpened by politicians and bureaucrats who have independent reasons for fostering a complicated and protectionist agricultural policy.

Besides these structural or "government failures" explaining the characteristics of the Common Agricultural Policy, four generally recognized classes or causes of market failures exist that also shape the CAP and that have partly been mentioned previously. These are externalities, public goods, insufficient information and market power. Externalities, negative and positive ones, arise when producers or consumers are neither charged nor compensated for the economic impacts of their decisions on others, i.e. private costs deviate from social costs. Examples in a farming context are nitrate leaching (negative externality) and the provision of cultural landscapes (positive externality). Market failure with regard to public goods is linked to the properties of these goods, namely non-rivalry and non-excludability (see e.g. Samuelson, 1954). Non-rivalry means that a good can be consumed by an additional consumer at no additional cost. The utility gain of one person enjoying a public good does not interfere with the consumption and benefit of another person. Non-excludability refers to the characteristic that consumers cannot be excluded from public good consumption. In an agricultural context, a range of non-excludable and non-rival, i.e. public goods, provided by farmers can be identified. They are closely linked to positive externalities and according to Romstad *et al.* (2000) refer to landscape values (biodiversity, cultural heritage, amenity value of the landscape, etc.), food security, food safety and food quality and contributions to the values of rural areas (rural settlement, economic activities, cultural values). While these public goods are provided by farmers, other public goods like for example air are used during the production process. As they do not have a market price, such public goods are typically used wastefully. Insufficient information about the characteristics of a good or service may also prevent markets from working properly. An example from agriculture would be information shortcomings of consumers when it comes to the environmental impact of food production, which might result in a demand for agricultural products that exceeds the level that exists in case of perfect information. The last cause of market failure is market power, which characterises a situation where a few buyers or sellers are able to exert significant power over prices, can impede production and exclude potential market participants. Economies of scale are typically a driver behind consolidations in markets. Agricultural markets are a good example for markets where consolidation on the buyer side encounters a high number of sellers acting independently and – in the pursuit of productivity gains – putting pressure on prices themselves. In such a setting, buyers (typically processors) may have enough market power to exert downward pressure on the prices they offer farmers. They can further put confidentiality clauses in contracts with farmers, requiring them to keep contract details secret and giving themselves an information advantage in negotiations. Consequently, the quantity supplied and prices paid to farmers would ultimately be lower than on competitive markets, implying welfare losses.

All types of market failure described in the previous paragraph can be tackled through government intervention. Indeed, European agricultural policy aims at correcting market failures. At the same time, its policy design needs to account for general CAP goals, characteristics of the agricultural sector, "government failures" described above, WTO rules that promote fair market conditions and megatrends affecting overall development. The complexity of this task is shown in Figure I-3.

It is evident that designing agricultural policy in a manner that incorporates all of the aspects shown in Figure I-3 is challenging. This is also reflected in constant adjustments of both the CAP and agricultural policies on a regional level. The basis for these adjustments ideally is research that empirically captures the impact of policy measures on the micro- and the macro-level and links (expected) effects to economic theory. Thus, empirical research is required to assess how agricultural policies affect the various aspects described above, from farmers' performance and production strategies to WTO requirements.

Figure I-3: Context of agricultural policy making in Europe



Source: Own depiction

I.3 Empirical evidence on microeconomic impacts of agricultural policy

Quite a number of researchers have dedicated their resources to the study of effects related to agricultural policies. Consequently, numerous papers and reports dealing descriptively, theoretically and empirically with various policy aspects have been produced. Empirical assessments remain particularly important as agricultural policies affect a heterogeneous group of actors (e.g. farmers, processors, retailers, consumers) and involve multiple goals as pointed out above. The heterogeneity of objectives increases the complexity of agricultural policies, which in turn requires careful impact evaluations (Esposti and Sotte, 2013). In the best case, such impact evaluations support evidence-based policymaking by providing rigorous empirical insights into the behaviour and response of farmers to changing policies.

As outlined earlier, agricultural policies, especially in Europe, are gradually addressing the major challenge of a sustainable increase of food and fibre production under changing climatic conditions. This shift, complex in its own, is impeded by a globalised world where (agricultural) goods are traded on a global scale, but regional/national regulations and production conditions are not and cannot always be harmonised given not least the land-based nature of agriculture. Trade regulations and/or implications of agricultural policies are thus a first aspect to be considered in impact evaluation studies. Against the background of agricultural policies shifting away from protective towards more market-oriented measures, a development that researchers have been calling for since decades (Condliffe, 1950; Johnson, 1960), various empirical works have documented effects of this trend on farms and the sector as a whole. Frick and Sauer (2018), for example, show that deregulation shifts productive activities from less productive farms towards more productive ones, increasing the aggregate productivity of the sector. Trade liberalisation also increases allocative efficiency if the production portfolio is based on market prices (Brauw, Huang and Rozelle, 2004). Further effects described in the literature are related to improvements of agricultural efficiency and/or productivity (Hassine and Kandil, 2009; Sotnikov, 1998; Sunge and Ngepah, 2020), although there seems to be a lack of consensus among economists on the relationship between free trade on one side and productivity and technical efficiency gains on the other. Generally, existing research has a strong focus on such agricultural production (value), and thereby farmers' welfare effects of trade liberalisation. This focus might be the result of trade theory, which would predict that producers of export-oriented goods profit from agricultural market liberalisation, while producers of import-competing products may lose (Huang, Li and Rozelle, 2003). Other contributions in the field of understanding international trade in agricultural products cover the behaviour of international commodity prices, linkages between agricultural trade and exchange rate policies, the role of market power and industrial organisations, the quantification of trade effects of agricultural policies, the political economy of agricultural trade, the roles of international institutions and development economic aspects. An overview of the development of professional thinking on these main areas is given in Josling *et al.* (2010). From a theoretical perspective, this thinking is complicated by the high political importance of national food security, which causes the arguments for freer markets to be unlikely to prevail. This might be one reason why the WTO, usually quoted as a major driver of liberalisation, has made no major progress in the multilateral arena since the 1994 Uruguay Round. Their regulations, though, continue to provide the basis for domestic support, but have rarely been questioned, even if some authors argue that much of the liberalisation that has happened took place outside WTO and regional agreements (Bureau, Guimbard and Jean, 2019).

Closely linked to trade regulations and/or implications of agricultural policies is decoupling. The rationale behind decoupling is to keep a certain level of income support for farmers while giving them flexibility in production decisions and in doing so making production choices more market-oriented. At the same time, decoupling shall alleviate the distortions induced by traditional domestic and trade policy measures that link payments to farm output[2]. However, in the course of time, evidence on a theoretical and empirical level disproved that such payments were actually neutral to production choices (Bhaskar and Beghin, 2009) and consequently are likely to still cause market distortions (Urban, Jensen and Brockmeier, 2016). While the scientific literature reveals that decoupled payments are less trade distorting than the prior system of compensatory payments (Rude, 2008), even with decoupling, some coupling channels exist, such as capitalisation in land value (Varacca *et al.*, 2022; Salhofer and Feichtinger, 2020), farmers' risk behaviour (Koundouri *et al.*, 2009; Hennessy, 1998), credit accessibility (Ciaian and Swinnen, 2009; O'Toole and Hennessy, 2015), uncertainty about future policies and labour allocation (Dewbre and Mishra, 2007). Furthermore, payments are not truly decoupled as they are typically linked to the number of hectares which a farmer 'farms' and to certain land-use restrictions (obligation for farmers to maintain land in a state fit for agricultural production). Some scholars also question whether decoupled payments are really adequate to alleviate existing market distortions in the presence of imperfect competition, which occurs in the agri-food sector (Yu, 2013). As it stands, the claim of neutrality of lump-sum subsidies is of rather optimistic nature. In light of the need for more

[2] Under an ideal decoupling program, no difference in the responses of decision makers and markets to any other exogenous shock affecting either the demand or the supply side would be observable. Hence, demand and supply curves as well as market equilibria would remain stable.

productive farming systems, however, at least the notion of decoupling of increased market orientation might have positive effects as farmers use their resources in a demand rather than a price optimised way. Positive production effects have indeed been reported in different studies (Kazukauskas *et al.*, 2013; Kazukauskas, Newman and Sauer, 2014). What is lacking, though, are robust ex-post analyses that take farm heterogeneity and possible trade-offs with environmental outcomes into consideration.

As pointed out earlier, potentially positive effects of deregulation on farm economic performance should not be pursued at the expense of the environment. In fact, any kind of productivity increase needs to be achieved in a(n) (environmentally) sustainable manner given that today's agriculture contributes to a large number of environmental issues (Campbell *et al.*, 2017). One form of agriculture that is commonly put forward as a type of farming with a comparatively low environmental footprint is organic agriculture (Reganold and Wachter, 2016). Although not a silver bullet – sustainability per unit product can be questioned (Meemken and Qaim, 2018) – it can be regarded as a useful component in the transition towards sustainable food systems. More specifically, smart combinations of organic and conventional practices could help to make sustainable productivity increases in global agriculture possible. Eyhorn *et al.* (2019) identify four important groups of policy interventions that can assist in accelerating the required transition towards sustainable food systems based on the sustainability contributions of these different farming approaches. Among those are the support and enhancement of transformative systems through comprehensive strategies that include push measures (e.g. support to research and advisory services to facilitate the adoption of organic farming practices, area-based payments), pull measures (e.g. consumer information campaigns) and enabling measures (e.g. data collection and institutional development). Fostering the demand of sustainable food products by raising consumer awareness on the linkages between agriculture, environment, health and social wellbeing and enhancing the commitment of retailers and caterers to offer such products represents another group of policy measures. Government authorities in many countries try to implement such measures via action plans that promote organic farming (Sanders, Stolze and Padel, 2011). Despite the relatively large number of organic action plans in Europe and the long history of support for organic agriculture, little literature has been devoted to a systematic analysis of the degree to which organic food and agriculture policies affect participation in organic farming. Analyses of organic policy instruments or labelling often provide comprehensive reviews of the instruments applied, yet only a few theoretically sound considerations of the policy tools that actually lead to growth of the organic sector exist (Daugbjerg and Halpin, 2008). Exceptions include studies by Daugbjerg *et al.* (2011), Michelsen (2002) and Lindström, Lundberg and Marklund (2020). All of these authors analyse rather traditional organic farming policy tools. Innovative measures, such as the appointment of organic flagship regions, an initiative that has gained popularity in Germany over the last years, are less of a research object.

Addressing this last-mentioned point as well as deregulation and classical agri-environment policy in a sense that main challenges of the agricultural sector are empirically investigated represents the key element and contribution of this dissertation. These empirical investigations are conducted using state-of-the-art statistical/econometric methodologies, thus generating robust measures of impact.

I.4 Aims, scope and structure of this thesis

In this dissertation I want to provide empirical insights into farm responses to changing agricultural policies and programs (namely agri-environment schemes, decoupling, promotion of organic farming). The main objective is to enlarge the knowledge base that policy-makers need in order to take decisions that are beneficial for the agricultural sector and society as a whole in terms of economic, environmental and social outcomes. This target was pursued taking into account the multifunctionality of modern agriculture and policy goals, respectively. The **four studies embedded** as well as the **two co-authored studies** (Table I-1) either measure policy effects holistically, e.g. both economic and environmental effects, or take a specific angle to thoroughly understand an effect. In the chapters covering these studies, they are thoroughly put in the context of existing literature, thus exceeding the rather general problem statement and research gap given here.

Table I-1: Overview of the studies in this dissertation

Title	Main research question(s)	(Empirical) case	Method(s)
a) Studies embedded in the dissertation			
1. The integration of ecology and bioeconomy based on the example of agri-environment schemes (Chapter 3)	Why do agri-environment schemes perform poorly given our knowledge of economic theory that should guide policy-makers when designing AES?	CAP of the EU	Descriptive analysis based on a comparison between economic theory and conventional AES implementation in Europe
2. The impact of agri-environment schemes on farm productivity: a DID-matching approach (Chapter 4)	How does participation in AES affect farm productivity? Is AES design in line with WTO requirements?	Bavarian arable and dairy farms; farm accountancy and farm-level AES (*Bayerisches Kulturland-schaftsprogramm*) participation data from 2006 to 2011 merged with secondary data at the county level containing information on the socio-economic, spatial and structural environment of the farm	Production function and frontier approaches to estimate and decompose productivity / productivity growth; Propensity Score Matching to control for selection bias; Difference-in-Difference estimation to identify treatment effects
3. Promoting organic food production in flagship regions – A policy evaluation study for Southeast Germany (Chapter 5)	Is the policy measure of appointing organic flagship regions an effective tool to promote the uptake of organic farming?	Repeated cross-section data (2016 and 2018) of Bavarian farms inside and outside of organic flagship regions	Discrete Choice Experiment to measure probability of adopting organic farming; Difference-in-Difference estimation to identify treatment effects
4. Revisiting the impact of decoupled subsidies on farm performance: a counterfactual analysis using microdata	Which effect did the 2003 reform of the Common Agricultural Policy, which decoupled farm subsidies	UK and French arable farms; farm accountancy data from 1995 to 2017 and 1990 to 2013 respectively	Latent-class production function; farm performance indicators; Propensity Score Matching to identify

(Chapter 6)	from production, have on farm performance?		comparable farms; Difference-in-Difference estimation to identify treatment effects
b) Additional co-authored articles cited in the dissertation			
5. Using machine learning to identify heterogeneous impacts of agri-environment schemes in the EU: A case study (Summary in Chapter 7)	How effective are agri-environment schemes? How heterogeneous are the identified effects?	Bavarian farms; farm accountancy data, official agricultural support data containing information about farm-specific scheme participation, secondary data at the county level to retrieve further information on the socio-economic, spatial and structural environment of the farm; all for the year 2014	Causal forests to estimate conditional average treatment effects; Shapley values to demonstrate the importance of considering the individual farming context in agricultural policy evaluation
6. Do agri-environment measures help to improve environmental and economic efficiency? Evidence from Bavarian dairy farmers (Summary in Chapter 7)	Which effect do agri-environment schemes have on farm-level environmental and economic efficiency?	Bavarian dairy farms; farm accountancy data from 2013 to 2018 merged with official agricultural support data and secondary data at the county level containing information on the socio-economic, spatial and structural environment of the farm	Multi-equation representation with a desirable technology and its accompanying undesirable by-production technology to estimate environmental and economic efficiency via Data Envelopment Analysis; Propensity Score Matching to control for selection bias; Difference-in-Difference estimation to identify treatment effects

The embedded studies address farm performance and management strategies in different policy contexts. Based on microeconomic production and impact evaluation theory, econometric techniques are used to obtain consistent and unbiased estimates, from which implications for both policy and management are derived. The studies address different farming sectors at two geographic levels: Bavaria and two selected EU member states. They contribute to the existing literature on agricultural policy and production decisions in several ways: Chapter 3 assesses the mismatch between economic theory and the implementation of agri-environment schemes, Chapter 4 tests whether CAP second pillar payments comply with WTO rules and are designed in a way that is attractive for farmers, Chapter 5 evaluates the effectiveness of organic farming promotion and Chapter 6 has a look at the effects of decoupling on overall farm performance. Finally, two supplementary studies examine how agri-environment schemes result in heterogeneous environmental impacts and which effect they have on economic and environmental efficiency.

The remainder of the dissertation is organised as follows. Chapter 2 introduces the theoretical background and the methodological approaches applied in the empirical work. Chapters 3-6 present the embedded studies. Chapter 7 summarises all studies (four embedded and two supplementary studies), highlighting authors' contributions, and provides a discussion across all dissertation topics in relation to the existing literature and concludes by providing policy implications, limitations and scope for further research. A last remark as concerns readability and formatting: A few tables continue over two pages. If not specified otherwise, the column names remain the same.

II Conceptual Framework and Methodological Overview

In order to holistically evaluate the impact of policies on agricultural production and farm performance, it is essential to have an understanding of production technologies, producer behaviour and impact evaluation. For this reason, this chapter gives a brief overview of methods applied in the empirical studies to measure both farm performance and actual policy effects. Given that the thesis uses a microeconomic approach, I focus on microeconomic production theory and its applications as well as on microeconomic impact analysis. Theoretical underpinnings are presented in some more detail in the studies embedded in this dissertation.

II.1 Production theory and production economics

A production process can be modelled by considering a firm that uses amounts of N inputs (e.g. labour, machinery, raw materials) to produce a single output. In an agricultural setting, we might think of a specialised arable farm producing cereals by making use of the inputs land, labour, seeds, fertilizers, pesticides and machinery. The technological possibilities of firms like our example farm can be summarised using the production function as a mathematical representation of the technology that converts inputs into outputs:

$$q = f(x) \tag{2.1}$$

where q represents the output and $\boldsymbol{x} = (x_1, x_2, \dots, x_N)'$ is an N x 1 vector of inputs. The production function thus describes the physical transformation of inputs into outputs. It represents the so called primal model as compared to dual approaches (e.g. cost or profit functions) which involve economic variables (e.g. prices, costs, revenues). Primal production models can be described without "the need to specify a behavioural objective (such as cost minimisation or profit-maximisation) (Coelli *et al.*, 2005: 47). Dual models on the other hand do depend on behavioural assumptions. Both types of models, though, are connected as shown by Shephard's duality theory (Shephard, 1953).

Before Shephard worked on this theory, production functions had already been used to study the (technological) relation between inputs and outputs. Pioneering works include Cobb and Douglas (1928), who analysed income distributions between capital and labour at the macroeconomic level. Microeconomic empirical studies first appeared around 20 years later with the works of Dean (1951), Johnston (1960) and Nerlove (1963). They all used cost rather than production functions, however, when Nerlove (1963) described the dual relationship between cost and production functions in detail, the foundation for analysing production measures was laid. These measures include elasticities of factor demand and supply, input substitutability or economies of size, scale and scope.

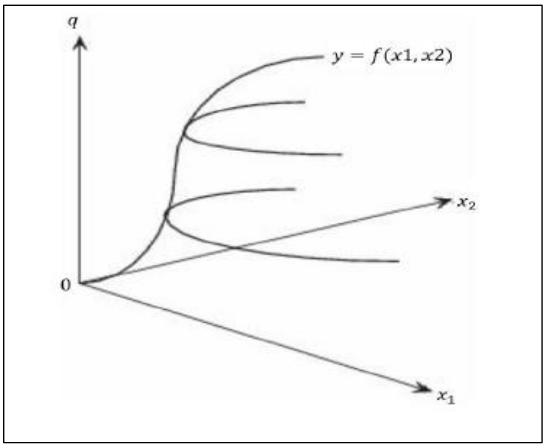
Early production and cost function studies focused on the description of production structures. The first authors to highlight the possibility of firms deviating from the frontier isoquant – the notion of technical inefficiency – were Debreu (1951) and Farrell (1957). Only some years later, parametric estimation and linear programming techniques were combined to detect parameter values that envelope the observed data (Aigner and Chu, 1968). It took another nine years until Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) proposed to estimate a stochastic frontier model with parametric distributional assumptions for the error term consisting of a random error accounting for statistical noise and a random variable associated with technical inefficiency. These models have been modified in many ways and a number of specifications concerning inefficiency distributions exist (e.g. Battese and Coelli, 1992; Battese and Coelli, 1995; Kumbhakar, Lien and Hardaker, 2014). Aside from stochastic frontier models, deterministic approaches can be used to construct the frontier. The most widely applied technique is data envelopment analysis. In contrast to stochastic approaches, deterministic ones generate the frontier by observed data. Consequently, some firms by construction mark the frontier. Since no empirical study of this dissertation makes use of a deterministic approach, it is not described further, but a focus is put on stochastic approaches.

They start with the production function as described by equation (2.1). According to Chambers (1988), a well-defined production function is associated with the following properties:

1. Non-negativity: $f(x)$ is finite, non-negative, real- and single-valued for all non-negative and finite x
2. Weak essentiality: $f(0) = 0$, i.e. the production of positive output is impossible without the use of at least one input
3. Monotonicity in x: $f(x^0) \geq f(x^1)$ for $x^0 \geq x^1$ (i.e. additional units of an input x will not decrease output)
4. Differentiability: $f(x)$ is continuous and twice-differentiable everywhere
5. Quasi-concavity in x: The input requirement set $V(y) = \{x | f(x) \geq y\}$ is a convex set, implying quasi-concavity of $f(x)$
6. Non-emptiness: The set $V(y)$ is closed and non-empty for any $y > 0$

A graphical illustration of the main properties is given in Figure II-1. Condition 1 is satisfied as q are non-negative and finite real numbers for all x on the horizontal axes. Weak essentiality is equally fulfilled since the origin is part of the function. Also, the function is monotonically increasing in x, implying that an increase in inputs leads to a non-negative output change. This corresponds to non-negative marginal products $MP_i = \frac{\partial f(x)}{\partial x_i}$. Especially in agricultural production, however, the monotonicity condition may be violated. An overuse of certain inputs like fertilisers, for example, in combination with uncertainties as regards weather or market developments may lead to situations where output is reduced when increasing inputs. Another potential violation is connected to the concavity condition. In Figure II-1 it is violated between the origin and the first horizontal curve. Firms may in fact be located in such a region with increasing marginal products because of regulatory factors or restricted access to certain inputs (e.g. land in an agricultural context). However, according to Coelli *et al.* (2005), rational decision-makers are not expected to choose a production plan that lets them end up in this production function segment or in a segment related to violations of condition 3. They typically choose a plan that lies within the so called *economically feasible region* of production where all theoretical properties of a production function are satisfied.

Figure II-1: Production function with one output and two inputs



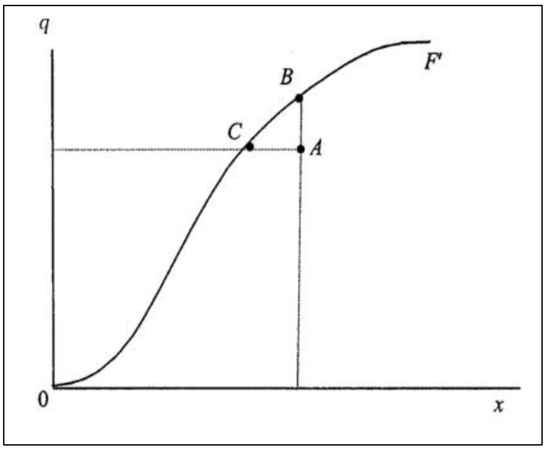
Source: Own depiction

The production function in equation (2.1) and shown in Figure II-2 represents the average expected output given input quantities. It does not consider the fact that some firms may be inefficient. If we define the line 0F' in Figure II-2 as a production frontier, which specifies the input-output relationship, it represents the maximum output attainable from each input level. Hence it is a reflection of the current state of the technology in the sector. Firms operate either on the frontier (in case they are technically efficient) or beneath the frontier (if they are not technically efficient). Equation (2.1) can thus be rewritten as:

$$q = f(x) * TE \tag{2.2}$$

where $0 < TE \leq 1$ represents technical efficiency. In the figure below, firms B and C operate on the production frontier and consequently are technically efficient ($TE = 1$), while firm A is technically inefficient ($TE < 1$). Theoretically, it could expand its output without altering its input use (movement towards firm B, output-oriented view) or reduce inputs while keeping the output produced constant (movement towards firm C, input-oriented view).

Figure II-2: Production frontiers and technical efficiency



Source: Own depiction

While the production function and frontier concepts described so far are useful to get an understanding of input-output relations, they have one major drawback: they only accommodate single-output technologies. In real-world settings, however, production processes are characterised by combinations of multi-inputs and multi-outputs. The technology can be represented through distance functions in such situations. To this end, the production possibility set is defined as the combination of all technologically feasible input and output combinations. If we assume weak disposability of outputs, the technology set can be described by an output distance function (ODF) following Shephard (1970) as

$$D^O(q,x) = \inf_\theta \left\{\theta > 0: \frac{q}{\theta} \in P(x)\right\} \tag{2.3}$$

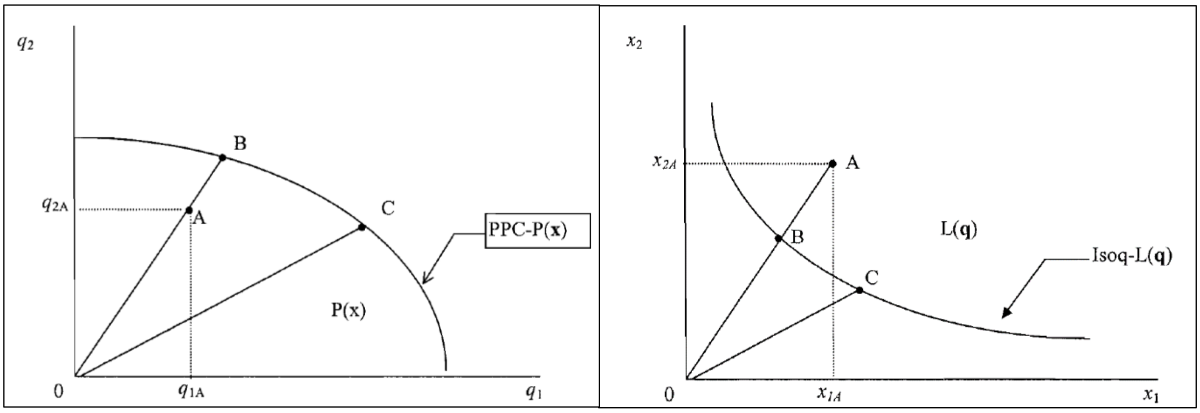
where $P(x)$ is the set of producible outputs for the input vector x. In the equation above, infimum replaces minimum, which allows for the possibility that a minimum does not exist (Coelli *et al.*, 2005: 47).

Analogously, input distance functions (IDF) specify how the input vector can be proportionally contracted while keeping the output vector constant:

$$D^I(q,x) = \sup_\lambda \left\{\lambda > 0: \frac{q}{\lambda} \in L(q)\right\} \tag{2.4}$$

In this equation, $L(q)$ is the input requirement set for producing the output vector q. It is useful to illustrate the concept of input and output distance functions graphically. The two dimensional diagrams in Figure II-3 represent output (left panel) and input (right panel) distance functions. In the left panel, the production possibility set $P(x)$ is the area bounded by the production possibility frontier and the q_1 and q_2 axes. The value of the ODF for firm A using input level x to produce the outputs is equal to the ratio $\theta = \frac{0A}{0B}$. This distance measure is the reciprocal value of the factor by which all outputs could be increased holding the input level constant and remaining within the production possibility set. For the points B and C in the left panel of the figure below, which are on the production possibility surface, it has a function value equal to 1. The IDF, where for a given output vector we can represent the production technology as in the right panel, makes use of the input set $L(q)$, which is the area bounded from below by the isoquant. If we take the example of firm A, we can see that the value of the distance function is equal to the ratio $\lambda = \frac{0A}{0B}$.

Figure II-3: Output distance function and production possibility curve (left) and input distance function and input requirement set (right)



PPC means production possibility curve, $L(q)$ is the input set

Source: Coelli *et al.* (2005: 48, 50)

Just as production functions, distance functions are characterised by certain properties. They follow directly from the axioms on the technology set and are for ODF according to Coelli *et al.* (2005: 47–48) the following ones[3]:

1. $D^O(0, x) = 0$ for all non-negative x;
2. $D^O(q, x)$ is non-decreasing in q and non-increasing in x;
3. $D^O(q, x)$ is linearly homogeneous in q (this property follows from the definition of distance functions rather than from the technology properties);
4. $D^O(q, x)$ is quasi-convex in x and convex in q[4];
5. If q belongs to the production possibility set of x (i.e. $q \in P(x)$), then $D^O(q, x) \leq 1$ and
6. distance is equal to unity (i.e. $D^O(q, x) = 1$) if q belongs to the frontier of the production possibility set.

For IDF the following properties apply:

1. $D^I(0, x) = 0$ for all non-negative x;
2. $D^I(q, x)$ is non-decreasing in x and non-increasing in q;
3. $D^I(q, x)$ is linearly homogeneous in x (this property follows from the definition of input distance functions rather than from the technology properties);
4. $D^I(q, x)$ is concave in x and quasi-concave in q[5];
5. If x belongs to the input set of q (i.e. $x \in L(q)$), then $D^I(q, x) \geq 1$ and
6. distance is equal to unity (i.e. $D^I(q, x) = 1$) if x belongs to the frontier of the input set (the isoquant of q).

Taking the example of the IDF, monotonicity in x and q requires the first derivative of the IDF with respect to x to be positive and the first derivative with respect to y to be negative. Concavity in x is a consequence of the convexity of the input requirement set. It necessitates the Hessian matrix of the IDF to be negative semidefinite. Quasi-concavity in q on the other hand requires the principal minors of the bordered Hessian matrix to be non-positive.

[3] Detailed proofs and derivations of these characteristics are given in Färe and Primont (1995).
[4] See Coelli *et al.* (2005) for mathematical definitions of convexity and quasi-convexity.
[5] See Coelli *et al.* (2005) for mathematical definitions of concavity and quasi-concavity.

Just as production function and frontier concepts, distance functions can be used to measure firm-level efficiency and to derive and decompose productivity indices.

II.2 Measuring productivity at the farm-level

Especially against the background of the global challenges outlined in the introduction, (sustainable) agricultural productivity growth is vital for future human well-being. It thus needs to be properly measured and monitored. Productivity itself essentially captures how much output is produced from a given set of inputs. *Partial* productivity measures then include output per unit of specific input, e.g. per unit of labour (resulting in labour productivity) or per unit of land (giving land productivity). However, partial productivity measures are incomplete as they ignore the simultaneous use of other inputs, such as, in an agricultural setting, capital inputs, fertilisers or pesticides. Given that partial productivity measures do not consider all inputs, measures of *total* factor productivity (TFP) are a more suitable performance indicator (Syverson, 2011). Researchers are further interested in total factor productivity growth, which is commonly described as the output growth that cannot be explained by input growth. TFP is formally defined as the ratio of aggregate outputs (Q) to aggregate inputs (X):

$$TFP = \frac{Q}{X} \tag{2.5}$$

A critical aspect of this measurement is the question of how to aggregate inputs and outputs that are typically measured in different units. One possibility is aggregation in terms of values. Such an approach requires the use of suitable price indices in order to guarantee that productivity differences are not confounded by differences in prices. An overview of different price indices can be found in O'Donnell (2012a). Another aggregation possibility is to weight inputs with output elasticities. Following Syverson (2011), a definition of TFP with K production inputs X_{kit} and output Q_{it} would then be

$$TFP_{it} = A_{it} = \frac{Q_{it}}{X_{1it}^{\alpha_1} + X_{2it}^{\alpha_2} + \cdots + X_{Kit}^{\alpha_K}} \tag{2.6}$$

where i and t are subscripts for firms and time, α_K denotes the K-th input's output elasticity and A_{it} represents a factor-neutral shifter of the production function. The shifter is linked to the aforementioned notion of TFP indicating variations in a production unit's output that are not explained by differences in input use.

From an empirical perspective, measuring productivity change rather than productivity levels is of major interest. One way to do this is to compare input changes to output changes by making use of input and output quantity indices. Examples for such indices are Laspeyres, Paasche or Törnqvist indices. Related TFP indices are termed Hicks-Moorsteen indices (Diewert, 1992). Another method that has gained popularity in empirical works that measure productivity change between production units and over time is the Malmquist TFP index. Introduced by Caves, Christensen and Diewert (1982), it is defined as a TFP index based on Malmquist IDFs and ODFs. Following Coelli *et al.* (2005: 68), the output-oriented Malmquist

TFP index between period s and period t is defined as the geometric average of two distance measures based on period-t and period-s technologies:

$$m_O(q_s, q_t, x_s, x_t) = \left[\frac{D_s^O(q_t, x_t)}{D_s^O(q_s, x_s)} * \frac{D_t^O(q_t, x_t)}{D_t^O(q_s, x_s)}\right]^{0.5} \tag{2.7}$$

If we assume that not all production units are efficient, i.e. $D_s^O(q_s, x_s) \leq 1$ and $D_t^O(q_s, x_s) \leq 1$, the index in 2.7 can be decomposed as follows:

$$m_O(q_s, q_t, x_s, x_t) = \frac{D_t^O(q_t, x_t)}{D_s^O(q_s, x_s)} * \left[\frac{D_s^O(q_t, x_t)}{D_t^O(q_t, x_t)} * \frac{D_s^O(q_s, x_s)}{D_t^O(q_s, x_s)}\right]^{0.5} \tag{2.8}$$

In this equation, the first term represents technical efficiency change (TEC), whereas the term in square brackets represents technical change (TC). TEC and TC are important sources of productivity change, however, if the technology exhibits non-constant returns to scale (RTS), productivity is also influenced by the scale of production (Balk, 2001). In an output-oriented setting, scale efficiency (SE) can be described as the ratio between the output distance value relative to a hypothetical technology (D_t^{*O}) and the output distance value relative to the actual technology (D_t^O):

$$SE_t^O(q, x) = \frac{D_t^{*O}(q, x)}{D_t^O(q, x)} \tag{2.9}$$

Scale efficiency change (SEC) can then be expressed as the ratio of scale efficiency between two periods using once more the geometric average of both reference technologies:

$$SEC = \left[\frac{D_t^O(q_t, x_t)/D_t^{*O}(q_t, x_t)}{D_t^O(q_s, x_s)/D_t^{*O}(q_s, x_s)} * \frac{D_s^O(q_t, x_t)/D_s^{*O}(q_t, x_t)}{D_s^O(q_s, x_s)/D_s^{*O}(q_s, x_s)}\right]^{0.5} \tag{2.10}$$

In order to obtain an index for TFP change (TFPC), the individual components of productivity growth can be summarised as follows[6]:

$$\begin{aligned} TFPC &= \frac{D_t^O(q_t, x_t)}{D_s^O(q_s, x_s)} * \left[\frac{D_s^O(q_t, x_t)}{D_t^O(q_t, x_t)} * \frac{D_s^O(q_s, x_s)}{D_t^O(q_s, x_s)}\right]^{0.5} * \left[\frac{\frac{D_t^O(q_t, x_t)}{D_t^{*O}(q_t, x_t)}}{\frac{D_t^O(q_s, x_s)}{D_t^{*O}(q_s, x_s)}} * \frac{\frac{D_s^O(q_t, x_t)}{D_s^{*O}(q_t, x_t)}}{\frac{D_s^O(q_s, x_s)}{D_s^{*O}(q_s, x_s)}}\right]^{0.5} \\ &= TEC * TC * SEC \end{aligned} \tag{2.11}$$

[6] Another source of productivity change is output mix efficiency. Due to space constraints, no details for this concept are given here. The interested reader may refer to Balk (2001) or O'Donnell (2008).

The individual components can be obtained using either explicit distance measures or derivative-based techniques. In Chapter IV, the latter approach was chosen following Kumbhakar and Lovell (2000).

Increased productivity, arising from the elements described above, especially innovation and changes in technology, has long been recognised as the most important source of economic growth in agriculture. However, thinking about the need to produce more agricultural goods with less environmental pressure, productivity has to be measured comprehensively, i.e. in a way that accounts for the environmental effects of economic activity. Despite its policy importance, there is still a lack of consensus among researchers on the most accurate methods for measuring such environmentally-adjusted TFP. Existing approaches show great heterogeneity of what is measured and how it is measured. Still, accounting for the environment when measuring the economic performance of the agricultural sector is likely to guide farm-level TFP studies in the future. Several analytical approaches to key issues have already been identified, ranging from eco-efficiency based on data envelopment analysis (Kuosmanen and Kortelainen, 2005) to multi-equation modelling of directional distance functions (Baležentis *et al.*, 2021).

In terms of estimating the functions mentioned in this chapter, several econometric models are available. Specific information on the models that are used in this dissertation is given in the chapters covering the empirical studies embedded. A strong focus is put on stochastic production frontier models following Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). These models include an idiosyncratic error term accounting for omitted variables, measurement errors and functional form misspecifications as well as a non-negative one-sided error term associated with technical inefficiency. They can be estimated using maximum likelihood techniques by making assumptions on the distributions of the error terms. Assumptions are also needed as regards the inefficiency term. It can for example be assumed either time-invariant (Pitt and Lee, 1981) or time-varying (Battese and Coelli, 1992), it can be modelled as a function of exogenous variables (Battese and Coelli, 1995) or in a way that separates firm heterogeneity from persisting and time-varying inefficiency (Kumbhakar, Lien and Hardaker, 2014).

Before I move on to describing the methodological background of policy evaluations in the next section, I briefly want to point out two important aspects linked to estimating production models, namely endogeneity and theoretical consistency. Endogeneity in production (frontier) models occurs if any of the independent variables are correlated with the error term (any of the two or both error terms, respectively) (Amsler, Prokhorov and Schmidt, 2016). Such a situation can for example arise if unobserved productivity shocks happen. Correlations between inputs and the error term can then be observed if producers respond to positive/negative shocks with higher/lower input use. One remedy would be to proxy unobserved productivity shocks with investment when estimating the function (Olley and Pakes, 1996). Levinsohn and Petrin (2003) criticised this approach in parts, because investments might not be made immediately and many firms in data sets report zero investment. They suggested to use intermediate inputs instead. More recent studies in the field of production economics also identified the inefficiency term when reflecting management skills as a potential source of endogeneity (Tsionas, Kumbhakar and Malikov, 2015). A way around this modelling problem was for example proposed by Griffiths and Hajargasht (2016), who use a method based on the Chamberlain–Mundlak device to relate a transformation of time-invariant effects to the regressors.

As regards the second aspect mentioned earlier, theoretical consistency, Lau (1986) emphasised its importance when choosing a functional form that specifies the relationships between the economic variables. It is essential to enable researchers to meaningfully interpret econometric results (Sauer, Frohberg and Hockmann, 2006). However, in practice, econometrically estimated functions are not necessarily consistent to economic theory, especially in an agricultural production context. Different econometric techniques (e.g. constrained maximum likelihood methods, Bayesian Markov chain Monte Carlo techniques) are available, though, to impose curvature on the estimated functions (O'Donnell and Coelli, 2005; Henningsen and Henning, 2009).

II.3 Impact Evaluation

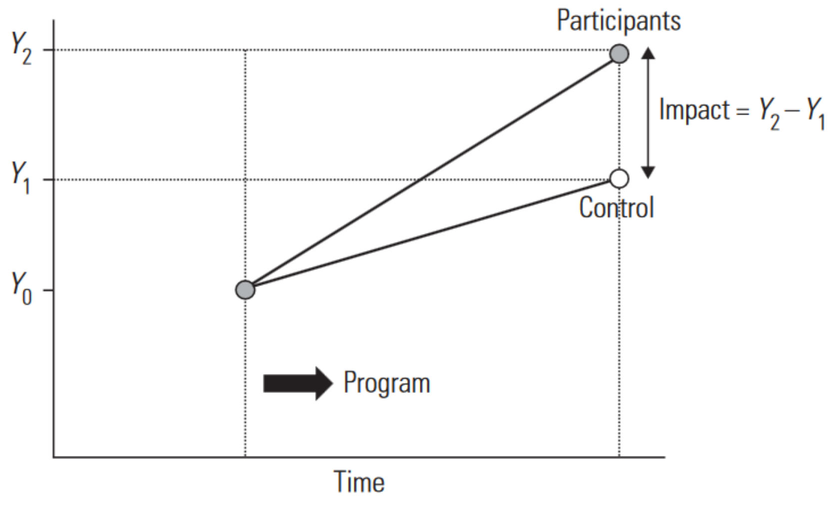
As outlined in the introduction, agricultural policies are designed to reach certain goals and beneficiaries. Methods to understand whether the measures taken actually work and to assess the level and type of impacts in economic, ecological and social domains are thus needed in order to help policy makers adjust and refine chosen policies if needed. They are further crucial to promote accountability in the allocation of resources across public programmes, to better understand what works, how it works and why and to fill knowledge gaps as regards how and if measured changes in a specific outcome are attributable to a particular measure or policy intervention (Khandker, Koolwal and Samad, 2010). Any effective impact evaluation should therefore be able to precisely analyse the mechanisms by which individuals programmes are targeting at are responding to the intervention. These mechanisms are sometimes difficult to grasp as they are subject to interlinkages, e.g. through markets, other policies or social networks. Their understanding is of particular importance given that the benefits of any sound impact evaluation study are long-term and ideally have spillover effects that should not be underestimated.

Impact evaluation encompasses qualitative and quantitative, ex ante and ex post methods. Qualitative analysis, as compared with quantitative approaches, aims to gauge potential effects that a policy may cause, the mechanisms behind such effects and the effect size from methods such as in-depth and group-based interviews. While qualitative results cannot be generalised, they can be critical for understanding the mechanisms through which impacts are generated. Possible impacts can be determined through ex ante or ex post designs by qualitative approaches as well as by quantitative ones (e.g. simulation or economic models). Ex ante designs attempt to predict outcomes of an intervention before the actual measures are implemented. Consequently, assumptions on the behaviour of individuals need to be made. Ex ante approaches often use structural models that interlink policies with micro-level behaviour and markets. They can assist in identifying potential weaknesses of programmes before they are put into practice as well as in forecasting potential impacts. Ex post impact evaluations, in contrast, use real-world data gathered either after an intervention or, ideally, before and after the implementation of a programme. Ex post evaluations are thus able to measure actual impacts and typically build upon quantitative methods. Quantitative approaches have proven valuable when it comes to measuring programme effectiveness, although they sometimes miss to uncover mechanisms underlying a programme’s impact (Khandker, Koolwal and Samad, 2010).

The studies embedded in this dissertation make use of quantitative ex post approaches, which is why the following sections focus on the quantitative methods applied. Useful overviews on qualitative and quantitative approaches and practices are provided for example by Duflo, Glennerster and Kremer (2008), Gertler (2011) and White and Phillips (2012).

Impact evaluation is not the only approach to evaluation. It can be distinguished from those, which encompass classical monitoring and evaluation (M&E) – where monitoring tracks defined indicators of progress over the course of an intervention and operational evaluation tries to understand whether the implementation of an intervention evolved as envisaged – however, by the question of causality. Causality in impact evaluation refers to the issue of attribution and isolating the effect of a programme from other factors and potential selection bias. In this respect, M&E approaches are a prerequisite of any impact evaluation. Through M&E, data in terms of initial goals, indicators and outcomes associated with the intervention is gathered and descriptively analysed. In experimental (or randomised) settings, such analyses typically give causal results. Where allocating a programme or intervention randomly across a sample of observations is not possible due to for example ethical issues, external validity, partial or lack of compliance, selective attrition and spillovers (Khandker, Koolwal and Samad, 2010), non-experimental methods need to be applied in order to obtain causal results. They allow to address the main challenge of impact evaluation, which is finding a proper counterfactual to treatment in order to get an idea of the hypothetical situation of what would have happened to treated units had they not been treated. The fundamental problem of impact evaluation is obviously that the same person cannot be observed in two distinct situations – being treated and untreated at the same time. In the case of randomisation, treated and untreated individuals are similar or equivalent prior to an intervention. Thus, the untreated units act as counterfactuals in a sense that they mimic what would have happened to participants of a programme had they not participated. Figure II-4 illustrates this case graphically. As a result of randomisation, prior to a program, observed units have the same values of an outcome variable Y, which can for example be income. After treatment implementation, the outcome variable of the treated group might have changed, reaching a value of Y_2 for example, while the value of the control group is Y_1. Consequently, the effect of the intervention can be calculated as $(Y_2 - Y_1)$.

Figure II-4: Ideal experiment with an equivalent control group



Source: Khandker, Koolwal and Samad (2010: 32)

Such a straightforward calculation is not possible in non-random settings. The challenge then lies in determining the counterfactual, which is not observed. A convincing and justifiable comparison group for program beneficiaries thus needs to be found. It is obvious that purely comparing the outcomes of treated and untreated units does not do the job as it can be assumed that the comparison group differs significantly from the treatment group in a range of observable and unobservable variables. These variables can be expected, on the other hand, to have an impact on the outcome. Main reasons for differences between treated and untreated units are linked to non-random treatment assignments (purposive program placement, self-selection into the program). Similarly to the pure group comparison, it will not be sufficient to calculate the difference in the outcome before and after the intervention for beneficiaries only as this would ignore the role of time and general trends.

Successful impact evaluations combine elements of time with the identification of a good control group. They can solve the selection bias problem through statistical designs. This problem can be expressed conceptually in the following way. Let Y_i represent the outcome for unit i. For treated units, $T_i = 1$, the outcome under treatment is represented as $Y_i(1)$. Non-participants, $T_i = 0$, are consequently represented in terms of outcome with the expression $Y_i(0)$. If the latter term is used for non-participating individuals as the comparison outcome for the outcomes of participants $Y_i(1)$, the average program effect is given by the following equation:

$$D = E(Y_i(1) \mid T_i = 1) - E(Y_i(0) \mid T_i = 0) \tag{2.12}$$

This representation does not consider, however, that treated and control groups may not be the same prior to the intervention, as stated earlier. Thus, the expected outcome difference between both groups may not be attributed entirely to the intervention. One can, though, add and subtract the expected outcome for non-participants had they participated in the program to get:

$$\begin{aligned} D &= E(Y_i(1) \mid T_i = 1) - E(Y_i(0) \mid T_i = 0) + E(Y_i(0) \mid T_i = 1) - E(Y_i(0) \mid T_i = 1) \\ &= ATE + [E(Y_i(0) \mid T_i = 1) - E(Y_i(0) \mid T_i = 0)] = ATE + B \end{aligned} \tag{2.13}$$

In this equation, ATE refers to the average treatment effect. It corresponds to the average change in outcomes of participants relative to non-participants, as if untreated units were also treated. The average treatment effect, in contrast to the average treatment effect on the treated (ATT), which is typically estimated in non-experimental settings, measures the average difference over the entire population of interest. The term B captures selection bias that arises when D is used to proxy the average treatment effect. It cannot easily be observed and if it is not taken into account, the exact difference in outcomes between participants in a program and non-participants will never be known. One approach[7] to account for it would be to assume that whether or not individuals receive treatment (conditional on a set of covariates X) is independent of the outcomes that are observed for them. This assumption is a key assumption of the method Propensity Score Matching (PSM). It is called *unconfoundedness* assumption or *conditional independence* assumption (Rosenbaum and Rubin, 1983) and can mathematically be described as follows:

[7] Main other approaches are randomised controlled trials, regression discontinuity designs, the use of instrumental variables and synthetic control groups.

$$\big(Y_i(1), Y_i(0)\big) \perp T_i \mid X_i. \tag{2.14}$$

On this basis, PSM constructs a statistical comparison group using a model of the probability of being part of the treatment T conditional on observed characteristics X, which is called the propensity score $P(X) = \Pr(T = 1 \mid X)$. Rosenbaum and Rubin (1983) demonstrate that if the unconfoundedness assumption and an additional assumption, common support (sizable overlap between participants and non-participants in $P(X)$), hold, matching on $P(X)$ is as good as matching on X. The PSM estimator for the ATT can then be specified as the mean difference in Y over the common support, weighting the comparison units by the propensity score distribution of participants (Khandker, Koolwal and Samad, 2010). In a cross-section setting, it can be written as follows (Heckman, Ichimura and Todd, 1997; Smith and Todd, 2005):

$$ATT_{PSM} = \frac{1}{N_T}\left[\sum_{i\in T} Y_i^T - \sum_{j\in C} \omega(i,j) Y_j^C\right] \tag{2.15}$$

PSM typically only requires cross-sectional data. If, however, an intervention runs several years or any impact is expected to occur a certain time period after the treatment, panel or repeated cross-section data can be used for impact analyses. In such cases, PSM can be combined with double-difference or difference-in-difference (DiD) estimation. DiD essentially compares treatment and control groups in terms of changes in outcome over time relative to the outcome observed for a pre-intervention baseline (Khandker, Koolwal and Samad, 2010: 71–72). In a simple two-period setting with $t = 0$ representing the time period before the treatment and $t = 1$ representing the period after program implementation (with Y_t^T and Y_t^C referring to the respective outcomes for treated and untreated units in t), the DiD estimator measures the average program impact in the following way:

$$DiD = E(Y_1^T - E_0^T \mid T_i = 1) - E\big(Y_1^C - Y_0^C \mid T_i = 0\big) \tag{2.16}$$

In this equation, $T_1 = 1$ denotes program participation at time $t = 1$, while $T_1 = 0$ denotes non-participation. A graphical representation of the equation is given in Figure II-5. The lowest line shows the true counterfactual outcomes, which cannot be observed. With the DiD method, observed or unobserved characteristics creating a gap between measured control outcomes and true counterfactual outcomes are assumed to be time invariant and uncorrelated with the treatment over time[8]. Thus, the gap between the two trends stays constant over time. The DiD method does not require treatment and control group to be similar before treatment. However, the assumption of constant trends and a missing influence of observables and unobservables then gets stronger. In order to get more robust results, one can use PSM with the baseline data to make sure that the control group is similar to the treatment group and then apply the DiD estimator to the matched sample. By doing so, observable heterogeneity in the initial stage can be controlled for.

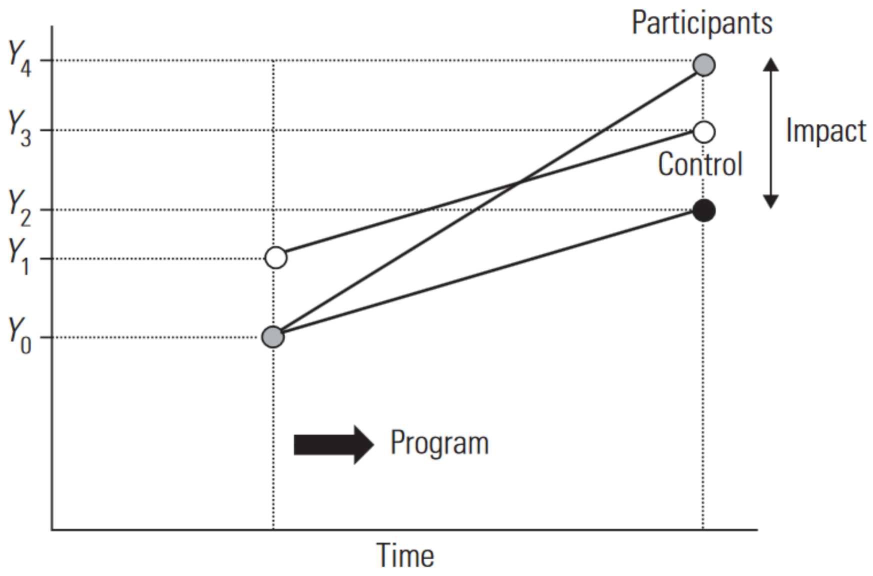
[8] Justifiable concerns can be put forward with this assumption. The interested reader can learn more about them in Angrist and Pischke (2015)

The DiD estimate can be calculated making use of a regression, which can be weighted to take potential biases into account. Generally, the equation to be estimated takes the following form:

$$Y_{it} = \alpha + \beta T_{i1} t + \rho T_{i1} + \gamma t + \varepsilon_{it} \tag{2.17}$$

The coefficient of interest is β. It gives the average treatment effect in that it captures the interaction between the post-program treatment variable T_{i1} and time t. The coefficients on the variables T_{i1} and t capture any separate mean effects of time as well as differences prior to the intervention.

Figure II-5: Graphical representation of the DiD method



Source: Khandker, Koolwal and Samad (2010: 75)

The two-period model just presented can be adjusted for multiple time periods resulting in a panel fixed-effects model. Such a model has the advantage of not only controlling for unobserved time-invariant heterogeneity, but also for heterogeneity in observables. It does so by regressing Y_{it} on T_{it}, time-varying covariates X_{it} and unobserved time-invariant individual heterogeneity τ_i, which may be correlated with both the treatment and other unobserved variables ε_{it}:

$$Y_{it} = \theta T_{it} + \delta X_{it} + \tau_i + \varepsilon_{it} \tag{2.18}$$

If one differences the right- and left-hand side of the equation above over time, the following equation is obtained:

$$(Y_{it} - Y_{it-1}) = \theta(T_{it} - T_{it-1}) + \delta(X_{it} - X_{it-1}) + (\tau_i - \tau_i) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{2.19}$$

$$\rightarrow \Delta Y_{it} = \theta \Delta T_{it} + \delta \Delta X_{it} + \Delta \varepsilon_{it}$$

As the potential source of endogeneity τ_i is dropped through differencing, the equation can be estimated using ordinary least squares (OLS). The standard errors might need to be corrected for serial correlation, though (Bertrand, Duflo and Mullainathan, 2004).

Part 2: Studies embedded

III The integration of ecology and bioeconomy based on the example of agri-environment schemes[9]

III.1 Abstract

The bioeconomy concept is considered an important element in the transition to a more sustainable future. Primarily characterized by its special emphasis on renewable resources and their efficient, innovative use, it is also oriented towards natural cycles and links resource use to environmental conservation. While petroleum-based products are already gradually being replaced by biological alternatives, the environmental burdens of the agricultural production process that generates these alternatives remain problematic and counteract the bioeconomic idea of sustainability. From an economic point of view, market failure is the cause of excessive environmental pollution. In order to counter environmental degradation resulting from market failure, agri-environment measures were introduced as an integral part of the European agricultural policy in the early 1990s. However, the fact that agriculture still puts tremendous pressure on the environment casts doubt on the effectiveness of the introduced measures. A poor implementation of the economic theory underlying the measures may explain their lack of effectiveness. This contribution examines this hypothesis and concludes that a close look at the theory and its implementation reveals a need for adjustments.

III.2 Introduction

In recent years, very few other concepts have enjoyed as much popularity in business, politics and science as that of bioeconomy. Where entrepreneurs discover new business areas, representatives of the political class praise the particularly sustainable form of economic activity that the concept describes, draw up political strategies and provide research funds with which science refines bio-based innovations. However, all the actors involved are united by the basic idea of efficiently using biological resources such as plants, animals and microorganisms. Based on this idea, the Bioökonomierat (Bioeconomy Council) of the Federal Government of Germany describes bioeconomy as “the production and use of biological resources (including knowledge) to provide products, processes and services in every economic sector within the framework of a sustainable economic system” (Bioökonomierat, 2019). Two aspects emerge from a closer look at this definition. For one thing, bioeconomy is not a twenty-first-century discovery. Rather, it is as old as humanity itself. For almost two million years, humans lived essentially on the raw materials provided by plants, animals and microorganisms, before fossil-based raw materials often replaced biologically based ones during the industrial revolution and the dawning petroleum age. On the other hand, the definition by the Bioökonomierat clarifies the central role of biological resources, so focussing on agriculture, forestry and fisheries as providers of biomass.

On the one hand being cornerstones of the concept of bioeconomy, agriculture and forestry illustrate at the same time that organically based management with naturally renewable raw

[9] This is a pre-copyedited, author-produced version of a chapter accepted for publication by the Bavarian Academy of Sciences in the collected edition “Ökologie und Bioökonomie – Neue Konzepte zur umweltverträglichen Nutzung natürlicher Ressourcen”. The version of record (Mennig, Philipp and Johannes Sauer. 2019. Integration von Ökologie und Bioökonomie am Beispiel von Agrarumweltmaßnahmen. In Bayerische Akademie der Wissenschaften (ed.), *Ökologie und Bioökonomie: Neue Konzepte zur umweltverträglichen Nutzung natürlicher Ressourcen*. München: Verlag Dr. Friedrich Pfeil, 17–30) is available here.

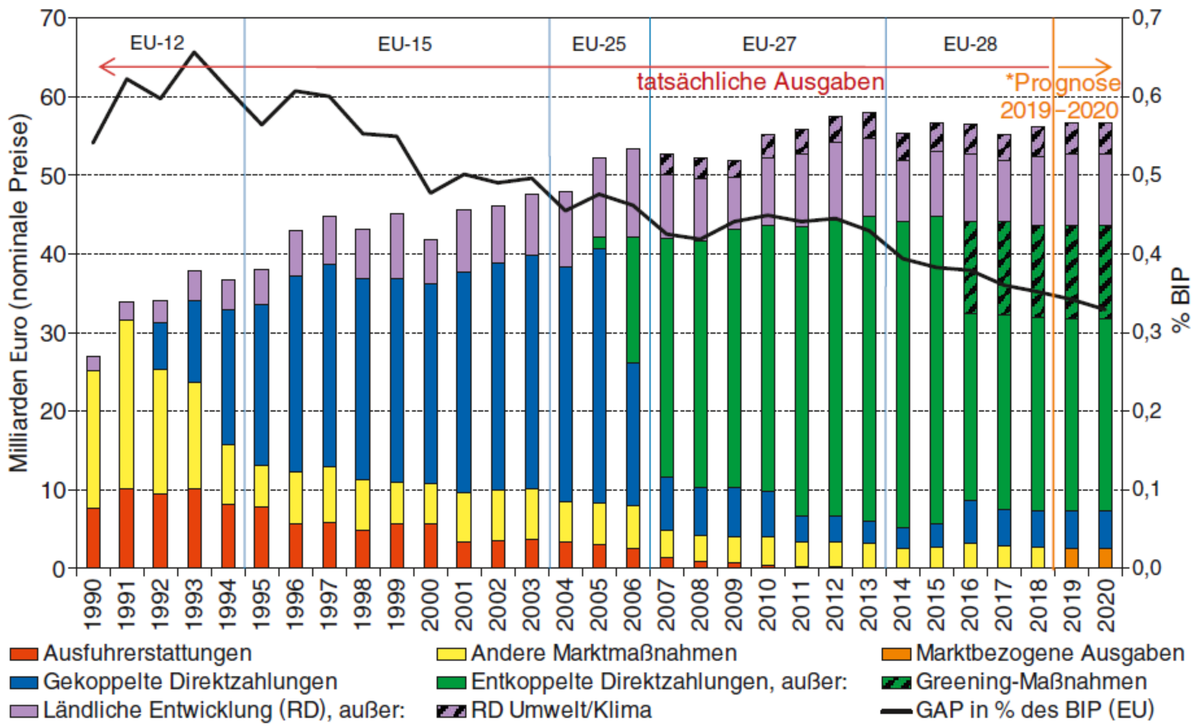
materials does not mean sustainable management per se. The realisation that (intensive) agriculture has adverse environmental effects and that ecological sustainability remains a distant goal is not something that has only recently come to fruition (Foley *et al.*, 2005). In response to the increasingly deteriorating environmental situation, agri-environment schemes (also called agri-environmental measures) based on economic theory were enacted in Europe to integrate ecology and (bio)economy in the late nineteen-eighties. Around 30 years later, a picture is emerging that casts doubt on the effectiveness of the schemes. The alarming decline in biodiversity in Europe and the consistently high nitrate levels in groundwater are examples. But why are the measures not having the desired effects? The theoretical foundations of environmental policy instruments, including agri-environment schemes, speak for themselves and have been confirmed empirically in many studies: Positive environmental effects can be expected if they are implemented correctly. Therefore, it is very reasonable to assume that their implementation does not correspond to the underlying economic theory. The following paper examines this hypothesis. Economic considerations are presented that explain how the integration of ecology and economy can succeed.

III.3 Agri-environment schemes in the EU

Environmental issues were of secondary importance when the Common Agricultural Policy (CAP) was launched in 1962 as the first joint policy of the then European Economic Community, which later became the European Union. The hunger and food shortages of post-war Europe shaped the CAP's initial and primary objectives, which were to increase productivity and secure incomes from agriculture. The CAP quickly achieved its goal of ensuring food supplies. However, in later years, the generous support for volume production as a central instrument of the CAP resulted in considerable overproduction. This huge increase in production was achieved by mechanising operations, land consolidation and the increased use of pesticides and mineral-based fertilisers. Only gradually did the environmental impact caused by intensive agricultural production become apparent and became part of the social discussion. However, with the increasing environmental awareness in the 1970s and 80s, demands for integrating environmental concerns into the CAP became louder. In the late 1980s, agricultural policy decision-makers reacted, among other things, by introducing agri-environment schemes as an integral element of the CAP, although it only became obligatory for the Member States to apply the measures from 1992 onwards.

They offer farmers voluntary participation payments for specified management methods that protect natural resources and preserve the cultivated landscape for a commitment period of usually five years.

Figure III-1: Development of the Common Agricultural Policy budget, 1990-2020



Explanations and translations: Financial resources of the (later) second pillar in purple; Ausfuhrerstattungen=Export refunds, Andere Marktmaßnahmen=Other market measures, Marktbezogene Ausgaben=Market-related expenditure, Gekoppelte Direktzahlungen=Coupled direct payments, Entkoppelte Direktzahlungen=Decoupled direct payments, Greening-Maßnahmen=Greening measures, Ländliche Entwicklung=Rural development (RD), RD Umwelt/Klima=RD Environment/Climate, GAP in % des BIP (EU)=CAP as % of GDP (EU). Milliarden Euro (nominale Preise)=Billions of euros (nominal prices), tatsächliche Ausgaben=Actual expenditure, Prognose=Forecast

*2019: Budget; 2020: according to the draft budget, coupled direct payments, inc. payment component for POSEI/SAI and Annex I of EU Directive 1305/2013.

Depiction based on: CAP spending over recent years: European Commission, Directorate-General for Agriculture and Rural Development, GDP: Eurostat and Global Insight

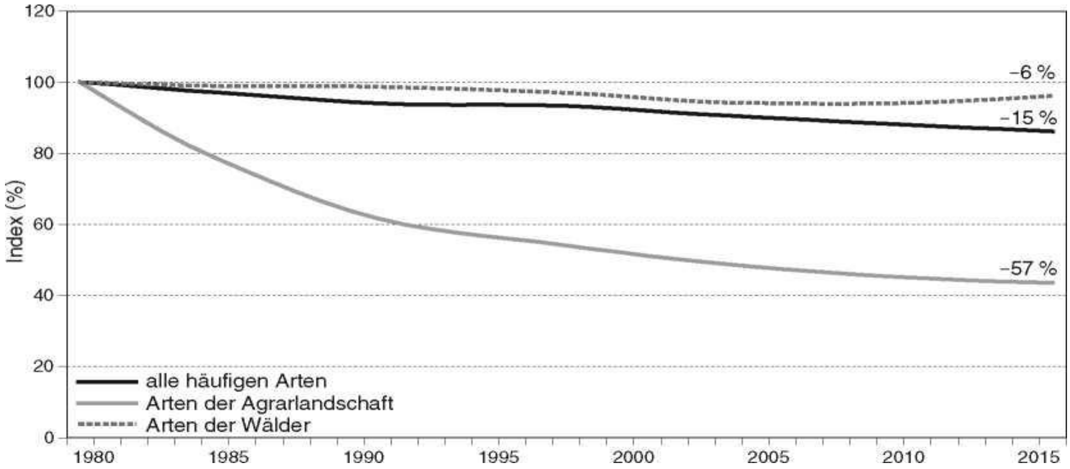
Agri-environmental measures occupy a place in the second pillar in the current two-pillar structure of the CAP, which has existed since “Agenda 2000”. While the first pillar includes direct payments to farmers for each hectare of agricultural land, the second pillar includes targeted support programmes for sustainable and environmentally friendly farm management and rural development. The precise structure of the second pillar support measures is the responsibility of the Member States and/or individual regions. As Figure III-1 shows, the financial volume of the first pillar, made up of the red, yellow, blue, green and orange bars, is significantly higher than that of the second (purple) pillar (associated forms of expenditure before the “Agenda 2000” reform correspond, in retrospect, to the first pillar, which was created later). However, a slight shift in spending in favour of the second pillar can be seen in the current EU funding period and during the previous one. Because of this trend, more funding has recently been available and remained available until 2020 for agri-environment schemes and compensatory allowances for naturally disadvantaged areas, the financial share of which must account for at least 30 percent of the second pillar’s budget.

During the 2014-2020 funding period, the budget of the second pillar amounted to €95.6 billion. A budget of €408.3 billion was earmarked for the first pillar. EU funding for rural development is supplemented by national and regional funding, so that the actual expenditure is over €95.6 billion.

In Brussels, for some years now, agricultural commissioners and representatives of the farming community have been emphasising the sustainability goals of the Union's policies, which also apply the specific goals of the CAP and which are laid down in Article 11 of the Treaty on the Functioning of the European Union, and relate these to the structuring of agricultural policy. The increasing budget of the second pillar as well as the cross-compliance and greening provisions of the first pillar, the receipt of direct payments for the fulfilment of specific standards in the fields of environmental protection and the safety of foodstuffs and animal fodder, as well as animal health and animal welfare, are viewed as a success in terms of reducing the environmental impact of agriculture. However, this view of success only partially corresponds to the scientific findings. Neither cross-compliance nor greening requirements can achieve significant positive environmental impacts (Solazzo *et al.*, 2016; Söderberg, 2011; Gocht *et al.*, 2017; Cortignani and Dono, 2018). This leaves agri-environment schemes as a means of reducing agriculture's ecological footprint. Extensification or integrated farm management – both examples of obligations under national or regional agri-environmental regulations – have been shown to improve the environmental footprint. Accordingly, a positive environmental effect can be expected from expenditure on second pillar measures and, above all, from their gradual increase in absolute and relative terms since 2000. However, a look at selected environmental indicators shows that this has not materialised.

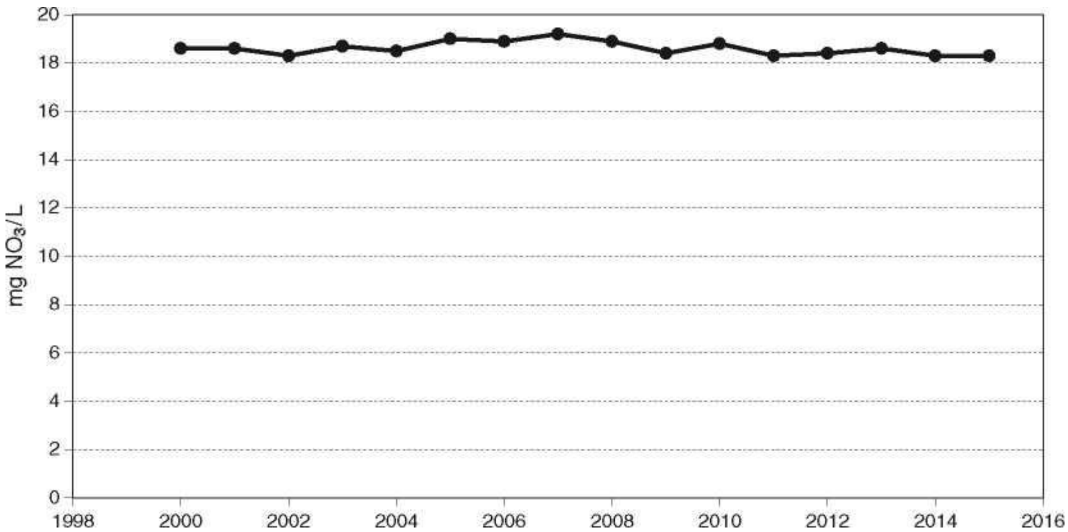
Specifically, changes in environments caused by agriculture have led to a loss of quality and in the extent of important habitats over recent decades. This affects the animal and plant species that depend on such habitats; their diversity has suffered considerably, which can be seen from the populations of selected bird species (Figure III-2). The populations of European farmland species have more than halved since 1980, despite agri-environmental support measures. Looking at water protection, a similar picture emerges, though albeit somewhat less dramatic. The pollution of European groundwater with nitrates did not change significantly between 2000 and 2015, despite every effort to reduce nitrogen inputs and increases in agri-environmental expenditure (Figure III-3). The Europe-wide limit value of 50 mg/L has even been exceeded at 13% of all the European monitoring sites observed (European Commission, 2018d) for many years. Only a few isolated environmental indicators point to positive developments. The emission of the greenhouse gases methane and nitrous oxide in the agricultural sector, for example, for which agriculture is the main emitter, has fallen markedly since 1990 (Figure III-4). However, the extent to which agri-environment schemes have contributed to this development is questionable. The reduction in methane emissions is mainly due to the decline in European livestock numbers. Fewer animals can be kept with the same or higher output thanks to breeding and improved management. The reason for the fall in nitrous oxide emissions is likely linked to the more efficient use of nitrogen fertilisers, not least due to technical progress, which is in the farmers' own economic interest.

Figure III-2: Population development of typical bird species in Europe (EU-28, excluding Croatia and Malta) 1980-2016 and the development of forest and agricultural land species



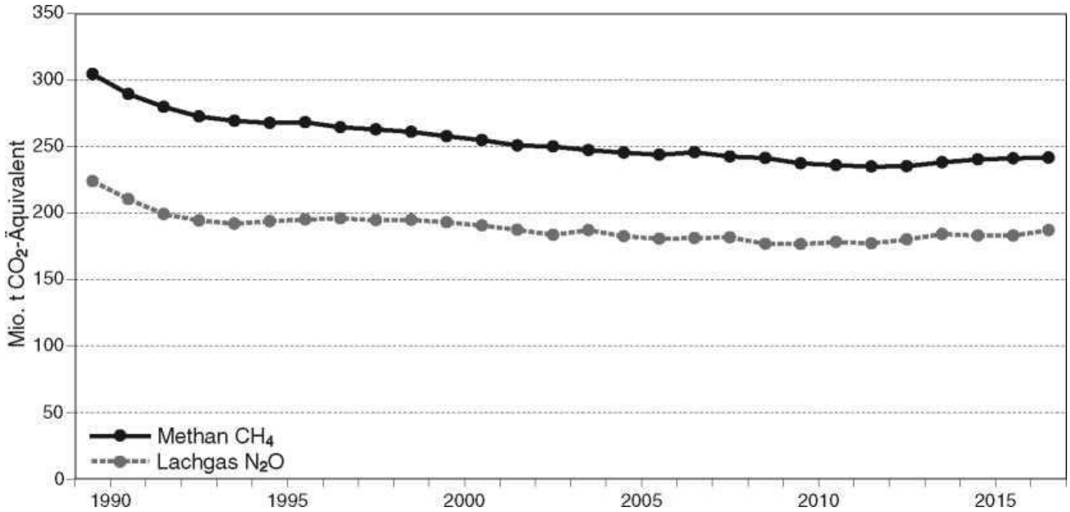
Own depiction based on data from EBCC/BirdLife/RSPB/CSO; PECBMS 2019, CC BY-NC 4.0. Translations: alle häufigen Arten=all common species, Arten der Agrarlandschaft=Species found in agricultural habitats, Arten der Wälder=Forest species

Figure III-3: Development of nitrate pollution (in mg NO_3/liter) in European groundwater (data from 19 European countries) 2000-2015



Own depiction based on data from Eurostat 2019, in accordance with data from the European Environment Agency (EEA).

Figure III-4: Development of the emissions of the greenhouse gases methane and nitrous oxide (in million tonnes of CO_2 equivalents) from agriculture in Europe (EU-28) 1990-2017



Own depiction based on data from EEA 2019. Translations: Mio. t CO_2-Äquivalent=Million tonnes of CO_2 equivalent, Methane CH_4=Methane CH_4, Lachgas N_2O=Nitrous oxide N_2O

One can thus observe the paradoxical situation whereby steadily increasing expenditure on agri-environment schemes is being offset by a trend towards an increasing burden on natural resources. Three explanations for this situation of seemingly ineffective support measures being financed with billions of euros of taxpayers' money are conceivable: Either the content of the measures is incorrect, the implementation of the economic theory on which the original introduction of the programmes was based is flawed or the theory itself is wrong. The content design can largely be ruled out; the results of experiments on extensification measures are too obvious. So can the hypothesis of an incorrect theory. Hence, it is necessary to investigate the degree of agreement between theory and its actual implementation in more detail. To this end, the following section first describes the inclusion of the environment in the various phases of the history of economics to grasp the basic idea of political measures for environmental protection.

III.4 The role of the environment in economic theory

The concepts of ecology and economy have a long history of using similar ideas and influencing each other. For example, the naturalist Charles Darwin and the classical economists Adam Smith and Thomas Malthus discovered analogies long before ecology emerged as a scientific discipline in the second half of the 19th century. Gómez-Baggethun *et al.* (2010) observed the first reflections on the relationship between economy and nature even earlier, from Plato and Pliny the Elder. A deeper academic interest in studying the uses of nature finally arose during the era of classical economics.

Classical economics, which developed towards the end of the 18th century, viewed natural capital in the form of land as an essential production factor. However, unlike in the economic school of physiocracy (first half of the 18th century), labour was included as a second, more important factor in the production function. By assessing the factor of land as non-substitutable, the classical economists concentrated on their theories concerning the scarcity of natural resources. Their thought processes did not consider the services provided by nature that had no direct market value, such as the pollination of crops or the nitrogen cycle. These gifts of nature were considered free of charge and did not directly provide added value.

Around 1870, towards the end of the classical economics era, nature increasingly disappeared from economic analyses as capital gained importance.

Proponents of the neoclassical theory that followed on from classical economics, focusing on marginal considerations, initially limited their analyses, like their predecessors, to marketable goods, largely excluding any environmental aspects. Between 1910 and 1930, however, economists such as Gray, Ramsey, Ise, Pigou and Hotelling first expressed concerns about external effects and the consequences of using natural resources for future generations (Martínez-Alier, 1987). Externalities and other causes of market failures that lead to environmental burdens and instruments for internalisation were highlighted. However, interest in environmental issues waned again in the 1930s. Theories and models were now devoted to the possible substitutability of production factors by technical innovations. Assuming the complete substitutability of natural capital and other capital forms, land completely disappeared from the production function.

Only with the environmental movement of the second half of the 20th century did sub-disciplines arise that revealed shortcomings in economic theory when it came to taking nature into account. It began with environmental economics that emerged in the early 1960s, whose proponents joined together to form the Society of Environmental and Resource Economics. The environmental economists expanded the neoclassical ideas in such a way that the effects of economic activity on the environment were explicitly (monetarily) evaluated and considered in the decision-making process. For the first time, all the services provided by nature, including those without a market price, were included in the analyses. Different types of values were identified and methods for their measurement were developed to obtain a holistic picture of the economic value of nature.

In addition, market failures as the cause of numerous environmental problems came back into focus and, along with them, the development of correction instruments.

Substantive differences within the Society of Environmental and Resource Economics caused some members to split off in the late 1980s. They founded the sub-discipline of ecological economics. To this day, a controversy exists about the exact differences between environmental economics and ecological economics (Turner, 1999). Both disciplines draw on the same, predominantly neoclassical pool of methods. While environmental economics mainly operates within the axiomatic boundaries of neoclassicism, ecological economics throws doubts on some neoclassical assumptions. In particular, it defines the economic system as a sub-system of the ecosphere. It expands the pursuit of market-driven, efficient allocation of resources to include questions of fair distribution and biophysical limits. However, the greatest disagreement is over the question of the substitutability of different types of capital. Environmental economists use the concept of weak sustainability, according to which the proceeds from extracting non-renewable resources can be invested in man-made capital, in the sense of non-decreasing capital stock. Natural capital and investment capital are treated as perfect substitutes. Proponents of ecological economics reject this concept, favouring strong sustainability as a concept that favours complementarity instead of substitutability. They also critically evaluate the monetisation of environmental services.

More recent economic thinking about environmental aspects has been shaped by the ecosystem services approach. Conceived by Ehrlich and Ehrlich (1981), this thinking focuses on society's dependence on ecosystems. Consequently, human well-being is directly related to the functionality of supporting, provisioning, regulating and cultural ecosystem services, which in turn are impaired by human economic activity. The concept gained awareness through the estimate by Costanza *et al.* of the total societal value of the earth's ecosystems made in 1997, including the complexity and interrelationships of natural processes.

Over time, the environment gained an increasingly prominent place in economic considerations. Above all, however, economists used their theories to explore the causes of environmental pollution and the means to reduce it. The intention is to outline these theories, on which agri-environment schemes are also based, in the following paragraphs.

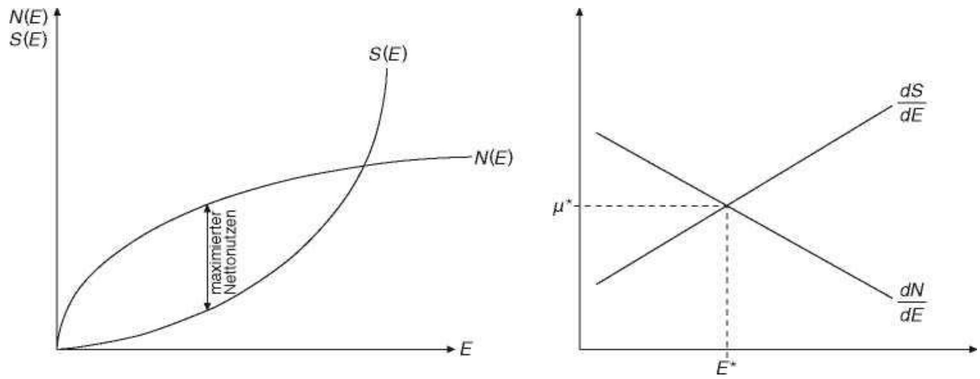
III.5 Economic theory as the basis of agri-environment schemes

As in other sectors, it is currently impossible to manufacture goods without any environmental impact in agriculture. A complete avoidance of environmental pollution would be tantamount to abandoning production, clearly an unviable option. From an economic point of view, a solution to this problem is a situation where the marginal costs correspond to the marginal benefits of pollution. It sounds strange at first to recognise a benefit in pollution. However, people benefit from the goods whose production causes environmental pollution, i.e. they generate a benefit through their consumption.

Figure III-5 shows how the efficient level of environmental pollution for a pollutant flows is determined. The production process produces emissions E, which cause damage amounting to S. At the same time, a benefit N arises from the goods produced. The optimal emission quantity E^* results from the maximum of the difference between the total benefit and the total damage (maximised net benefit).

In perfect markets, the efficient level of environmental pollution μ^* is achieved. However, perfect markets are a theoretical construct. In real markets, market failures often prevent efficient allocations; they can be identified as a cause of excessive environmental pollution from an economic point of view. The main reasons for market failures in the agri-environmental sector are public goods, imperfect property rights, incomplete information and (negative) external effects. Negative external effects – or externalities – refer to costs that do not affect the polluter, but which have an impact on third parties who are uninvolved.

Figure III-5: Overall and marginal damage and marginal benefit function and the efficient level of pollution in the course of a production process



S=damage; N=benefit; E=emissions; E*=optimal emission quantity with maximised net benefit; μ*=efficient pollution level; see text for further explanations

Source: Own depiction

In the case of agricultural production, for example, nitrate enters the groundwater through leaching. However, the costs of this pollution – treatment of the drinking water – are not included in the market price of the good produced. In the market equilibrium, the good is thus offered in too great a quantity, and the actual contamination thus exceeds that which can be expected in the social optimum.

Various instruments are available to correct this form of market failure – the internalisation of external effects. These include Pigouvian taxes or subsidies, the trade in pollution rights and the bargaining solutions according to Coase (Coase theorem; Coase, 1960) have proven to be economically efficient. With agri-environment schemes, European agricultural policy uses a tool from the second pillar in the broad field between subsidies and Coase's theorem. Increasingly, they are listed in EU publications with the designation of payments for ecosystem services (PES). Based on the concept of ecosystem services by Ehrlich and Ehrlich (1981), PES are intended to create markets for environmental services. Wunder (2005: 3) defines payments for ecosystem services as voluntary transactions in which a service buyer acquires a defined ecosystem service (at least one) from a service provider (at least one), provided that the service provider can guarantee the actual provision of the service (conditionality). The accessibility of the definition explains the term's popularity, but it blurs the essential economic concept on which it is based – Coase's theorem. In 1960, British economist Ronald Harry Coase showed that under certain conditions (absence of transaction costs, complete information, clearly defined property rights, a small number of participants), an optimal level of external effects could be achieved through a negotiated settlement between the economic agents involved (efficiency thesis).

Before the implementation of agri-environmental measures in Europe is compared with economic theory, one central criterion of the PES approach needs to be explained. Payments for ecosystem services assume that the provider creates an environmental service; in other words, the "provider gets principle" applies. In contrast, there is the "polluter pays principle," as propagated by the OECD since the 1970s, where the polluter pays for the environmental impact. For agri-environment schemes such as PES, the "provider gets principle" applies. However, it is questionable whether agricultural production provides overall positive ecosystem services compared to a situation without any agricultural activity, which would justify payments for positive externalities. On the contrary, agriculture burdens ecosystem services in many areas. According to Hanley *et al.* (1998), property rights play a role in choosing one of the two principles, although political and cultural considerations do as well.

III.6 Theory and implementation of agri-environment schemes

Structured according to the aspects and tools for correcting market failures described, Table III-1 compares economic theory and its implementation in the agri-environmental sector. The implementation deviates from the theoretical guidelines in essential points due partly to methodological difficulties. The Coase theorem as a construct behind PES is based on assumptions (e.g. no transaction costs and few participants), which can hardly be fulfilled in the case of regional or even national agri-environmental programmes that are offered horizontally, i.e. uniformly over a wide area. It is also difficult to implement the conditionality required in the definition of PES, which links the payment of compensation to ensuring the provision of an ecosystem service.

In the case of agri-environment schemes, this corresponds to results-based approaches in which farmers are rewarded depending on the environmental performance achieved. As comprehensible as this procedure seems, it is complex to implement, which is why result-based measures remain a rarity. Problems include the increasing transaction costs linked to individual farm monitoring, the allocation of causation (polluter) and environmental effect (e.g. groundwater quality), and the risk on the part of farmers that factors beyond their control may impede the provision of ecosystem services. Because of these obstacles, policymakers resort to action-based approaches that offset the costs and loss of income resulting from scheme participation. Nevertheless, as a rule, the same payment rates apply over the entire area of the measure, without any regional differentiations. Payments for agri-environmental measures thus resemble a subsidy. However, according to the theory, the subsidy amount should match the shadow price obtained when calculating the efficient pollution degree (μ^* in Figure III-5) and not be based on income losses and participation costs. However, what is undisputed is the fact that, given the lack of monetary values for ecosystem services, the shadow price can hardly be determined or only determined approximately with a great deal of effort. Recourse to action-based payments thus initially appears sensible, but it harbours two types of weakness. Firstly, in agriculture, varying natural conditions greatly influence yields. With uniform payment rates, the opportunity costs of participating in agri-environment schemes consequently vary, depending on the location. In high-yield locations, the incentive for profit-maximising land managers to participate in the programme is low, whereas in areas of extensive land use, the same form of management would have taken place even without any agri-environment schemes. The results are, on the one hand, windfall effects, on the other hand, regions in which there is hardly any environmental protection through agri-environmental measures – while neither can be in the sense of targeted agri-environmental policy, the latter point (despite the theoretical economic efficiency) is dramatic in relation to areas such as biodiversity, as well as in protecting water and soil.

Table III-1: Comparison of the economic theory and the implementation of agri-environment schemes

Economic theory **Coase theorem**	**Implementation** **Agri-environment schemes in Europe**
Assumptions: (1) No transaction costs (2) Complete Information (3) Clearly defined property rights (4) Few participants	▪ Transaction costs arise because the state acts as an intermediary between the buyers and sellers of ecosystem services. ▪ Complete information would mean a perfect understanding of ecosystem services and their interrelationships. This may be doubted. ▪ In the case of agri-environment schemes, many ecosystem service sellers (farmers) face many buyers (society).
Economic theory **PES**	**Implementation** **Agri-environmental measures in Europe**
Payments for ecosystem services are (1) *voluntary transactions* in which (2) a defined *ecosystem service* is acquired (3) from a *service buyer* (at least one) (4) from a *service provider* (at least one) (5) given that the service provider can guarantee the actual provision of the service (*conditionality*).*	▪ Since the state acts as the proxy for the buyers of ecosystem services, it cannot be assumed that the buyers act voluntarily. ▪ In the case of an agri-environmental measure, the ecosystem service is not defined, but rather the farmer's management restriction (e.g. farming without chemical crop protection) is. ▪ In the case of an agri-environmental measure, the farmer does not have to guarantee the actual provision of the service (exception: "payment by result" schemes). The farmers are not rewarded for the provision, but their costs and income losses from participation are compensated.

Economic theory **PES**	**Implementation** **Agri-environment schemes in Europe**
… purchased from a service provider (at least one) ...	In the case of agricultural production, it is questionable to which extent the farmer does provide ecosystem services since their provision would be higher without farming in many areas (for example, biodiversity and water treatment).
Economic principles – environmental law **PES**	**Implementation** **Agri-environment schemes in Europe**
Negative externality: *Polluter pays principle* Positive externality: *Provider gets principle* Frequently used in OECD countries since the 1970s	Despite predominantly negative externalities, the “provider gets” principle applies (among other things due to difficulties in assigning diffuse substance inputs, weather conditions and the agricultural lobby (Hanley *et al.*, 1998). Both these principles lead to the same result from an economic point of view.
Economic theory **Subsidy**	**Implementation** **Agri-environment schemes in Europe**
▪ The amount of subsidy should correspond to the shadow price obtained when calculating the efficient “pollution level” (zero emissions are not efficient from an economic point of view). ▪ Compared to taxes, subsidies in the environmental sector have specific disadvantages, for example, intensification on other land (Baumol and Oates, 1998). ▪ Efficient allocation of resources when internalising the negative external effect (the “Pareto optimum”)	▪ The level of subsidy corresponds to the average loss of income and the average costs of participation in agri-environment schemes; windfall effects ▪ Efficient allocation of resources in the agricultural sector can mean low participation in agri-environment schemes on high-yield sites (high opportunity costs), which is not desirable from an environmental perspective.

*In a PES definition revised by Wunder (2015), only conditionality remains an essential criterion.

III.7 Conclusion

The transformation from an economy based largely on fossil raw materials to a knowledge-based bioeconomy is inevitable given the dwindling oil reserves and the environmental damage caused by using non-renewable resources. Therefore, the hype about the bioeconomy as a future concept that cuts dependencies on fossil resources and meets sustainability criteria is all too understandable. However, the use of biogenic raw materials alone is only one piece of the mosaic in the recipe for success, as long as their provision by agriculture and forestry is accompanied by considerable environmental pollution. Agri-environment schemes represent one means of integrating ecology and economy in the agricultural production process. Though, their current structure in Europe prevents satisfactory results in terms of environmental sustainability. A return to economic theories may serve as a beacon on the path to the desired sustainability in the sub-sector of ecology. Certainly, the complexity of reality only permits a 1:1 implementation of the economic theory of a model world to a limited extent. Nonetheless, economic concepts are the guiding principle. The use of modern technology (such as remote sensing) cuts transaction costs for result-oriented agri-environmental measures, enabling payments to be made to the amount of the services actually provided. Moreover, improved monitoring programmes on individual farms can be used to record all measurable ecosystem services, based on a holistic approach. On the basis of the Coase theorem, payments for ecosystem services could consequently result from a negotiation process between action planners and service providers, provided the “provider gets principle” is adhered to. Different site conditions and opportunity costs would be explicitly considered in this case. Even in a “polluter pays” scenario, Coase’s negotiating solution offers a solid foundation. Of course, the economic efficiency of any new measures would have to be examined in greater detail.

IV The impact of agri-environment schemes on farm productivity: a DID-matching approach[10]

IV.1 Abstract

According to WTO standards, agri-environmental schemes (AES) payments should distort neither trade nor production but instead only compensate for income forgone and costs incurred. At the same time, contract design shall give farmers enough flexibility to react to changing market and production conditions. We apply a difference-in-difference propensity score matching estimator to test if AES have an unintended effect on farm productivity. Our results suggest that schemes designed for arable land overcompensate farmers and thus do fail to comply with WTO rules. For dairy farms, we find that AES participation reduces farm productivity, implying that action-based scheme design not considering changing market and production situations might be too restrictive, potentially preventing farmers from participating.

IV.2 Introduction

Agricultural intensification has a significant impact on the environment. Examples are emissions to air (Cara, Houzé and Jayet, 2005) and water (OECD, 2008a), soil erosion (Morgan, 2005; Pimentel and Burgess, 2013) and the loss of biodiversity and habitats (Tscharntke *et al.*, 2005; Kleijn *et al.*, 2006). One response to growing social concerns about the trend towards more intensive farming in Europe has been the introduction of agri-environment schemes (AES) as compulsory elements of the Member States' rural development plans in the course of the 1992 MacSharry reform of the Common Agricultural Policy (CAP). AES offer farmers an incentive to adopt environment friendly practices on a voluntary basis. As part of the second pillar of the CAP, which focuses on rural development policy, 20 billion EUR or 22% of the expenditure for rural development were spent on AES in the programming period 2007-2013 (European Commission, 2017). Agri-environment measures are co-financed by member states, which indicates that total AES spending was even higher. While in real terms CAP funding will decrease in the period 2014-2020 compared to the previous programming period, the European Commission (2017) forecasts an increase in spending on agri-environmental measures to 25 billion EUR. When it comes to designing these measures policy makers face two main challenges: On the one hand efficient scheme design must attract a large number of farmers while on the other hand the compliance with standards of the World Trade Organization (WTO) not to distort trade or production must be guaranteed.

The objective of this paper is to evaluate scheme design by measuring whether AES are framed in a way that does not affect farm productivity (negatively or positively) taking into account selection bias. Furthermore, we investigate whether the schemes meet WTO green box requirements. Our analysis focuses on the German federal state Bavaria for at least three reasons. First, Bavaria has a long tradition in the implementation of agri-environmental programs. Second, the variety and design of Bavarian arable land and permanent grassland

[10] This is a pre-copyedited, author-produced version of an article accepted for publication in the European Review of Agricultural Economics following peer review. The version of record (Mennig, Philipp and Johannes Sauer. 2020. *The impact of agri-environment schemes on farm productivity: a DID-matching approach*. European Review of Agricultural Economics. 47(3): 1045–1093) is available online at https://doi.org/10.1093/erae/jbz006.

AES are similar to schemes all over Europe. Third, it is a representative region within European regions with respect to topography, agri-ecologic conditions, production structure and policy approach.

European taxpayers are expecting policy makers to spend the CAP budget, and consequently also the budget share foreseen for AES, efficiently. It is therefore of paramount importance to assess both AES design and the environmental and economic effects that the measures are intended to achieve. Proper AES design can guarantee high participation rates (Pavlis *et al.*, 2016; van Herzele *et al.*, 2013; Birge *et al.*, 2017) while evaluation studies measuring the effects of AES can help improving the ecological effectiveness and economic efficiency of the schemes. A vast amount of literature deals with the impact of AES, mainly focusing on environmental aspects with an emphasis on the effects on biodiversity (Kleijn and Sutherland, 2003; Princé, Moussus and Jiguet, 2012; Feehan, Desmond and Culleton, 2005; Lindenmayer *et al.*, 2012). Impacts on soil quality in relation to fertilizer application (Marconi, Raggi and Viaggi, 2015; Marriott *et al.*, 2005; Richards *et al.*, 2015), on water quality (Poole *et al.*, 2013; Parrott and Burningham, 2008) or on greenhouse gas emissions (Peerlings and Polman, 2008) are less frequently assessed. A second group of studies focuses on the (cost-)effectiveness and efficiency of agri-environment measures (Ansell *et al.*, 2016; Balana *et al.*, 2015; Pacini *et al.*, 2015), whereas a third group deals with the identification of factors influencing farmers' decisions to take up AES (Zimmermann and Britz, 2016; Pavlis *et al.*, 2016; Lastra-Bravo *et al.*, 2015). Due to the voluntary nature of AES, the motives for participation or non-participation are crucial aspects. Beedell and Rehman (2000) state that business factors, farm structure, farmers' characteristics, attitudes and contextual factors influence farms' response to agri-environmental policies. Farmers' willingness to participate in agri-environment programs is considered to be driven by profit maximizing behaviour (Gasson and Errington, 1993; Maybery, Crase and Gullifer, 2005) and therefore depends on economic effects at farm level that are expected to result from participation.

A farmer's decision to participate will result in future management restrictions and less flexibility for farm development. Restrictions arise, because participation in AES in Europe is usually tied to management plans for the fields or subjects under program for at least five years. Such long contract periods shall guarantee the achievement of environmental objectives. For farmers enrolled in agri-environment programs five year management plans mean fewer possibilities to adapt to changing market or production conditions. According to Lastra-Bravo et al. (2015), economic factors still play a key role for farmers' willingness to participate in AES, with scheme restrictions and inflexibility as reasons not to participate. Espinosa-Goded, Barreiro-Hurlé and Ruto (2010) investigated farmers' preferences in cases of agri-environmental policy changes and discovered that farmers were willing to adopt an AES as long as they could maintain their agricultural activities without facing severe restrictions on farm management. Following Niens and Marggraf (2010), scheme participation may increase if payments are regularly adjusted in accordance with market prices. More generally, scheme uptake is found to be low if restrictions are high (Wales Rural Observatory, 2011). Consequently, for reaching higher uptake rates, policy makers must design AES in a way that does not restrict farm economic performance flexibility. At the same time, according to the conditions of the Uruguay round reform program, green box payments, to which AES belong, may not have, or at most minimal trade distorting effects or effects on production, they must be government-funded (not by charging consumers higher prices) and must not involve price support. In addition, payments under environmental programs must fulfill two criteria: a) Eligibility for such payments shall be dependent on the fulfilment of specific conditions, including conditions related to production methods or inputs; b) The payment shall be limited to extra costs or loss of income (WTO, 1995b: 95).

Only a few studies have attempted to measure the impact of AES participation on farm level structure and economic performance empirically. Lynch, Gray and Geoghegan (2007) studied the impact of AES on farmland prices in the United States and found reductions in price due to preservation, In a similar study Wu (2000) and Fleming (2014) found that acreage reductions due to AES have been offset by bringing non-cropland into production. Roberts and Lubowski (2007) used a binomial probit regression to analyse the likelihood that cropland retirement induced by the Conservation Reserve Program (CRP) was extended beyond contract period. They observed that temporary cropland retirement payments under CRP can generate long-term land-use changes. Recent works concentrating more directly on farm level economic indicators include Blazy, Barlagne and Sierra (2015) and Alary *et al.* (2016). The former assessed the performance of two AES in the French West Indies based on a simulation of the performance of a soil-climate-crop system under different scenarios. They highlighted that the AES promoted environmental benefits but reduced crop yield and farmers' income. Alary *et al.* (2016) developed a bio-economic farm model based on the optimization of a utility function to capture income effects of conservation agriculture in Brazil. Their findings suggest that applying conservation techniques can be economically attractive. In Europe, Sauer, Walsh and Zilberman (2013) investigated the effects of different agri-environmental schemes on individual producer behaviour (i.e., production intensity, performance and structure) for a sample of UK cereal farms. They conclude that farms enrolled in AES are efficiently adjusting their production decisions given the respective scheme constraints. Farms affected by these schemes tend to adopt a less specialised and more diversified production structure. Yield effects were studied by Salhofer and Streicher (2005) for ten agri-environmental programs in Austria using fixed-effects and difference-in-difference estimations. They found that out of ten programs, only three had significant negative effects on yields, while one program showed a significant positive effect. Negative effects of organic farming, which usually is a special agri-environment measure, on farm productivity were shown by Oude Lansink, Pietola and Bäckman (2002) for Finnish crop and livestock farms. Mosnier *et al.* (2009) used a bio-economic modelling approach to measure the effect of the CAP mid-term review 2003 on arable farms in the Southwest of France and concluded that decoupling, modulation, and "buffer strips" reduced the total gross margin. Another French study by Mary (2013) analysed the impact of CAP subsidies on total factor productivity using a FADN dataset of French crop farms between 1996 and 2003. He applied a system GMM approach to investigate the impact of both pillar 1 and pillar 2 payments and showed that several subsidies had affected productivity negatively. However, he did not emphasize AES and neglected potential selection bias. Chabé-Ferret and Subervie (2013) examined additional and windfall effects of five French AES, making use of difference-in-difference matching and a structural household model. Their results indicate that AES deliver desired impacts, but suffer from windfall effects. A matching approach was also used by Pufahl and Weiss (2009) in their assessment of AES effects on input use and farm output of individual farms in Germany. Their results revealed a positive effect on the area under cultivation and on fertilizer expenditures. The impact of agri-environmental programs on fertilizer use was also studied by Laukkanen and Nauges (2014) who used panel data from Finland to demonstrate that payments have a fairly small effect on fertilizer use. Arata and Sckokai (2016) used a difference-in-difference propensity score matching estimator to perform a comparative analysis of the effects of AES on farmers' performance across five EU member states. Their results suggest that the effects of AES largely depend on the share of the agri-environmental payment of farm revenue. If this share is larger than 5%, participation in AES is generally effective in promoting greener farming practices.

Our article aims at contributing to the literature by providing a production economic framework to estimate AES effects on farm productivity while considering selection bias occurring due to the voluntary nature of agreement-based schemes. While our matching approach is similar to Arata and Sckokai (2016) and Pufahl and Weiss (2009), our outcome variable productivity has not been studied under this setting before. Our findings support the reconsideration of AES designs and question whether non-participation can be justified by fears of productivity losses at farm level. We use a detailed sample of individual farmers on scheme participation, farm and farmers' characteristics covering the period 2006-2011, thus focusing on the introduction of new AES in the EU programming period 2007-2013.

IV.3 Theoretical framework

Given accelerating deregulation and efforts to integrate environmental issues into agricultural policy, the measurement of productivity and structural change in agricultural sectors remains high on the policy and research agenda (Adamopoulos and Restuccia, 2014; Gollin, Lagakos and Waugh, 2014; Bustos, Caprettini and Ponticelli, 2016). Farm productivity in its simplest form can be defined as the ratio of output(s) that it produces to the input(s) that it uses. If the measurement involves all factors of production and all outputs produced we refer to it as total factor productivity (TFP). By exploiting scale economies, a technically efficient production unit might be able to increase its productivity further by moving closer to the relevant production frontier given its feasible production set. In a dynamic perspective, productivity gains are further realized through technological advances most commonly referred to as technical change (TC). So, observing that a farm has increased its productivity over time might have been due to efficiency improvements, the exploitation of scale or technical change, or some combination of these factors.

In a theoretical setting, we model production decisions and how AES impact them. A farmer's decision in relation to AES is whether to join or not. If farmer i joins, he receives an additional payment, P_i, for adhering to an environmental plan. If he farms outside of any program, he does not have to deal with additional environmental restrictions, $\overline{E}_i$, and their associated implementation costs, C_i. The choice of farmer i between entering an AES or not will be determined by his or her utility associated with the respective option (Hynes and Garvey, 2009). The utility derived from entering the AES can be expressed as:

$$U_{AESi}(P_i + I_i + C_i, \overline{E}_i, Z_i) \tag{4.1}$$

whereas the utility from not enrolling can be given by:

$$U_{noAESi}(I_i, 0; Z_i) \tag{4.2}$$

where, I_i is family farm income and Z_i is a vector of farm and farmer characteristics that affect utility. The 0 in equation (4.2) indicates that if the farmer does not decide to enrol land under AES, no additional effort in terms of environmental protection is required on his part. Equation (4.1) indicates that the net-effect of the AES payment $(P_i + C_i)$ is added to farm income. Based on the two utilities, a decision function can be formulated as in Chambers and Foster (1983):

$$Y_i = U_{Si}(I_i, 0; Z_i) - U_{AESi}(P_i + I_i + C_i, \overline{E}_i, Z_i) \tag{4.3}$$

Although the value of Y_i is not directly observed, a discrete participation indicator is observed, given by

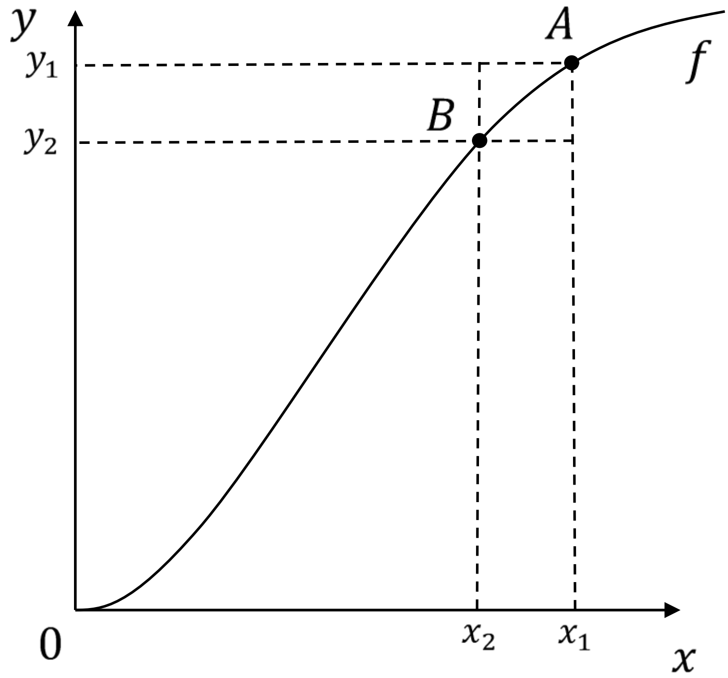
$$Y_i^* = \begin{cases} 0, & if \quad Y_i > 0 \\ 1, & otherwise \end{cases}$$

where 1 represents AES participation and 0 indicates non-participation.

AES participation thus affects the farmer's utility together with the farm and farmer characteristics and income. We assume a utility maximizing farmer and consequently assume profit maximization because income largely depends on farm profit. In such a scenario the AES payment affects income.

Profit maximization requires the simultaneous adjustment of outputs and inputs, which is also a characteristic of production functions. A production function can be thought of as the basis for measuring productivity as the ration of the output(s) that a firm produces to the input(s) that it uses. To illustrate the effects of AES enrolment on farm productivity we consider a simple production process in which a single input x is used to produce a single output y. In Figure IV-1, f represents a production frontier. It represents the maximum output attainable from each input level and reflects the current state of technology. Farms operate on that frontier in case they are technically efficient or beneath the frontier if they are technically inefficient. AES typically restrict the use of certain inputs such as mineral fertilizers or pesticides. A farmer switching to a scheme might have to reduce his input level from x_1 to x_2. This results in an output loss of $y_1 - y_2$. However, the ratio of output and input and thus productivity should remain relatively constant. But in agricultural production, the input saving by adhering to scheme requirements will usually be smaller than the output lost due to lower yields (Oude Lansink, Pietola and Bäckman, 2002), especially if farmers operate at increasing returns to scale as can be assumed for Bavaria with its small family farm structure. Additionally, being bound to scheme restrictions for five years, farmers cannot react to technological advances, changing market or climatic conditions in a way as non-participants do. They might consequently face productivity losses as measured in our framework. Scheme participation might even entail additional costs for the farmer such as labour costs connected to more environmentally friendly farming practices. Following the rationale behind the AES concept, the farmer is consequently reimbursed for his additional costs and for foregone revenue. Certainly, the compensation is received as a payment, but actually the payment is based on the output-input ratio. For AES to be neutral in regard to production, treating the payment as an output should only take a participant from point B back to point A. Empirical work with micro data typically uses revenue-based productivity measures and so do we. In our setting farmers can be considered as price-takers that use inputs in a way as to minimize costs and maximize revenue. Thus, a farmer optimizes rather profitability than productivity. However, considering the revenue-based productivity measure and given prices, productivity and profitability will be strongly correlated.

Figure IV-1: Production frontier



Source: Own depiction

AES can be considered as production determinants in so far as it has been argued that these green payments, although not directly connected to production, are not fully decoupled. OECD (2006) discuss theoretically and show practically how decoupled payments still influence production by having an effect on, inter alia, risk perception and investment decisions. Following US decoupling policy in agriculture around the year 2000, a large empirical literature emerged analyzing the impact of decoupled payments on farm outcomes (e.g. Femenia, Gohin and Carpentier (2010), Key, Lubowski and Roberts (2005)). Overall, this literature suggests that decoupled payments can still distort farm behaviour. For Europe, the results of studies concerning the effects of decoupled CAP payments on production are somewhat controversial. Evidence has been found that the degree of coupling turns out to be low as well as that payments continue to have a strong effect on agricultural production (e.g. Sckokai and Moro (2009), Howley, Hanrahan and Donnellan (2009)). It is likely, however, that farmers use first and second pillar payments also to reinvest or for operating inputs. According to OECD (2001a), in imperfect capital markets all sorts of agricultural programmes affecting farmers' income will affect investment decisions. Offermann, Nieberg and Zander (2009) confirm that subsidies are not production neutral by investigating the dependency of organic farms on direct payments finding that for new EU member states "many farmers plan to use the additional financial resources to expand their farm size" (p. 278).

When it comes to AES, it is on the one hand important to ascertain that programmes are actually fulfilling their promise by reducing environmental damage or providing ecosystem services. On the other hand, further information is needed to what extent AES are actually compensating farmers for nonmarket production activities, to what extent windfall gains for farmers can be avoided and what specific conditions related to production methods or inputs have to be fulfilled and to what extend these conditions actually constrain production. We thus focus on two cornerstones of the Uruguay Round Agreement on Agriculture for agri-environment programs, namely the conditions a) and b): a) "Eligibility for such payments shall be determined as part of a clearly-defined government environmental or conservation programme and be dependent on the fulfilment of specific conditions under the government programme, including conditions related to production methods or inputs"; b) "The amount of payment shall be limited to the extra costs or loss of income involved in complying with the government programme" (WTO, 1995b: 59). This leads us to two hypotheses:

Hypothesis 1: When neglecting the AES payment, compliance with the conditions of the government program (including conditions related to production methods or inputs) has a negative effect on farm-level productivity.

Hypothesis 2: The amount of payment is limited to the extra costs or loss of income resulting from compliance with the AES (treating payment as output).

IV.4 Material and methods

IV.4.1 Agri-environmental schemes in Bavaria

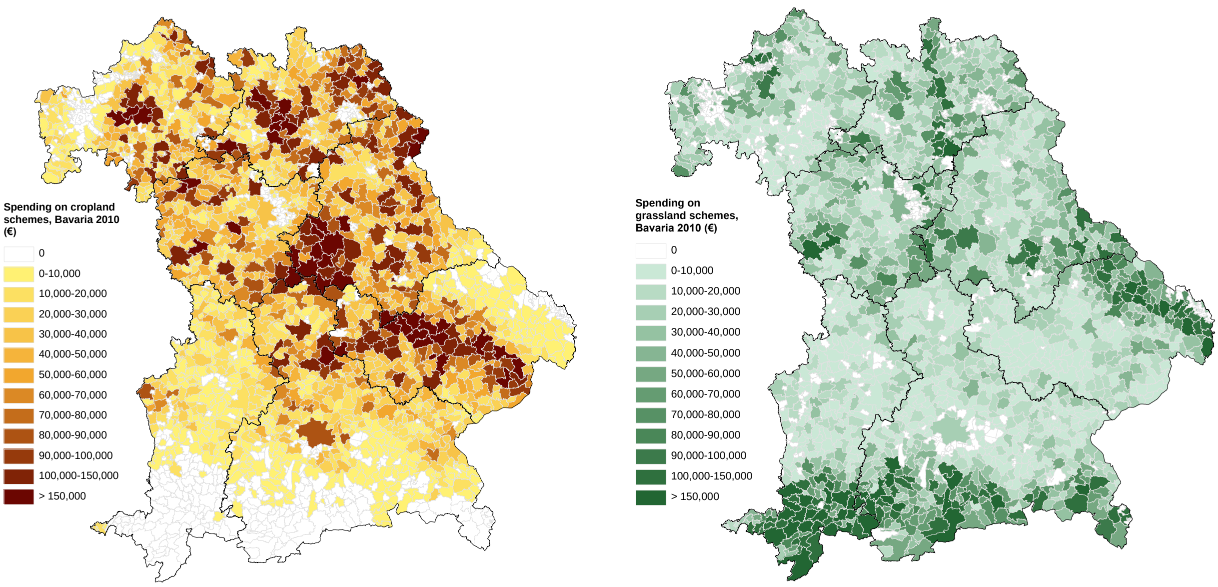
Bavaria is not only the largest Federal State in Germany, but also a big player in German agriculture. In 2015, Bavaria generated 20% of the German gross value added in the sectors agriculture, forestry and fishery. Around one third of all German farms are located in Bavaria and the average farm size (29.5 ha in 2015) is smaller than the German average farm size (StMELF, 2016: 3). Bavarian agricultural production is diverse as a result of varying natural conditions. Dairy farming is dominating in the alpine region, the alpine foreland and in the Bavarian Forest, where mainly grassland is used for fodder production. In the southern Bavarian Tertiary Hills as well as in some northwestern parts of Bavaria, fertile soils enable farmers to engage in intensive crop farming. Farms specialized in pig fattening or breeding and poultry keeping can be increasingly found in eastern Bavaria. Also field vegetables, hop and wine account for small parts of Bavarian agricultural production.

In line with this large variety of farming systems and landscapes, the Bavarian Rural Development Program 2007-2013 included AES tailored to different agricultural subsystems. The schemes were part of two programs, the Nature Conservation Program, which translates to *Vertragsnaturschutzprogramm*, and the Bavarian Cultural Landscape Program, which translates to *Bayerisches Kulturlandschaftsprogramm (KULAP)*. We do not consider the first one in our analysis as it includes very specific schemes applicable only to a small number of farms in nature conservation areas. Our study focuses on the KULAP as a core funding instrument of Bavarian agri-enviromental policy, already initiated in 1988. Individual KULAP measures are subsumed in the categories *organic farming*, *measures for the farm segment grassland*, *measures for the farm segment arable land*, *field specific grassland measures*, *field specific measures for arable land* and *measures for special farming practices*. According to the type of scheme, either the whole agricultural land of the farm has to be cultivated following the scheme guidelines (*organic farming*) or all grassland/arable land of the farm (*measures for the farm segment grassland* and *measures for the farm segment arable land*) or only individual fields (*field specific grassland measures* and *field specific measures for arable land*). *Measures* *for special farming practices* were not always tied to one of those categories and only accounted for around 5 % (56.1 million €) of the KULAP budget. Around 38 % (409.3 million €) were spent on grassland measures and around 31 % (335.7 million €) on measures related to arable land. In total, the KULAP funds added up to around 1.07 billion € for the program period 2007-2013, accounting for the biggest expenditure item of the Bavarian Rural Development Program.

AES in terms of the KULAP 2007-2013 were mainly issued as five-year contracts with yearly payments and monitoring of the adherence to the scheme's requirements. They were offered without regional restrictions (horizontal) and were targeted towards the protection of biotic and abiotic resources. Farmers could voluntarily enrol parts of their farm or the total farm in an AES. For some schemes, combinations on the same field or on different fields were possible. Participating farmers received a fixed payment per hectare or reference unit for a given AES. These payments were calculated based on income foregone and scheme adoption costs. In general, the total payments were proportional to the land subscribed under AES, however, there was a maximum of 40,000 € per farm and year.

The AES design is refined between each programming period, which is why we start our analysis with the beginning of the funding period 2007-2013. We focus on the KULAP AES for grassland and for arable land and on the *measures for special farming* (except for two schemes focusing on animal health and hedgerow management, which were rather investment measures). Key regions for grassland and arable schemes are depicted in Figure IV-2.

Figure IV-2: Key regions for agri-environment schemes for arable land and grassland in Bavaria, 2010



Source: Own depiction

IV.4.2 Data

The empirical analysis is based on farm accounting panel data (2007-2011) matched to the official agricultural support data containing information about farm specific scheme participation (InVeKoS) providing information on farm characteristics (e.g., area under cultivation, sales, labour, capital endowment). We also match it to secondary data concerning the socioeconomic, spatial and agri-structural environment at county or municipality level. The period of interest covers the years 2007-2011 as the new Bavarian Rural Development Program started in 2007 and the commitment period spans five years. The year 2006 was included in order to perform propensity score matching (PSM) to identify treatment and control group based on observable characteristics before AES participation. Farms for which there were missing observations in one of the six years were excluded from the sample. The same holds for farms with missing values for relevant variables and for organic farms. Organic farms have not been taken into account because of their distinctly different technology and support scheme.

The farm accounting data contains different farm types. For our productivity analyses, we concentrated on specialized conventional dairy and specialized conventional arable farms as the Bavarian AES are basically designed for either grassland or arable land. A farm is considered specialized if more than 66% of overall farm revenues are generated by the primary production line. Farms with a revenue from the primary production of less than 66% of the total revenue were excluded from the dataset, which means that most mixed crop-livestock systems were not incorporated. The distinction between different farm types is necessary in a framework where productivity change is estimated using a stochastic frontier analysis (SFA). A prerequisite for the application of SFA is that the research objects share the same production technology. Consequently, our analyses were done for dairy and arable farms separately. All financial variables were deflated to the base year 2010 by using price indices for agricultural producers and purchasing prices as provided by the German Statistical Office to proxy physical output and input.

Farms that enrolled in one of the new AES in 2007 are defined as participating farms. Such an agreement binds farmers to stick to the contract conditions for at least five years. If a participating farmer decided to engage in an additional scheme after 2007 his participation status was not affected. In the first years of the new programming period, some of the farmers were still in an AES of the old program (2000-2006). Such observations were excluded from our analyses if the design of the respective scheme changed significantly between the two programming periods. Farms that were not enrolled in any scheme between 2007 and 2011 are labelled non-participating farms.

IV.4.3 Evaluation problem and matching

The main challenge for empirical policy impact evaluation is to determine what would have happened to the beneficiaries if the specific program had not existed. This situation can never be observed. Randomized control trials are considered as the gold standard approach in impact evaluation frameworks. However, in the case of policy measures such as AES, withholding the treatment from a random group of people and providing access to another random group of people is unethical. The participation in agri-environment programs is voluntary. Consequently, farmers will only enrol if the costs of participation are lower than the expected return (*non-random treatment assignment*). Costs as well as expected benefits, however, depend on farm, farmers' and program characteristics. Due to differences of these (un)observable characteristics even at the time the program starts, the results for participants and non-participants would potentially differ if there was no AES. To avoid such selection bias, it is crucial to determine methods and statistical control groups.

Matching is a widely used non-experimental method of evaluation that can be used to estimate the average effect of a particular program. It compares the results for program participants to those of matched non-participants. Matches are assigned according to similarities in pre-defined observed characteristics. Suppose program participation status is given by $P = 0$ if the farmer does not participate and by $P = 1$ if he does. Let Y^1 be the outcome conditional on participation and Y^0 the outcome conditional on non-participation. In evaluation studies the essential parameter is the *average treatment effect on the treated* (ATT):

$$ATT = E(Y^1 - Y^0 \mid P = 1) = E(Y^1 \mid P = 1) - E(Y^0 \mid P = 1). \tag{4.4}$$

The ATT measures the average program effect in the group of participating farms. The last term of the equation – the hypothetical outcome of a participant in the case of non-participation – cannot be observed. If program participation was random, then $E(Y^0 \mid P = 1)$ could be replaced by the observed result of non-participants $E(Y^0 \mid P = 0)$. As mentioned earlier, farm enrolment in AES is not random as participation is voluntary and tied to entry requirements. A way of solving the resulting selection bias issue was proposed by Rubin (1977). His solution is based on the assumption that given a set of observable covariates X, potential (non-treatment) outcomes are independent of the participation status:

$$Y^0, Y^1 \perp P \mid X. \tag{4.5}$$

Under this *conditional independence assumption* the mean of the potential outcome is the same for $P = 1$ and $P = 0$ when observable differences have been adjusted for. In that case the last term of equation (4.4) can be replaced by the observed outcome of a non-participant with equal characteristics:

$$ATT = E(Y^1 \mid P = 1, X) - E(Y^0 \mid P = 0, X) \tag{4.6}$$

Rosenbaum and Rubin (1983) showed that matching based on the propensity score $p(X)$ is sufficient to reach an equal distribution of the characteristics of participants and non-participants. The propensity score is defined as the conditional probability of an individual to be classified as a program participant given observed characteristics or variables X:

$$p(X) \equiv Pr(P = 1 \mid X) \tag{4.7}$$

Similar participants and non-participants are selected based on identical propensity scores (*selection on observables*). The ATT is thus estimated as follows:

$$ATT = E[Y^1 \mid P = 1, p(X)] - E[Y^0 \mid P = 0, p(X)] \tag{4.8}$$

In order to be able to estimate a hypothetical non-participation outcome for each participant the *common support condition* must hold, meaning that the data must contain sufficient control farms. Heckman, Ichimura and Todd (1997) and Imbens (2015) stress the importance of not violating the *common support condition*. Implementing the common support condition guarantees that any combination of characteristics observed among the treated can also be observed in the control group (Bryson, Dorsett and Purdon, 2002). Furthermore, the assumptions that all participants and non-participants get the same treatment or non-treatment and that program participation only affects beneficiaries, not having indirect effects on non-participants (*stable unit treatment value assumption*) must be met.

Heckman, Ichimura and Todd (1997) and Smith and Todd (2005) stated that, for several reasons, there may be systematic differences between participant and non-participant outcomes, even after conditioning on observables. These reasons include the influence of unobserved differences or level differences in outcomes that might arise when participants and non-participants reside in different regions. To obtain more robust matching results, Smith and Todd (2005) suggest to use a difference-in-difference (d-i-d) matching estimator. A prerequisite for the use of a d-i-d estimator is the availability of panel data. Suppose t represents a time period after the start of the program and t' a time period before the program implementation. The conditional d-i-d estimator compares the conditional before–after outcomes for participants and non-participants:

$$ATT = E\left[Y_t^1 - Y_{t'}^0 \mid P = 1, p(X_{t'})\right] - E[Y_t^0 - Y_{t'}^0 \mid P = 0, p(X_{t'})] \tag{4.9}$$

Thus we calculated the ATT for our sample using the observed outcome (y), the AES participation status of the farm (p) and farm characteristics (x) for participants $i\,\{y_i, p_i, x_i\}_{i=1:N,P=1}$ and non-participants $j\,\{y_j, p_j, x_j\}_{j=1:N,P=0}$. This semi-parametric propensity score matching approach is combined with the results of a productivity analysis.

IV.4.4 Productivity analysis

The following description of measuring productivity change in terms of total factor productivity (TFP) change draws primarily upon the works of Orea (2002), Coelli *et al.* (2005) and Kumbhakar and Lovell (2004). For our analysis we make use of the Malmquist TFP index decomposed into scale components, technical change (TC) and technical efficiency change (TEC). The underlying conceptual framework is a production function or frontier, as a single-output special case of the more general output distance function.

In 1982, (Caves, Christensen and Diewert) developed an approach to measure TFP change. They proposed a TFP index based on Malmquist input and output distance functions, nowadays known as Malmquist TFP index. It measures the productivity change between two data points by using the ratio of the distances for each data point relative to a common technology. All inputs and outputs are characterized by the vectors x_t and y_t at time $t = 1, \dots, T$. The reference technology is represented by the production frontier, which gives the greatest possible output given defined inputs at a certain point of time. The index can be calculated both input- and output-oriented. For output-oriented estimates, the input vector is assumed to be fixed and the output is maximized under the given production technology. The output-oriented Malmquist TFP index can thus be computed as the geometric mean of two Malmquist indices for the periods s and t:

$$m^O(x_s, x_t, y_s, y_t) = [m_s^O(x_s, x_t, y_s, y_t) * m_t^O(x_s, x_t, y_s, y_t)]^{0.5} \tag{4.10}$$

Generally, production processes are subject to efficiency losses. The index of equation (4.10) can thus be rewritten as:

$$m^O(x_s, x_t, y_s, y_t) = \frac{d_t^O(x_t, y_t)}{d_s^O(x_s, y_s)} * \left[\frac{d_s^O(x_t, y_t)}{d_s^O(x_s, y_s)} * \frac{d_s^O(x_s, y_s)}{d_t^O(x_s, y_s)}\right]^{0.5} \tag{4.11}$$

where $d_s^O(x_t, y_t)$ is the output-oriented distance function for the distance of the respective farm observation at time t to the technology frontier at time s. The term before the square bracket indicates technical efficiency change between the periods s and t, while the geometric mean within the square brackets measures technical change between both periods.

Coelli *et al.* (2005) state that efficiency change and technical change are the only two sources of productivity growth if the production technology exhibits constant returns to scale. They further claim that it may be possible that, even if the technology remains the same in both periods, and, in the case where the firm under consideration is technically efficient in s and t, there is scope for improving productivity through improvements in scale efficiency. As agriculture is subjected to structural change, which also arises from production technologies experiencing variable returns to scale, it is crucial to add a corresponding component in TFP measurements. We therefore make use of the decomposition of the generalised Malmquist productivity index taking into account scale effects as proposed by Orea (2002). Scale changes result from the combination of inputs and from changes in scaling of the production frontier by technical change. The Malmquist TFP index as defined by Orea (2002) complies with the requirements of identity, separability and monotonicity. Generally, well-established measures of productivity change include Fisher, Törnqvist, Hicks-Moorsteen and Malmquist TFP indexes, while essential components of productivity change include technical change, technical efficiency change and scale efficiency change. In agricultural economics, the Malmquist index has been used in empirical work quite extensively (e.g. Song, Han and Deng (2016), Coelli and Prasada Rao (2005), Karagiannis and Tzouvelekas (2005)). Main advantages of this index involve that it does not require information on the input and output prices and that it allows the decomposition of productivity changes into different components. By following the decomposition approach proposed by Orea (2002), i.e. adding a scale change component to the traditional Malmquist TFP measure, we overcome the Malmquist index problem that decomposition is only meaningful if the technology exhibits constant returns to scale (see O'Donnell (2012b)). Malmquist and Hicks-Moorsteen productivity indexes seem to be the most widely used indexes for measuring productivity growth. However, in the literature, there is no consensus on which productivity index is better. Balk (2001) justifies the Malmquist productivity index whereas O'Donnell (2012b) advocates the Hicks-Moorsteen index.

Computing output-oriented efficiency measures requires the estimation of a production frontier. We estimate the frontier parametrically using balanced panel data of Bavarian farms. The stochastic frontier production function model was proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). For panel data it has the following form:

$$ln\, y_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} + v_{it} - u_{it} \tag{4.12}$$

where y_{it} represents the output of the i-th firm at time t, $\boldsymbol{x}_{it}$ is a Kx1 vector containing the logarithms of inputs, $\boldsymbol{\beta}$ is a vector of unknown parameters, v_{it} is a symmetric random error and u_{it} is a non-negative random variable associated with technical inefficiency. With the distributional assumption of Aigner, Lovell and Schmidt (1977) for the two error components, v and u, and a maximum likelihood estimation, the efficiency estimates can be singled out. Aigner, Lovell and Schmidt (1977) assume that the error term is iid $N(0, \sigma_v^2)$ – independently and identically distributed with mean zero and standard deviation σ^2. Following Battese and Coelli (1995) and their more generalized assumption of truncated normal distribution, u are also iid $N(0, \sigma_u^2)$, independently and identically distributed half normal random variables with a scale parameter σ_u^2. Technical efficiency of production for the i-th firm at the t-th observation is then defined as

$$TE_{it} = exp(-u_{it}) \tag{4.13}$$

For our analysis we used the model proposed by Battese and Coelli (1995), which permits the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies. Kellermann (2015) compared a variety of stochastic frontier models that have been most widely used in empirical TFP growth studies. He found that “there are no clear-cut criteria available to guide researchers when choosing ‘the’ appropriate model” (Kellermann, 2015, p. 125). In his study he concluded that the methodology chosen should fit the characteristics and structure of the data at hand as well as the purpose of the analysis. Since we did not only investigate TFP change, but also examined technical efficiency change, we had to make use of a model that assumes farm efficiency to be time-variant. Further, we needed a model suitable for panel data. The BC95 model was formulated for panel data sets. It is well-accepted in productivity research and has been used extensively in analyses of productivity growth (examples include Jin *et al.* (2010), Brümmer, Glauben and Thijssen (2002) and Rae *et al.* (2006)).

IV.5 Empirical model

The empirical analysis was done with balanced panel data sets for dairy and arable farms separately. For dairy farms data for 5,478 Bavarian farms with continuous records for the period 2006 to 2011 was used, whereas 2,250 observations for the same period were available for Bavarian arable farms.

The matching strategy building on the conditional independence or unconfoundedness assumption requires that the outcome variable must be independent of treatment conditional on the propensity score. The better the data at hand, the easier the conditional independence assumption can be justified. Omitting important variables in the estimation procedure can seriously increase bias in resulting estimates (Dehejia and Wahba, 1999). It is thus important to include all variables known to be related to both treatment assignment and the outcome (Hill, Reiter and Zanutto, 2004). Generally poor performance of the estimator is observed if only a relatively small set of variables is included. Stuart (2010: 6) states that including variables that might be unassociated with the outcome can result in a slightly increased variance, whereas excluding potentially important confounders has a high cost in terms of increased bias. Heckman, Ichimura and Todd (1997) and Heckman *et al.* (1998) show that data quality is a crucial ingredient to any reliable estimation strategy. They point out that estimators are only found to perform well when they are applied to data satisfying the following criteria: (i) the same data sources (i.e., the same surveys or the same type of administrative data or both) are used for participants and nonparticipants, (ii) participants and nonparticipants reside in the same region, and (iii) the data contain a rich set of variables that affect both program participation and outcomes. Our data clearly fulfils these criteria. Conditional probabilities for participation in AES are computed by estimating a logit model. Table IV-16 in the appendix reports the parameter estimates for Bavarian dairy farms, Table IV-17 shows the respective results for arable farms. These estimates are based on pre-participation data from 2006. Underlying descriptive statistics are given in the appendix. Besides the determinants for AES participation, the explanatory variables of the logit models include pre-treatment outcomes for the reference year 2006 and regional characteristics. Using pre-treatment outcomes guarantees that participants and control units feature a similar factor endowment and production technology in the starting situation 2006. By additionally making use of regional characteristics we are able to obtain matching pairs within the same region. Both, pre-treatment outcomes and regional characteristics are essential when aiming to reduce selection bias (Cook, Shadish and Wong, 2008). The binary model is based on variables affecting farmers' participation and outcomes (Liu and Lynch, 2011). The decision of how many variables to include in a propensity score binary model is a widely discussed issue in the literature.[11] All in all, the choice of our variables is based on economic theory, statistical significance and previous empirical findings (especially Pufahl and Weiss (2009), Arata and Sckokai (2016), Vanslembrouck, van Huylenbroeck and Verbeke (2002)).

Measuring productivity change in terms of the Malmquist TFP index as described in the previous section requires the estimation of technical efficiency change, technical change and scale change which is performed within a stochastic frontier analysis framework. In our estimation procedure we use a single-output production function for farms selected in the matching process. Total farm sales represent the output variable; land, labour, capital (costs of depreciation), material expenses (e.g., expenses for fertilizer, seed, crop protection, fodder), other expenses (e.g., expenses for maintenance, rents, insurances) and livestock units are considered as input variables. Respective descriptive statistics are given in Table IV-14 in the appendix. A flexible translog function is estimated because of it superior

[11] Augurzky and Schmidt ((2001: 27)) emphasize that "the main criterion of success for matching remains the balance of the relevant covariates and not the proper estimation of the selection equation". According to Rubin and Thomas ((1996)) one should include all variables even if they are not statistically significant, with the exception of a few cases.

performance in terms of theoretical consistency. It is widely used in empirical studies and unlike e.g. a Cobb-Douglas production function it does not per se violate important curvature properties as for example concavity (Färe *et al.*, 2005). Building upon equation (4.12) the empirical model of the production frontier with a translog specification is as follows:

$$
\begin{aligned}
lny_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n lnx_{nit} \\
+ \frac{1}{2}\sum_{n=1}^{N}\sum_{j=1}^{N} \beta_{nj} lnx_{nit} lnx_{nit} + \sum_{n=1}^{N} \beta_{tn} t lnx_{nit} + \beta_t t \\
+ \frac{1}{2}\beta_{tt} t^2 + v_{it} - u_{it}
\end{aligned}
\tag{4.14}
$$

$$i = 1,2,\dots,I, t = 1,2,\dots,T$$

where y_{it} is the total output in terms of sales of the i-th farm at time t, for our testing purposes once adjusted for AES payments that are designed to cover cost incurred and income foregone and once not. Using sales as output has the advantage that quality differences are taken into account. All input variables are defined respectively, where x_{nit} denotes a n-th input variable. t is a time trend representing technical change. The v_{it}s are random errors, assumed to be iid and have a $N(0, \sigma_v^2)$-distribution, independent of the u_{it}s. The u_{it}s are the technical inefficiency effects. The time trend interacts with the input variables, allowing for non-neutral technical change.

As the first component of productivity change, technical efficiency change TEC is calculated by $\frac{TE_{it}}{TE_{is}}$, where

$$TE_{it} = d_t^O(\boldsymbol{x}_{it}, y_{it});\ TE_{is} = d_s^O(\boldsymbol{x}_{is}, y_{is}) \tag{4.15}$$

d measures the distance to the frontier in the periods s and t. Technical change (TC) between the periods s and t is calculated as the geometric mean of the partial derivatives of the production function with respect to time. That is,

$$TC = exp\left\{\frac{1}{2}\left[\frac{\partial \ln y_{is}}{\partial s} + \frac{\partial \ln y_{it}}{\partial t}\right]\right\} \tag{4.16}$$

In order to capture productivity changes due to scale changes (SC), we make us of the approach proposed by Orea (2002) and include a scale change component in the TFP measure:

$$SC = exp\left\{\frac{1}{2}\sum_{n=1}^{N}[\varepsilon_{nis}SF_{is} + \varepsilon_{nit}SF_{it}]\ln\frac{x_{nit}}{x_{nis}}\right\} \quad (4.17)$$

where $SF_{is} = (\varepsilon_{is} - 1)/\varepsilon_{is}$, $\varepsilon_{is} = \sum_{n=1}^{N}\varepsilon_{nis}$ and $\varepsilon_{nis} = \frac{\partial \ln y_{is}}{\partial \ln x_{nis}}$. TFP change is then calculated as the sum of the single component:

$$TFPC = TEC + TC + SC \quad (4.18)$$

IV.6 Results

IV.6.1 Propensity score matching

The estimated logit model as the matching basis is statistically significant at the 1% level or higher. It correctly classifies about 84% of all observations (86.14% for participants, 78.14% for non-participants) for dairy farms and about 71% of all observations for arable farms (73.02% for participants, 68.39% for non-participants). Estimation results are given in the appendix.

Propensity score matching can be regarded as successful if significant differences of covariates among participating and non-participating farms are controlled for. Table IV-1 and Table IV-2 report unadjusted and adjusted means of covariates among participants (columns 1 and 3) and non-participants (columns 2 and 4) of AES for the pre-treatment year 2006. We tested different matching estimators (nearest neighbour matching with and without replacement, radius matching, kernel matching). In terms of overall matching quality nearest neighbour matching without replacement, random ordering and a caliper of (0.1), which matches participating and non-participating farms that are closes in terms of the propensity score value, performed best. [12] To ensure overlap and common support we used the caliper and a sort of trimming by deleting all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group.

Table IV-1: Means and standardized bias of selected variables before and after matching for the pre-treatment year 2006 (dairy farms)

Variables	(1) Potential treatments	(2) Potential controls	(3) Selected treatments	(4) Selected controls	(5) Bias before	(6) Bias after
Labour	1.58	1.46***	1.46	1.50	27.2	-1.4
Land	52.68	33.18***	36.90	40.64*	46.8	-4.6
Livestock units per ha	1.34	2.01***	1.77	1.68	-43.3	2.0
Yield index unit	2964	3502***	3534	3322	-45.7	2.8
Fertilizer per ha	96.53	124.75***	119.99	110.89	-44.1	2.2
Pesticides per ha	43.52	39.37*	43.09	41.58	12.3	4.5
Share of rented land	0.52	0.39***	0.45	0.47	54.5	-2.2
Material per ha	1309	2043***	1771	1637	-35.5	-6.5
Other capital per ha	698.68	824.54***	778.33	759.35	29.3	4.4

[12] According to Smith and Todd ((2005)), the details of the matching procedure chosen do not have a consistent effect on the estimated biases. Thus, the choice between, for example, nearest neighbour or kernel matching does not make a big difference to the estimated bias. In general, the choice of the matching estimator always involves a trade-off between bias and efficiency. Caliendo and Kopeinig ((2008: 45)) state that "there is no 'winner' for all situations and that the choice of the estimator crucially depends on the situation at hand", especially on the data structure.

Farmland rental value	227.04	255.33***	254.91	255.95	-39.9	-1.5
Workforce	33150	37504***	35783	35515	-32.2	-2.0
Dummy variable 'Swabia'	0.18	0.12**	0.13	0.12	16.8	-1.9
Dummy variable 'Middle Franconia'	0.13	0.07***	0.09	0.09	19.8	0.0
Dummy variable 'Upper Franconia'	0.16	0.03***	0.05	0.05	46.2	-2.4
Dummy variable 'Lower Bavaria'	0.15	0.23***	0.28	0.28	-18.5	1.7
Population density	131.95	149.98*	132.19	131.56	-12.0	0.4
Number of observations	715	275	153	153		

Table IV-2: Means and standardized bias of selected variables before and after matching for the pre-treatment year 2006 (arable farms)

Variables	**(1)** Potential treatments	**(2)** Potential controls	**(3)** Selected treatments	**(4)** Selected controls	**(5)** Bias before	**(6)** Bias after
Labour	1.81	1.21***	1.31	1.27	57.4	2.6
Farm sales per ha	2711	1760***	1740	1782	47.9	-2.1
Material per ha	1301.10	990.26***	972.08	989.30	44.4	-2.5
Other capital per ha	898.68	665.61***	671.69	652.19	33.9	2.8
Yield index unit	3761	4500***	4303	4357	-52.3	-3.8
Pesticides per ha	243.74	156.58***	150.51	160.56	47.3	-5.5
Share of arable land	0.76	0.95***	0.93	0.92	-77.7	4.1
Workforce	30528	37258***	31144	30901	-17.8	0.6
Altitude	380.17	360.53**	360.05	369.61	23.7	-2.5
Population density	129.48	190.99**	135.73	127.59	-24.6	3.3
GDP per capita	22891	25377***	22767	22502	-28.6	3.0
Number of observations	187	157	97	97		

For variable definitions and units see appendix; frequencies for dummy variables. Significantly different means between observations from the potential (selected) treatment group and from the potential (selected) control group in a t-test for equality of means at the 10% (*), 5% (**) and 1% (***) level are indicated.

(5) and (6): Following Rosenbaum and Rubin (1985), for a given covariate X, the standardized difference before matching is the difference of the sample means in the full treated and nontreated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups. The standardized difference after matching is the difference of the sample means in the matched treated (that is, falling within the common support) and matched non-treated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups:

$$SB_{before}(X) = 100 * \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{\frac{[V_1(X) + V_0(X)]}{2}}}, \qquad SB_{after}(X) = 100 * \frac{\bar{X}_{1M} - \bar{X}_{0M}}{\sqrt{\frac{[V_{1M}(X) + V_{0M}(X)]}{2}}}$$

Since we do not condition on all covariates but on the propensity score, it has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment group. The basic idea of all testing approaches is to compare the situation before and after matching. After conditioning on the propensity score there should not remain big differences between the covariates. As demonstrated in Table IV-1, AES participating farms differ significantly from non-participants with regard to nearly all variables. They cultivate e.g. more agricultural land, operate on more detrimental soils and show a higher labour input. These findings are in line with results presented by Pufahl and Weiss (2009). Columns (3) and (4) report the adjusted means of the selected variables for the treatment and control group after the matching procedure has been applied. In the matching procedure without replacement some observations are lost because when performing nearest neighbour matching with a caliper not for each farm a match was found. The differences between participating farms and controls are much smaller after matching and in only a few cases significantly different from zero at the 5% level. We additionally used a more comprehensive indicator than a two-sample t-test, the so called standardized bias (SB), suggested by Rosenbaum and Rubin (1985). For each variable X it is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups. The SB indicator is used in many evaluation studies, e.g. by Lechner (1999), Mayne, Lee and Auchincloss (2015) and Sianesi (2004b). According to Caliendo and Kopeinig (2008), a SB below 3% or 5% after matching is seen as sufficient in most empirical studies. The SB is reported in the columns 5 and 6 of Table IV-1 and Table IV-2. After matching the overall SB is 3.5% for dairy farms and 2.7% for arable farms.

IV.6.2 Average productivity change

Before estimating the average treatment effect, productivity change is measured for the farms selected in the matching procedure based on equation (4.14). Following our hypotheses, we will report estimates for the two scenarios where the AES payment is first added as an output (hyp. 2) whereas in the second scenario it is not considered (hyp. 1). As the maximum likelihood estimations of the production frontiers are fairly similar for both scenarios, results and interpretations are primarily given for the first scenario. Estimates for the other case be obtained from the authors. Results for the estimated translog dairy production function are presented in Table IV-3. The model includes a time-squared variable and time interacted with each (log) input variable. This approach allows for non-monotonic and non-neutral technical change. As the data has been mean corrected prior to estimation, the first order parameters can be interpreted as the elasticities at the sample means. The sum of the production elasticities suggests slightly increasing returns to scale at the sample mean. The time coefficient of 0.02 indicates mean technical progress of 2% per year. The coefficients of time interacted with land (0.02), labour (-0.01), material (0.02), depreciation (-0.01), other capital (0.00) and livestock (-0.04) indicate that technical change has been land-saving and material-saving but capital-using. Maximum likelihood estimation results for arable farms are given in the appendix.

Table IV-3: Maximum likelihood estimation of the translog specification for dairy farms

Variables	Coeff. (std.err.)	z-statistic
Ln total farm sales		
Ln land	0.01 (0.00)	3.25***
Ln labour	0.13 (0.02)	7.60***
Ln material	0.42 (0.01)	32.68***
Ln other capital	0.08 (0.01)	6.23***
Ln depreciation	0.10 (0.01)	10.88***
Ln livestock	0.41 (0.02)	18.52***
t	0.02 (0.00)	9.17***
$(\ln \text{land})^2$	0.19 (0.11)	1.80*
Ln land*ln labour	-0.29 (0.09)	-3.31***
Ln land*ln material	-0.08 (0.05)	-1.66*
Ln land*ln other capital	0.26 (0.05)	4.85***
Ln land*ln depreciation	-0.03 (0.04)	-0.96
Ln land*ln livestock	-0.03 (0.05)	-0.64
Ln land*t	0.03 (0.01)	2.46**
$(\ln \text{labour})^2$	-0.25 (0.08)	-3.03***
Ln labour*ln material	0.06 (0.04)	1.47
Ln labour*ln other capital	0.07 (0.04)	1.56
Ln labour*ln depreciation	0.02 (0.03)	0.56
Ln labour*ln livestock	0.25 (0.08)	3.04***
Ln labour*t	-0.01 (0.01)	-0.91

$(\ln \text{material})^2$	0.22 (0.03)	8.24***
Ln material*ln other capital	-0.05 (0.03)	-1.51
Ln material*ln depreciation	-0.01 (0.02)	-0.32
Ln material*ln livestock	-0.14 (0.04)	-3.28***
Ln material*t	0.02 (0.01)	2.62***
$(\ln \text{other capital})^2$	-0.03 (0.03)	-1.04
Ln other capital*ln depreciation	-0.02 (0.02)	-1.10
Ln other capital*ln livestock	-0.17 (0.05)	-3.18***
Ln other capital*t	0.00 (0.01)	0.31
$(\ln \text{depreciation})^2$	0.03 (0.02)	1.87*
Ln depreciation*ln livestock	0.03 (0.03)	0.93
Ln depreciation*t	-0.01 (0.01)	-1.51
$(\ln \text{livestock})^2$	0.11 (0.05)	2.21**
Ln livestock*t	-0.04 (0.01)	-2.73***
t^2	-0.10 (0.00)	-19.54***
_cons	0.18 (0.01)	16.89***
sigma_v	0.13 (0.00)	28.76***
sigma_u	0.72 (0.18)	4.07***
lambda	5.72 (0.18)	30.92***
Log likelihood	583.36	
Wald $\chi2$ (35)	18910.76	
Prob > $\chi2$	0.00	
Observations	1530	

*, ** and *** indicate statistical significance at the 10%, 5% and 1%.

For the widely used translog functional form, it is advisable to take a closer look at how well the estimated representations of the production technology are in line with the requirements implied by microeconomic theory – namely, monotonicity and quasi-concavity. Several authors (e.g. Sauer, Frohberg and Hockmann (2006), Henningsen and Henning (2009)) have emphasized the importance of theoretical consistency for correct interpretation of the obtained parameters and efficiency scores and, accordingly, for the results of the decomposition of TFP growth. As the data has been mean corrected prior to estimation, the first order parameters can be interpreted as the elasticities at the sample mean. They show correct signs and therefore fulfil the monotonicity requirement at the sample mean, which is, according to Sauer, Frohberg and Hockmann (2006) the minimum requirement that needs to be met to obtain meaningful results. After checking for monotonicity for all observations we find some violations as reported in Table IV-4. In order to check the curvature conditions of quasi-concavity, we construct a (bordered) Hessian matrix for each data point and report the percentage of violations in Table IV-4. On the input side the model seems to be in line with the curvature requirements, however, we do find some violations on the output side. The monotonicity condition is violated to some extent for the input variable land. Table IV-4 reports results for the estimation including AES payments. When ignoring payments estimates look similar.

Table IV-4: Percent of violations of monotonicity and curvature conditions

	Dairy farms	Arable farms
Monotonicity		
Land	18.63	17.78
Labour	0.00	0.01
Material	0.00	0.00
Other capital	0.01	0.04
Depreciation	0.00	0.60
Livestock	0.00	-
Curvature		

Input	1.7	0.6
Output	13.2	9.1

Average technical efficiency for dairy farms in the period 2007 to 2011 was 0.902 (0.812 for arable farms). Based on the frontier results, TEC, TC, SC and total factor productivity measures ($TFPC$) are calculated. Results for dairy and arable farms respectively are depicted in Table IV-5 and Table IV-6. Overall, participating dairy farms and their matched controls realized a change in productivity growth of about 2.25% per annum (0.47% for arable farms). The productivity growth is mainly driven by a technical change rate of about 2.22% p.a., the scale component only adds little to overall growth. We note that TFPC is quite volatile, primarily due to the effect of volatile TEC and TC, which might be a consequence of climatic factors and milk price volatilities. In the milk sector, the existence of the milk quota system might additionally explain the annual fluctuations: dairy farmers very often produced well over the quota in one year and then switched to a production well under the milk quota in the following year, resulting in significant changes in milk production efficiency from year to year (see, e.g. Schaper, Lassen and Theuvsen (2009)).

The sharp TFP decline for dairy farms in 2009/10 might be explained by the 2009 EU dairy market crisis. Increasing TEC estimates in 2010/11 give evidence of a beginning reallocation of resources after this critical phase.

Table IV-5: Decomposition of TFP change by year for dairy farms

Year	TEC	TC	SC	TFPC
Scenario 1 (AES payment included as output):				
2007/08	0.0084	0,1723	-0.0001	0.1807
2008/09	0.0117	0,0766	0.0040	0.0922
2009/10	-0.0621	-0,0197	-0.0007	-0.0825
2010/11	0.0536	-0,1174	-0.0002	-0.0636
p.a.	0.0002	0.0222	0.0008	0.0225
Scenario 2 (AES payment not included):				
2007/08	0.0096	0.1753	-0.0001	0.1848
2008/09	0.0116	0.0778	0.0044	0.0938
2009/10	-0.0649	-0.0201	-0.0009	-0.0859
2010/11	0.0556	-0.1193	0.0000	-0.0637
p.a.	-0.0002	0.0225	0.0008	0.0219

Table IV-6: Decomposition of TFP change by year for arable farms

Year	TEC	TC	SC	TFPC
Scenario 1 (AES payment included as output):				
2007/08	0.0742	0.1278	-0.0013	0.2007
2008/09	-0.0531	0.0512	0.0167	0.0148
2009/10	-0.0821	-0.0272	-0.0147	-0.1239
2010/11	0.1098	-0.1067	-0.0020	0.0011
p.a.	-0.0037	0.0075	-0.0008	0.0047
Scenario 2 (AES payment not included as output):				
2007/08	0.0795	0.1263	-0.0013	0.2046
2008/09	-0.0582	0.0492	0.0172	0.0082
2009/10	-0.0864	-0.0301	-0.0155	-0.1320
2010/11	0.1100	-0.1106	-0.0022	-0.0028
p.a.	-0.0042	0.0048	-0.0009	0.0016

IV.6.3 Treatment effects

In a next step, it is tested whether there is a significant difference in total factor productivity changes between farms participating in AES and non-participating farms. The impact of AES on farm level productivity is measured on the basis of the matching results for observed variables from the baseline data. However, treated and untreated farmers may also differ according to unobserved dimensions like environmental awareness or managerial attitude and ability. If these characteristics are not taken into account, the comparison between participating and non-participating farms will lead to biased estimates for the treatment effect. Yet, variables like environmental preferences or managerial ability are not measured in our dataset and thus cannot be controlled for; however, to a certain degree these unobservables should be correlated with observables like education and age that we do consider. In order to solve this problem, we assume that the effect of these unobservable factors on farm practices is constant through time. Subtracting the difference in practices estimated by matching before implementation of the AES from the difference estimated after implementation gives the difference-in-difference estimate. Assuming that selection bias on unobservables is constant over time amounts to assuming that the average treated farmer and his average matched twin would have behaved the same way in the absence of the AES (*common trend assumption*). According to Chabé-Ferret and Subervie (2012) and our own experiences in agricultural sector analyses the *common trend assumption* is plausible in farm contexts, because unobserved determinants of AES participation are likely to be constant over time.

The average effect of AES participation is estimated by comparing the changes in individual outcomes between participants (Δy^1) and their matched counterparts (Δy^0) between 2007 and 2011 (d-i-d analysis). One way of calculating the difference-in-difference estimate is to consider the TFP change of participating and non-participating farms over the five year contract period. The productivity changes of both groups are tested for significant differences based on a t-test formula. Dairy farms enrolled in an AES experienced an average productivity growth of 2.02% per year when the AES payment is included, whereas non-participating farms reached a value of 2.48%. Table IV-7 shows the effect of program participation for matched dairy farms. It depicts the group mean of the annual productivity changes per farm, the standard deviation is given in parentheses. The d-i-d estimator does not suggest a significant causal impact of AES participation on dairy farm productivity during the period of investigation (2007-2011). There is some evidence of a negative productivity effect of AES participation as proven by scenario 2 results, still we fail to reject our first hypothesis. Though not ultimately convincing, the AES seems to be in line with the GATT Uruguay Round postulation of not having an effect on production. One might speculate that scheme restrictions for dairy farms in conjunction with the five year contract period result in yield losses that are not proportional to reduced input use, that participating farmers lack the flexibility of non-participating ones. Concerning our second hypothesis and based on the theoretical outline, we would expect the AES payment to offset for output losses and extra costs. Consequently, scenario 1 should not reflect differences in TFP change between participants and non-participants. Indeed there is no significant gap for dairy farms. But again results point towards scheme design that is not in accordance with WTO requirements. The AES payment does not seem to be high enough to compensate farmers for costs and yield losses. Since we assume profit maximising behaviour, it is unlikely that farmers would join a program making them worse off. We conclude that authorities have difficulties in predicting outcomes and market developments when they design agri-environment programs and decide on the amount of payment to guarantee for a five year time horizon. Market turbulences as they occurred in the dairy sector in 2009 can hardly be foreseen. Program designers might need to think about developments towards dynamic payments and schemes. A contrary result is found for arable farms (Table IV-8). Participating farms experienced an average productivity growth of around 1.2% per year when considering the AES payment, whereas non-participating farms did not significantly increase their productivity, but even show a negative growth rate. The difference is significant at the 5% level. This finding signals inefficient spending of public money and overcompensations for farmers. Considering scenario 2 results this statement needs to be more nuanced. Despite not being statistically significant, our results indicate that AES enrolment not considering scheme payments has a positive effect on the productivity of arable farms. This finding might seem counterintuitive at first glance because one would expect productivity to remain unchanged or to decrease as the fulfilment of specific AES is expected to result in less output generated with generally less inputs. However, we even find significant evidence that participating farms boost their productivity as compared to non-participating farms. Having a closer look on the most popular KULAP schemes for arable farms, we might explain our results. Farmers participated mainly in schemes aiming at diversified crop rotations, the planting of cover crops and the use of low-till methods. These measures did not put limits on fertilizer or pesticides use, but rather restricted the choice of which crops to grow on which area. Diversified crop rotations maintain and promote soil fertility, they regulate weed and disease pressure and contribute to nutrient supply. Davis *et al.* (2012) have shown that more diverse cropping systems suppress weeds effectively, prevent water pollution and protect the soil while meeting or exceeding the performance of less diverse systems. Low-till methods like mulch sowing reduce soil erosion, stabilize the soil structure, optimize the water balance, conserve nutrients and foster the activity of soil organisms. According to Kreitmayr (2004), under optimal conditions mulch sowing does not lead to yield losses as compared to traditional sowing techniques. Farms participating in arable schemes might thus not face less yield, but instead profit from savings effects (e.g. energy, work, pesticides, fertilizer) in inputs and/or increased output despite constant input use and consequently increase productivity. The amount of payment they receive is then not limited to the extra costs or loss of income involved in complying with the AES. It can rather be interpreted as an incentive to provide ecosystem services, which is not compliant to the WTO rationale. In fact, a pure profit maximizing farmer would not switch to a production system with AES if this did not result in a gain. Therefore overcompensations can be expected as depending on the individual cost structure mainly those farmers will participate where the AES payments covers more than extra costs or income losses. A uniform amount per hectare not taking into account farm heterogeneity raises the question of equality. Bavarian arable farms cultivate a big variety of crops on different site conditions, while dairy farms operate to a great extent on permanent grassland. The difference in TFP growth found for arable farms suggests that scheme payments are set too high and do not reflect real cost and income effects. It further demonstrates the difficulties authorities face in correctly estimating future market developments that should have an influence on the AES payment. Five year contracts for scheme participants might be necessary for reaching environmental goals, however, inflexibility in AES price setting can have an unwanted effect on production as we just demonstrated.

Table IV-7: Average treatment effect on the treated for AES from 2007-2011, dairy farms

Variable of interest	Unit	Treatments Δy_i^1	Controls Δy_j^0	ATT $\Delta y_i^1 - \Delta y_j^0$	t-value	Pr(|T| > |t|) Pr(T > t)
Scenario 1:						
Annual TFP change	%	2.022 (1.067)	2.485 (1.184)	-0.463	1.14	0.255

Scenario 2:						
Annual TFP change	%	1.913 (0.880)	2.475 (1.184)	-0.562	1.14	0.127

Table IV-8: Average treatment effect on the treated for AES from 2007-2011, arable farms

Variable of interest	**Unit**	**Treatments** Δy_i^1	**Controls** Δy_j^0	**ATT** $\Delta y_i^1 - \Delta y_j^0$	**t-value**	**Pr(|T| > |t|) Pr(T>t)**
Scenario 1:						
Annual TFP change	%	1.288 (0.725)	-0.385 (0.246)	1.674	-2.11	0.037**
Scenario 2:						
Annual TFP change	%	0.808 (0.655)	-0.513 (0.441)	1.321	-1.63	0.949

Note: For hypotheses testing a distinction between the two scenarios was made. The results in column 7 refer to the respective scenario and hypothesis.

Scenario 1:

$$H_0 : TFPC_{non-participants} = TFPC_{participants}$$
$$H_A : TFPC_{non-participants} \neq TFPC_{participants}$$

Scenario 2:

$$H_0 : TFPC_{non-participants} = TFPC_{participants}$$
$$H_A : TFPC_{non-participants} > TFPC_{participants}$$

Instead of using a t-test, a difference-in-difference estimation can be implemented based on a regression procedure. On the basis of the discussion by Ravallion (2008), the d-i-d estimate can be calculated using the following regression framework

$$TFPC_{it} = \alpha + (DD)T_i t_i + \beta T_i + \delta t_i + \gamma_i + \varepsilon_{it} \tag{4.19}$$

where T is the treatment variable, t is a time dummy for, in our case 2007 and 2011, γ captures time-invariant individual heterogeneity and the coefficient (DD) gives the estimate for the impact of treatment on outcome Y, in our case TFP change. A basic assumption behind the simple implementation of d-i-d with a t-test is that other covariates do not change across the years (i.e. ceteris paribus). Fixed-effects regression can control both for covariates and farms' unobserved and time-invariant characteristics that may influence productivity change as well. Thus, in the regression based d-i-d analyses the overall scenario 2 treatment effect of Table IV-7 and Table IV-8 is tested for robustness with fixed-effects estimations. The regression procedure confirms the results of the t-test with a, however not significant, TFP change effect of AES participation of -0.5% for dairy farms and a positive, significant effect for arable farms of 1.7%. Detailed estimates for can be found in the supplementary online appendix.

The decomposition of the Malmquist productivity index offers the possibility to assess the impact of AES on its single components. We find a significant effect of AES on the technical efficiency of arable farms (see Table IV-22 appendix), which supports our explanation that schemes designed for arable land (especially diversified crop rotations, cover crops, low-till methods) in fact increase productivity through cultivation methods that meet or exceed the performance of less diverse systems despite not substantially changing input use. As expected we do not find a significant effect for dairy farms. However, results suggest that AES participation affects the development opportunities of dairy farms. The difference in technical change between participants and non-participants is obvious (see Table IV-23 appendix). Again, these results are in line with our assumption that scheme restrictions for dairy farms do not give them enough flexibility to react to new developments.

Heterogeneity in the sample allows for a more detailed analysis with respect to different subgroups of farmers. We therefore consider further differences in soil quality. Bavaria has a high landscape diversity, ranging from alpine grasslands to moorlands, from fertile Loess to heavy soils. First, participating and non-participating farms were grouped according to their yield index unit, an indicator for soil quality, assuming that the AES effect on farm productivity significantly differs with unfavourable site conditions and more extensive farming. Hence, farmers might adapt more easily to scheme requirements. In our arable farm sample, we compared productivity changes of participating and non-participating farms with yield index units higher than and lower than the sample median of 4281. Again scenarios with and without the AES payment were investigated. Since the t-test formula and the fixed effects regression yield similar results, only t-test findings are given in Table IV-9. The altitude of farmland cultivated was chosen as a site specific factor for dairy farms (Table IV-10).

Table IV-9: TFPC with different soil quality

Variable of interest	Unit	Treatments Δy_i^1	Controls Δy_j^0	ATT $\Delta y_i^1 - \Delta y_j^0$	t-value	Pr(|T| > |t|)
Yield index unit > 4281:						
Annual TFP change	%	1.036 (0.577)	1.668 (0.893)	-0.632	1.04	0.302
Yield index unit < 4281:						
Annual TFP change	%	1.587 (0.870)	-2.110 (1.115)	3.697	-2.58	0.011**

Table IV-10: TFPC at different altitudes

Variable of interest	Unit	Treatments Δy_i^1	Controls Δy_j^0	ATT $\Delta y_i^1 - \Delta y_j^0$	t-value	Pr(|T| > |t|)
Altitude < 476:						
Annual TFP change	%	2.842 (1.675)	3.013 (1.697)	-0.170	0.44	0.663
Altitude > 476:						
Annual TFP change	%	1.122 (0.601)	2.003 (1.158)	-0.880	1.26	0.208

It is evident that better soils boost productivity change. Assuming that the AES payment compensates for income losses and extra costs, adding the payment as output should level average annual productivity change of participating and non-participating farms. For better soil conditions we do not find a significant difference, whereas with less fertile soils participating farms clearly profit from scheme adherence and the AES payment. Results indicate that such farms can adapt more easily to scheme demands and can thus create an extra benefit. The analysis for dairy farms with different altitudes shows less clear outcomes, but also implies that a uniform payment in a one-fits-all scheme design does not offer equal opportunities for all farmers.

A critique of any non-experimental study is that there may be unobserved variables related to both treatment assignment and the outcome, violating the assumption of ignorable treatment assignment and consequently biasing the treatment effect estimates. Since ignorability cannot be tested directly, researchers have designed sensitivity analyses to assess its plausibility, and how violations of ignorability may affect study conclusions. One type of sensitivity analysis is to examine how strong the correlations between a hypothetical unobserved covariate and both treatment assignment and the outcome would have to be to make the observed treatment effect go away. Developed by Rosenbaum, this method is predicated on the assumption that, via its simultaneous effect on selection and outcome, the impact potential hidden bias has on matched treatment estimates can be gauged with reference to a parameter Γ. A more detailed exposition of this so called Rosenbaum bounds method can be found in Rosenbaum (2002).

The sensitivity analysis in our paper is based on the Wilcoxon sign rank test and the Hodges-Lehmann (HL) point estimate for the sign rank test with an upper and lower bound. A detailed explanation can be found in Peel and Makepeace (2012). The sensitivity analysis is only presented for arable farms where a significant effect was found, results for dairy farms follow a similar pattern. The tests show that only through the increase of Γ up to 2.6 the upper bound of the p-value exceeds the 5%-level. The 10%-level is not even exceeded for $\Gamma = 3.5$. This indicates that the results are quite robust to unobserved bias.

Table IV-11: Sensitivity analysis based on Rosenbaum bounds for arable farms (Scenario 1)

parameter	Wilcoxon p-value		HL treatment estimate	
Γ[1]	Lower bound[2]	Upper bound[3]	Lower bound[4]	Upper bound[5]
1	0.022236	0.022236	0.016228	0.016228
1.1	0.018473	0.023615	0.016005	0.016427
1.2	0.015053	0.024396	0.015794	0.016613
1.3	0.012572	0.025874	0.015581	0.016817
1.4	0.010151	0.026443	0.015342	0.017015
1.5	0.008706	0.027859	0.015084	0.017188
1.6	0.006296	0.028302	0.014893	0.017390
1.7	0.004919	0.029656	0.014683	0.017576
1.8	0.002636	0.030969	0.014524	0.017784
1.9	0.000258	0.032099	0.014337	0.017967
2.0	0.000013	0.034161	0.014113	0.018147
2.1	0.000000	0.036223	0.013937	0.018338
2.2	0.000000	0.039285	0.013733	0.018504
2.3	0.000000	0.042347	0.013563	0.018675
2.4	0.000000	0.045409	0.013416	0.018833
2.5	0.000000	0.048471	0.013266	0.019010
2.6	0.000000	0.052533	0.013090	0.019153
2.7	0.000000	0.056595	0.012919	0.019318
2.8	0.000000	0.060657	0.012754	0.019487
2.9	0.000000	0.064719	0.012575	0.019606
3.0	0.000000	0.069781	0.012407	0.019744
3.1	0.000000	0.074843	0.012247	0.019890
3.2	0.000000	0.079102	0.012089	0.020041
3.3	0.000000	0.084443	0.011927	0.020218
3.4	0.000000	0.090559	0.011756	0.020340
3.5	0.000000	0.095194	0.011605	0.020462

[1] Odds of differential assignment due to unobserved factors

[2] Lower bound significance level (on assumption of under-estimation of treatment effect)

[3] Upper bound significance level (on assumption of over-estimation of treatment effect)

[4] Lower bound point estimate (on assumption of under-estimation of treatment effect)

[5] Upper bound point estimate (on assumption of over-estimation of treatment effect)

IV.7 Discussion

Agri-environment schemes are part of a group of policies that have to fulfil several criteria that were developed in the aftermath of the Uruguay Round Agreement on Agriculture (1994) as the first meaningful framework to liberalize farm trade. One of these criteria states “that [agri-environment programs] have no, or at most minimal, trade distorting effects or effects on production” WTO (1995b: 59). Both an increase and a decrease in farm productivity as a result of scheme participation would constitute such a distorting effect ceteris paribus. While a trade distorting effect has to be avoided, it is desirable from a nature conservation perspective to increase the UAA contracted under agri-environment programs. Against this background it is crucial to design schemes that do not influence productivity because of being too restrictively or inflexibly designed. Ruto and Garrod (2009) note that farmers fear productivity losses by scheme enrolment and that their willingness to participate in AES would increase if they were less restrictive over the land to be included and the management practices to be followed. Our study empirically measures the productivity effects of Bavarian agri-environment measures as a significant AES program in the European Union. The average annual TFP change estimates we obtained (2.25% for dairy farms, 0.47% for arable farms) confirm relevant earlier studies on the development of total factor productivity in agricultural production. Brümmer, Glauben and Thijssen (2002) report technical change as the main source for TFP change in the German dairy sector and average TFP growth of around 6% between 1991 and 1994. They also find considerable fluctuations of technical and efficiency change rates around zero as do Sauer and Latacz-Lohmann (2015) who calculated an average TFP increase of German dairy farms for the period 1996-2010 of around 1.2%. Tiedemann and Latacz-Lohmann (2011) find an average yearly TFP change of 0.5% for German arable farms between 2000 and 2006 whereas Wettemann (2017) gives an average annual increase of around 1.3% for the period 2002-2010.

The estimates for technical efficiency obtained from the frontier specification reveal an average level of technical efficiency per farm of 90% for dairy farms and 80% for arable farms. The first value confirms findings for Bavarian dairy farms by Kellermann *et al.* (2011) who state that nearly 50% of all farms they investigate show efficiency values of at least 90%. For arable farms, Wettemann (2017) calculates average efficiency scores in a northern German region between 88% and 96%. However, he uses a smaller sample with fully specialized arable farms, whereas our sample still contains some mixed crop-livestock farms to a small extent. There is a large body of literature on comparing technical efficiency and productivity of conventional and organic farms (e.g. Mayen, Balagtas and Alexander (2010), Oude Lansink, Pietola and Bäckman (2002)). Payments for organic farming are typically integrated in rural development plans and constitute payments under environmental programs. We intentionally excluded organic farms as we were interested in the productivity effect of AES that are open for all farmers without completely changing production structure. In terms of UAA under agri-environment programs having environmental protection purposes, farm segment and field specific schemes cover a larger area than the AES program organic farming. Not all farmers will switch to organic farming, whereas participating in farm segment or field specific agri-environment schemes might be feasible and attractive for a large fraction of farmers if schemes are properly designed. It is thus advisable to investigate the effect that large scale measures have. Still, we can compare our results to some extent to the existing literature on the productivity effect of organic farming. According to a Finland based study by Oude Lansink, Pietola and Bäckman (2002), organic arable and livestock farms use a less productive technology than their conventional counterparts. Similar results are reported by Mayen, Balagtas and Alexander (2010) and Kumbhakar, Tsionas and Sipiläinen (2009) for U.S. dairy farms. Flubacher, Sheldon and Muller (2015) on the contrary found that organic production has a positive effect on the productivity of milk-farms in Switzerland. Guesmi *et al.* (2012) studied organic grape farms in Spain and showed that they are less productive than conventional farms. In general, organic farming practices seem to have a negative effect on productivity. Both organic farming and the AES we explored rest on restrictions. Our findings for the dairy sector underpin the results detected for organic dairy farms given the nature of the KULAP grassland measures. In their design – ban of mineral fertilizer and pesticides use, limit to livestock density etc. – they strongly resemble rules of organic farming. Arable measures of the KULAP on the other hand have a different focus than measures for organic arable farming as mentioned earlier. This might explain why we do not find a negative effect of AES on TFP change for arable schemes.

We are aware of possible endogeneity problems that might arise due to omitted variable bias or due to farmers‘ decisions concerning the use of different inputs, which are met against the background of their respective productivity effects or market chances of the products generated. Endogeneity could then lead to distortions in the estimations (van Beveren, 2012), which is why results have to be interpreted with some caution.

Another critical issue in productivity analysis is the use of implicit quantities obtained through deflation by price indices. Depending on the ratio of prices at farm level and official price indices for the whole agricultural sector, productivity of individual farms will either be overestimated or underestimated.

Concerning the matching approach, propensity score matching clearly does not solve all problems of the empirical evaluation of policy measures. The approach rests on the assumption that the ‘appropriate’ (observable) control variables are chosen in the empirical analysis. Heckman and Navarro-Lozano (2004) illustrate the importance and the difficulty of choosing the conditioning variables. In so far as economic theory can only provide limited guidance as to which variables to include or exclude in the logistic regression, a matching analysis does not necessarily solve the fundamental selection problem. Treatments and controls might still systematically differ in some unobserved characteristics. Further, a large number of observations very often is lost in a matching analysis if an adequate match is not available. This clearly limits the extent to which the results can be generalised to the full farm population level. The validity of the matching procedure further relies on the assumption that the treatment affects participating farms only. In practice, policy measures will not only have a direct impact on treated farmers but might also exert indirect effects on non-participating farms through the adjustment of factor markets and output prices.

Being based on income losses and additional costs, AES payments are supposed to cover foregone revenue. Most payments have the same level for the whole federal state, not taking into account spatially or timely varying prices and costs. We do control for inputs and outputs, however, we do not know the prices farmers obtain for their goods. The assumption we make is thus a c.p. situation where both groups, treated and untreated, face consistent price changes.

IV.8 Conclusions

Evaluating the effects of AES is an important policy challenge considering the amounts spent on such programs and since this determines whether programs are condemned as trade distorting or can be classified as ‘decoupled’ and therefore conform with WTO regulations. Besides, there is still scepticism among farmers about negative production effects of AES that hinder them from participating in these schemes when they are not adequately compensated. We used a semi-parametric propensity score matching estimator combined with a d-i-d approach to evaluate AES with respect to their effects on productivity.

We observe a significant positive effect of the AES on TFP change of arable farms. For dairy farms, no significant effect was found, which might be due to a better fit of grassland scheme payments to the extra costs or income loss involved in complying with the government program. The findings for arable farms violate the criteria of the Uruguay Round Agreement Act that green box payments shall not have a trade distorting effect or an effect on production. Due to the very nature of how AES are designed in Europe, mainly as classical action-based agri-environment measures which pay farmers for prescribed management activities for a five year period, overestimations or underestimations of the amount of the payment occur easily as farm heterogeneities and future developments are difficult to capture.

Result-based agri-environment measures, however, that partly already exist, instead link payments to the provision of a desired environmental outcome. They are increasingly seen as a promising way to improve the conditionality of CAP funding, resulting in improved environmental effectiveness. They would give farmers flexibility in their decisions of how to generate the required ecosystem services. Clearly, measuring actual outcomes in terms of ecosystem service provision may be more costly than measuring actions, but digitalisation and remote sensing developments can be seen as a promising opportunity. However, even result-based schemes need to adjust the payment according to farm individual conditions as our results suggest. Clearly, costs for providing ecosystem services depend on farm structure and site conditions. Our findings support this notion of a higher efficiency of result-based schemes. WTO relevant unwanted production effects could be avoided while at the same time only the amount of tax money would be spent that is justified by the actual provision of ecosystem services through the farmer. Public acceptance of such programs will crucially depend on the extent these schemes actually internalise externalities rather than creating rents to farmers. However, even in result-based schemes estimating the environmental effect directly remains an essential but very difficult undertaking if all possible ecosystem services as well as resource flow specifics and dynamics are to be considered. Farm advisory services can make use of our findings to more effectively address farmers' fears of productivity losses when enrolling in an AES and thus increasing the probability of enlarging the area farmed under an AES.

Despite the limitations of our study mentioned above, the results obtained can thus provide an important contribution to improve our understanding of the effects of AES at farm level economic performance and to amend the design of policies to promote desired outcomes. The evaluation and comparison of the effects of farm programs in various regions and the exact spatial distribution of treatment effects (within Germany but also between different EU member states) could further improve our knowledge about farmers' response to specific farm policies. By making use of a different methodological approach one might additionally be able to directly assess the opportunity cost of implementing environmental measures. Furthermore, the WTO rationale of limiting scheme payments to the extra costs or loss of income involved in complying with the government program could be assessed against the background of economic theory. Profit maximizing farmers are assumed to participate in AES only if scheme participation either does not affect or increases their outcome. Considering farm heterogeneity and horizontal payments it is obvious that the payment does not only compensate for costs and income losses only.

IV.9 Appendix

IV.9.1 Descriptive statistics

Table IV-12: Descriptive statistics 2006 (dairy farms, logit model, 990 observations)

Variables	Units	Mean	Std. Dev.	Min	Max
Farm characteristics					
Dummy variable 'AES participation'	0 = no, 1 = yes	0.72	0.45	0	1
Labour	man-work units	1.55	0.45	0.29	3.52
Land	hectares	47.32	25.96	7.68	212.79
Age of farmer	number	47.53	9.37	19	84
Capital depreciation	€/ha	583.03	300.33	13.18	2028.43
Material	€/ha	1511.83	1694.94	283.37	31889.93
Other capital	€/ha	733.74	400.75	150.82	6101.81
Fertilizer expenditures	€/ha	104.40	65.56	0	324.44
Pesticides expenditures	€/ha	42.35	34.58	0	181.85
Total farm sales	€/ha	2883.32	1896.97	258.48	32871.97
Share of rented land	%	0.48	0.25	0	1
Share of arable land	%	0.50	0.29	0	1
Share of grassland	%	0.50	0.29	0.	1
Yield index unit	number	3109.78	1224.74	500	7353
Livestock units	Number/ha	1.56	0.53	0.43	3.65
Share of agricultural income	%	0.91	0.44	-3.60	6.87
Dummy variable 'no agric. education'	0 = no, 1 = yes	0.08	0.27	0	1
Dummy variable 'in education or skilled worker'	0 = no, 1 = yes	0.65	0.48	0	1
Dummy variable 'master's certificate'	0 = no, 1 = yes	0.27	0.44	0	1
Dummy variable 'university degree'	0 = no, 1 = yes	0.01	0.08	0	1
Regional characteristics					
GDP per capita	€	22651.37	4937.25	15579	59457
Gross value added in agriculture	mio. €	458.49	163.07	32.53	818.55
Unemployment rate	%	0.06	0.02	0.03	0.13
Population density	habit./km^2	136.91	153.89	69.59	2686.99
Workforce	Insurable employees per 100 habit.	26.52	4.83	16.94	71.34
Altitude	meters	497.55	138.83	144	929
Dummy variable 'Swabia'	0 = no, 1 = yes	0.16	0.37	0	1
Dummy variable 'Lower Franconia'	0 = no, 1 = yes	0.04	0.20	0	1
Dummy variable 'Middle Franconia'	0 = no, 1 = yes	0.11	0.32	0	1
Dummy variable 'Upper Franconia'	0 = no, 1 = yes	0.13	0.33	0	1
Dummy variable 'Upper Palatinate'	0 = no, 1 = yes	0.17	0.37	0	1
Dummy variable 'Lower Bavaria'	0 = no, 1 = yes	0.17	0.38	0	1
Dummy variable 'Upper Bavaria'	0 = no, 1 = yes	0.22	0.42	0	1

Table IV-13: Descriptive statistics 2006 (arable farms, logit model, 344 observations)

Variables	Units	Mean	Std. Dev.	Min	Max
Farm characteristics					
Dummy variable 'AES participation'	0 = no, 1 = yes	0.54	0.50	0	1
Labour	man-work units	1.53	1.12	0.13	9.26
Land	hectares	60.25	53.88	7.27	397.37
Age of farmer	number	48.45	9.78	22	78
Capital depreciation	€/ha	377.73	275.00	0.46	1451.78
Material	€/ha	1159.25	731.34	165.65	4351.39
Other capital	€/ha	792.31	715.06	105.57	9043.81
Fertilizer expenditures	€/ha	218.07	83.85	0	555.17
Pesticides expenditures	€/ha	203.96	195.00	0	1159.98
Total farm sales	€/ha	2277.17	2099.51	278.89	11125.49
Share of rented land	%	0.43	0.32	0	1
Share of arable land	%	0.85	0.26	0.28	1
Share of grassland	%	0.05	0.07	0	0.41
Yield index unit	number	4098.15	1453.47	500	7770
Dummy variable 'farm status'	0 = part-time, 1 = full-time	0.73	0.44	0	1
Share of agricultural income	%	84.26	202.31	-667.71	3391.51
Dummy variable 'no agric. education'	0 = no, 1 = yes	0.10	0.31	0	1

Dummy variable ‘in education or skilled worker’	0 = no, 1 = yes	0.57	0.50	0	1
Dummy variable ‘master’s certificate’	0 = no, 1 = yes	0.29	0.46	0	1
Dummy variable ‘university degree’	0 = no, 1 = yes	0.03	0.18	0	1
Regional characteristics					
GDP per capita	€	24025.20	8526.90	15579	85765
Gross value added in agriculture	mio. €	441.78	159.51	27.04	818.55
Unemployment rate	%	0.05	0.02	0.03	0.10
Population density	habit./km^2	157.56	240.93	69.59	4170.77
Workforce	Insurable employees per 100 habit.	25.74	8.17	16.45	61.06
Altitude	meters	371.20	82.88	127	591
Dummy variable ‘Swabia’	0 = no, 1 = yes	0.04	0.20	0	1
Dummy variable ‘Lower Franconia’	0 = no, 1 = yes	0.17	0.37	0	1
Dummy variable ‘Middle Franconia’	0 = no, 1 = yes	0.05	0.22	0	1
Dummy variable ‘Upper Franconia’	0 = no, 1 = yes	0.06	0.25	0	1
Dummy variable ‘Upper Palatinate’	0 = no, 1 = yes	0.10	0.30	0	1
Dummy variable ‘Lower Bavaria’	0 = no, 1 = yes	0.23	0.42	0	1
Dummy variable ‘Upper Bavaria’	0 = no, 1 = yes	0.34	0.47	0	1
Farmland rental value	€/ha	231.68	71.62	96.44	350.18

Table IV-14: Descriptive statistics 2007-2011 (dairy farms, frontier model)

Variables	Obs	Units	Mean	Std. Dev.	Min	Max
Total farm sales	1530	€	124525.60	84310.29	14076.51	836212.10
Land	1530	hectares	38.40	19.07	2.00	148.30
Labour	1530	man-work units	1.48	0.47	0.29	3.50
Depreciation	1530	€	22889.33	16697.55	466.98	150201.30
Material	1530	€	64203.86	58953.53	4409.53	621784.10
Other capital	1530	€	26820.37	18949.75	3454.99	346438.50
Livestock units	1530	number	65.91	32.86	2.41	235.80

Table IV-15: Descriptive statistics 2007-2011 (frontier model, arable farms)

Variables	Obs	Units	Mean	Std. Dev.	Min	Max
Total farm sales	970	€	117615.20	110435.3	12103.11	774204.50
Land	970	hectares	69.13	58.44	5.84	334.76
Labour	970	man-work units	1.29	0.91	0.01	9.63
Depreciation	970	€	18284.56	18391.47	86.58	138750.10
Material	970	€	59623.04	50532.15	761.01	331243.50
Other capital	970	€	38363.76	37437.41	1845.87	286371.30

IV.9.2 Data description

As concerns farm characteristics, the dummy variable *AES participation* indicates, whether farms were participating in at least on AES over the whole period 2007-2011. *Labour* is measured in man-work units as defined by the FADN. *Revenue milk* and *revenue animal* refer to sales revenue for milk and cattle, while *total revenue* describes total farm sales. *Share of rented land*, *share of arable land* and *share of grassland* give the shares of the total agricultural land that belongs to the respective category. The *yield index unit* is an indicator for site quality, with higher numbers indicating better soil quality and site conditions. *Livestock units* measures all farm livestock as defined by the Bavarian State Ministry for Food, Agriculture and Forestry. *Share of agricultural income* describes that part of the overall farm household income generated by agriculture. The education dummy variables indicate the education level of the farmer.

Concerning regional characteristics, these variables describe the socioeconomic surrounding in which the farmers in different Bavarian regions are operating. They are measured on county or community level. Dummy variables are used to categorize the farms into the different administrative districts of Bavaria, which also represent different natural environments.

IV.9.3 Model estimates

Table IV-16: Parameter estimates for logit model (dairy farms)

Variables	Coefficient	Wald χ2 (Sign.)
Intercept	-6.383	0.06
Farm characteristics		
Ln labour	0.194	0.18
Ln land	1.522	20.43***
Ln age	-0.308	0.38
Ln capital depreciation per ha	-0.135	0.49
Ln material per ha	-0.611	2.04
Ln other capital per ha	0.273	0.94
Ln farm sales per ha	-0.732	2.76*
Ln fertilizer per ha	-0.002	1.56
Ln pesticides per ha	0.008	3.20*
Ln farmland rental value	-0.732	2.76*
Share of rented land	-1.085	4.88**
Share of arable land	-18.014	0.61
Share of grassland	-16.025	0.48
Yield index unit	-0.092	0.14
Ln livestock farm	-2.291	45.16***
Share of agricultural income	-0.208	1.08
Dummy variable ‘in education or skilled worker’	0.175	0.23
Dummy variable ‘master’s certificate’	0.225	0.29
Dummy variable ‘university degree’	0.423	0.06
Dummy variable farm status	-0.833	2.92*
Regional characteristics		
Ln GDP per capita	2.579	11.56***
Ln gross value added in agriculture	0.425	1.64
Unemployment rate	-9.333	0.67
Population density	-0.001	1.06
Ln workforce	-0.303	1.06
Ln altitude	0.563	0.88
Dummy variable ‘Swabia’	0.678	3.76*
Dummy variable ‘Lower Franconia’	1.874	4.45**
Dummy variable ‘Middle Franconia’	1.496	10.96***
Dummy variable ‘Upper Franconia’	2.160	10.43***
Dummy variable ‘Upper Palatinate’	1.558	11.63***
Dummy variable ‘Lower Bavaria’	1.404	16.40***
Regression statistics		
Number of observations	990	
LR χ2 (32)	455.40	
Prob > χ2	0.0000	
Pseudo R^2	0.3899	

Table IV-17: Parameter estimates for logit model (arable farms)

Variables	Coefficient	Wald χ2 (Sign.)
Intercept	24.279	3.53*
Farm characteristics		
Ln labour	0.573	1.35
Ln land	0.433	1.69
Ln age	-0.029	0.00
Ln capital depreciation per ha	0.206	1.30

Ln material per ha	1.116	2.66
Ln other capital per ha	0.162	0.25
Ln farm sales per ha	-1.162	4.20**
Ln fertilizer per ha	0.001	0.25
Ln pesticides per ha	-0.004	3.17*
Share of rented land	-0.097	0.03
Share of arable land	-6.916	11.83***
Share of grassland	-2.561	0.71
Yield index unit	-1.166	7.67***
Ln farmland rental value	-1.162	4.20**
Share of agricultural income	-0.104	2.19
Dummy variable 'in education or skilled worker'	0.028	0.00
Dummy variable 'master's certificate'	0.162	0.12
Dummy variable 'university degree'	0.806	0.83
Dummy variable farm status	-0.101	0.04
Regional characteristics		
Ln GDP per capita	-0.597	0.44
Ln gross value added in agriculture	-0.095	0.17
Unemployment rate	0.271	0.00
Population density	-0.006	2.16
Ln workforce	-0.093	0.01
Ln altitude	0.561	0.42
Dummy variable 'Swabia'	-0.201	6.31**
Dummy variable 'Lower Franconia'	0.182	10.52***
Dummy variable 'Middle Franconia'	0.293	3.15*
Dummy variable 'Upper Franconia'	-0.290	8.54***
Dummy variable 'Upper Palatinate'	0.783	8.97***
Dummy variable 'Lower Bavaria'	0.725	6.44**
Regression statistics		
Number of observations	344	
LR χ2 (31)	113.20	
Prob > χ2	0.0000	
Pseudo R^2	0.2387	

Asterisks denote statistical significance 1 per cent (***), 5 per cent (**) or 10 per cent (*) level.

Table IV-18: Maximum likelihood estimation (translog specification, arable farms)

Variables	**Coeff. (std.err.)**	**z-statistic**
Ln total farm sales		
Ln land	0.06 (0.03)	2.26**
Ln labour	0.22 (0.0)	8.18***
Ln material	0.73 (0.03)	24.50***
Ln other capital	0.08 (0.02)	3.45***
Ln depreciation	0.05 (0.01)	3.31***
t	0.01 (0.01)	1.75*
(ln land)^2	0.32 (0.09)	3.75***
Ln land*ln labour	-0.07 (0.04)	-1.60
Ln land*ln material	-0.27 (0.08)	-3.51***
Ln land*ln other capital	-0.01 (0.06)	-0.24
Ln land*ln depreciation	0.03 (0.04)	0.72
Ln land*t	-0.01 (0.02)	-0.54
(ln labour)^2	0.08 (0.06)	1.34
Ln labour*ln material	0.11 (0.05)	2.00**
Ln labour*ln other capital	-0.09 (0.05)	-1.82*
Ln labour*ln depreciation	0.04 (0.03)	1.68*
Ln labour*t	-0.02 (0.01)	-1.06
(ln material)^2	0.02 (0.09)	0.23
Ln material*ln other capital	0.10 (0.07)	1.56
Ln material*ln depreciation	0.01 (0.03)	0.19
Ln material*t	0.02 (0.02)	1.09
(ln other capital)^2	-0.04 (0.08)	-0.49
Ln other capital*ln depreciation	-0.00 (0.03)	-0.10

Ln other capital*t	-0.01 (0.02)	-0.44
(ln depreciation)^2	-0.00 (0.02)	-0.28
Ln depreciation*t	-0.01 (0.01)	-0.72
t^2	-0.08 (0.01)	-7.26***
_cons	0.26 (0.02)	12.68***
sigma_v	0.21 (0.01)	22.19***
sigma_u	3.30 (0.11)	29.96***
lambda	15.97 (0.12)	138.48***
Log likelihood	-187.23	
Wald χ2 (27)	8345.96	
Prob > χ2	0.00	
Observations	970	

Asterisks denote statistical significance 1 per cent (***), 5 per cent (**) or 10 per cent (*) level.

Table IV-19: Performance of different matching algorithms in terms of standardized bias (median after matching)

	Dairy farms	Arable farms
Kernel matching (bwidth. 0.1)	4.2	3.5
Radius matching (cal. 0.1)	4.9	3.8
NN matching with replacement (cal. 0.1)	4.3	6.1
NN matching without replacement (cal. 0.1)	3.5	2.7

Table IV-20: Fixed-effects regression results for dairy farms, scenario 2

Variables	Coefficient	Std. Err.	t
Annual TFP change			
Tt	-0.0046	0.0041	-1.14
T	-	-	-
t	0.0248	0.0029	8.67***
_cons	0.0053	0.0011	4.32***
F(2,304)	144.63		
Prob > F	0.0000		
R-sq within	0.2910		
R-sq between	0.2249		
R-sq overall	0.1718		
Observations	612		
Number of groups	306		

Table IV-21: Fixed-effects regression results for arable farms, scenario 2

Variables	Coefficient	Std. Err.	t
Annual TFP change			
Tt	0.0167	0.0080	2.10**
T	-	-	-
t	-0.0039	0.0057	-0.68
_cons	0.0028	0.0017	4.94***
F(2,188)	88.28		
Prob > F	0.0000		
R-sq within	0.3030		
R-sq between	0.2341		
R-sq overall	0.2687		
Observations	388		
Number of groups	198		

Asterisks denote statistical significance 1 per cent (***), 5 per cent (**) or 10 per cent (*) level.

Table IV-22: Impact of AES on technical change, technical efficiency change and scale change for dairy farms (scenario 1)

Variable of interest	Unit	Treatments Δy_i^1	Controls Δy_j^0	ATT $\Delta y_i^1 - \Delta y_j^0$	t-value	Pr(|T| > |t|)
Annual TC	%	2.120 (1.128)	2.327 (1.256)	-0.207	1.27	0.204
Annual TEC	%	0.031 (0.028)	0.008 (0.014)	0.023	-0.09	0.930
Annual SEC	%	0.010 (0.041)	0.007 (0.027)	0.003	-0.81	0.421

Table IV-23: Impact of AES on technical change, technical efficiency change and scale change for arable farms (scenario 1)

Variable of interest	Unit	Treatments Δy_i^1	Controls Δy_j^0	ATT $\Delta y_i^1 - \Delta y_j^0$	t-value	Pr(|T| > |t|)
Annual TC	%	0.738 (0.322)	0.760 (0.413)	-0.022	0.13	0.895
Annual TEC	%	0.347 (0.025)	-1.121 (0.693)	1.468	-1.98	0.053*
Annual SEC	%	-0.040 (0.079)	-0.114 (0.097)	0.007	-0.58	0.560

IV.9.4 Description of KULAP measures

In total, there were 14 individual KULAP measures, categorized into grassland measures, measures for arable land and for special farming practices. Some of the measures were further subdivided following different levels of restriction. The grassland measures as well as the measures for special farming practices mainly aimed at an extensification of production. They primarily restricted the use of mineral fertilizers and/or pesticides and set a limit to livestock units per hectare. Measures for arable land encompassed the implementation of diversified crop rotations, planting of cover crops, low-till methods, agro-ecological concepts or the conversion of arable land to grassland. Payments for special farming practices were mainly granted for measures with a focus on the conservation of the Bavarian cultural landscape. Being horizontal according to the Rural Development Program, these measures were in fact only applicable in certain parts of Bavaria, e.g. in the alpine region or in the wine-growing districts in the north. In order to keep farmers from switching to different types of land use or abandoning farming, these measures knotted payments to environmental farming practices such as grazing or limiting the use of pesticides. Basically, all KULAP measures involved some kind of restriction, either concerning the use of certain inputs or the farmer's choice of how to cultivate the agricultural land.

V Promoting organic food production in flagship regions – A policy evaluation study for Southeast Germany[13]

V.1 Abstract

Mitigating the environmental impact of agriculture is a major issue in current negotiations on the future of the Common Agricultural Policy. Organic farming is commonly put forward in these discussions as a promising way to reduce the negative environmental impact of agriculture. Consequently, different promotional strategies aiming at the adoption of organic farming practices have been developed. In 2013, the German federal state of Bavaria initiated an innovative programme that resulted in 'organic flagship regions' being appointed in the years that followed. These regions are allocated support with the main goal of motivating farmers to switch to organic production. By applying a difference-in-difference estimator, we evaluate whether the programme has achieved its aims, i.e. whether more farmers have adopted organic farming practices within the flagship regions as compared to farmers outside such regions. The Theory of Planned Behaviour provides the conceptual framework to identify the main factors influencing a farmer's decision to go organic. Our results suggest that the programme fails to motivate farmers to switch to organic production and that there is a need to more effectively target decision-influencing factors.

V.2 Introduction

The past six decades have seen a rapid increase in worldwide agricultural production. Advances in crop cultivation and livestock breeding as well as in the application of mechanisation and innovative agricultural practices, mineral fertilisers and pesticides have resulted in a dramatic boost in productivity. While this development has helped to strengthen global food security, it has also placed a serious burden on the environment and continues to do so through modern, intensive agriculture (Bowler *et al.*, 2019; Foley *et al.*, 2005; Matson *et al.*, 1997; Pingali, 2012; Smith *et al.*, 2013; Tilman *et al.*, 2001). The more evidence scientists around the world have gathered on the environmental footprint of this type of farming over the years, the faster consumer concerns regarding food safety and environmental pollution caused by intensive land-use have grown. In the late 1980s, the agricultural sector and policy makers in Europe reacted by rediscovering, developing and promoting food production practices that are less harmful to the environment. Organic farming is one of these practices, and it has gained considerable attention thanks to the holistic approach that it takes. At least through the 1992 MacSharry reform of the Common Agricultural Policy (CAP), it became an essential element of European agricultural policy, which since then grants financial support to organic farms through Member States' agri-environment programmes. In stimulating the uptake of organic farming, European decision-makers draw upon research promoting it, under certain assumptions, as a solution to sustainable food security challenges (Badgley *et al.*, 2007; Erb *et al.*, 2016). It is indeed the case that organic agriculture performs better than conventional farming with regard to water protection (Benoit *et al.*, 2015; van Huylenbroeck, Mondelaers and Aertsens, 2009), soil fertility (Crittenden and Goede, 2016; Gomiero, Pimentel and Paoletti, 2011), biodiversity (Bengtsson, Ahnström and Weibull, 2005; Crowder *et al.*,

[13] This is a pre-copyedited, author-produced version of an article accepted for publication in Q Open following peer review. The version of record (Mennig, Philipp and Johannes Sauer. 2022. *Promoting organic food production through flagship regions*. Q Open. 2(1): 1-31) is available online at https://doi.org/10.1093/qopen/qoac010.

2012) and resource efficiency (Thünen-Institut, 2019; Lin *et al.*, 2017), at least per unit of area. However, in terms of product units, organic farming practices do not necessarily have a lower environmental impact than conventional methods (Tuomisto *et al.*, 2012; Seufert and Ramankutty, 2017). It is this finding, in combination with the yield gap of 20-25% between organic and conventional systems (Smith *et al.*, 2020; Ponti, Rijk and van Ittersum, 2012) that has brought authors like Reganold and Wachter (2016) or Seufert and Ramankutty (2017) to the conclusion that a mix of organic and other innovative agricultural systems is needed in order to safely feed the planet.

Organic farming thus seems to represent an important element of a group of strategies designed to improve the sustainability of both current and future food systems. Naturally, its promotion remains high on agri-environmental policy agendas – especially as only 1.5% of the world's farmland is organically managed (Schlatter *et al.*, 2020: 36). In the European Union (EU), this share reaches 7.5% (Eurostat, 2020c). In line with the EU's current plans to adjust the profile of the CAP towards increased care of the environment, climate change action and preservation of landscapes and biodiversity (European Commission, 2018c, 2018a, 2018b), this share is set to rise to 25% in 2030, according to the *Farm to Fork Strategy* (European Commission, 2020a). One step has already been taken towards stimulating both the supply of and demand for organic products, by putting new organic regulations in place that will be effective from 1 January 2021. These new regulations, which in many cases promote organic farming with national or regional programmes flanking EU-wide efforts, will apply in all EU member states. One such regional programme is the Bavarian agenda, 'BioRegio Bayern 2020'. Initiated in 2012 by the Bavarian State Ministry of Food, Agriculture and Forestry (StMELF), it aims at doubling organic production in Bavaria by 2020, accompanied by continuous enhancement of the entire organic sector. The aim is for both goals to be achieved through a holistic approach that combines measures in education, consulting, funding, marketing and research (StMELF, 2017). A particularly innovative scheme among those is the organic flagship region programme ("Staatlich anerkannte Öko-Modellregionen in Bayern"). In this programme, 12 municipal associations were selected as organic flagship regions from a competition organised in 2013 and 2014 by the StMELF. The competition was open to all Bavarian municipalities, who could cooperatively submit innovative projects and concepts aiming at expanding organic production and consumption within their region. All submissions had to clearly describe how local authorities, producers, processers, retailers, consumers and other local actors could be involved in and contribute to the expansion of (certified) organic farming. The 12 municipal associations with the most convincing concept notes appointed as organic flagship regions receive support from the StMELF in various ways, the main element being the creation and public financing of a project manager position in each region.

Wherever public funds are used to finance policy measures, as is the case with the organic flagship region programme, governments must show that resources are being spent sensibly. Consequently, every intervention needs to be accompanied by monitoring and evaluation in order to promote learning and enhance policies' effectiveness and efficiency. We conducted such monitoring and evaluation for the Bavarian organic flagship region programme, analysing the extent to which its primary goal of extending organic food production by convincing farmers to switch to organic practices was reached. Our study combines elements of social-psychology (theory of planned behaviour) and behavioural economics (discrete choice experiment) with a classical impact evaluation method (difference-in-difference), first to understand the factors that influence the adoption of organic farming practices in Bavaria, and second to investigate whether the programme reasonably addressed these factors. The former – the organic farming adoption process – has been studied thoroughly by several authors applying different methods for various farm types and regions (see for example Andow *et al.* (2017); Burton, Rigby and Young (2003); Flaten *et al.* (2005); Knowler and Bradshaw (2007); Lampach, Nguyen-Van and To-The (2019); Läpple and Kelley (2015); Läpple and Kelley (2013); Padel (2001); Pietola and Lansink (2001); Serra, Zilberman and Gil (2008)). They identified a range of factors that have impacted the decision to convert from conventional to organic farming. The most relevant ones include, as already listed by Kallas, Serra and Gil (2010: 411–412), farmer characteristics, farm structure, farm management and exogenous parameters, as well as attitudes and opinions. Especially the social-psychological factors referred to above have been identified as crucial elements in the formation of behavioural intent, an example being a farmer's decision to pursue organic farming (Läpple and Kelley, 2013; Issa and Hamm, 2017; Toma and Mathijs, 2007). Therefore, for any organic farming programme to be effective, particularly in the short-run, it needs to be designed in such a way that it does not neglect these influenceable factors. Current support measures for organic farming are mainly framed in an incentive-based manner, providing subsidies under Pillar II of the CAP based on income foregone and cost incurred as well as investment allowances and aid for marketing and promotion of organic products (EU, 2019). Alongside such EU aid, most EU countries develop their organic sectors with additional programs. Germany, for example, launched an organic action plan in 2017, which contains a mix of measures relating to consumption, production, administration and research, in five fields of action, these being the formation of a future-oriented and coherent legal framework, facilitating access to organic farming, exploiting and expanding current demand , improving the performance of organic agricultural systems, and properly rewarding the provision of ecosystem services (BMEL, 2019). Despite the large number of comparable organic action plans in Europe and the long history of support for organic agriculture, little literature has been devoted to a systematic analysis of the degree to which organic food and agriculture policies affect participation in organic farming. Analyses of organic policy instruments or labelling often provide comprehensive reviews of the instruments applied, yet only a few theoretically sound considerations of the policy tools that actually lead to growth of the organic sector exist (Daugbjerg and Halpin, 2008). One of these studies is a paper by Daugbjerg *et al.* (2011) in which the authors examine whether Danish and UK organic farming policy measures between 1989 and 2007 have affected participation, using a piece-wise linear representation of policy. They found that six out of the fourteen policy measures in the two study countries, primarily direct supply-side instruments, significantly influenced the uptake of organic farming practices. Similarly, in his qualitative analysis covering various European countries, Michelsen (2002) detected an unclear, but rather positive, effect of policy instruments toward organic agriculture on organic sector size. While these authors analysed supply-side and demand-side, respectively legal, financial and communicative organic policy measures, others such as Lindström, Lundberg and Marklund (2020), Lesjak (2008) and Chabé-Ferret and Subervie (2013) focussed on either demand-side or supply-side measures. Concerning demand-side instruments, Green Public Procurement has been found to have a positive impact on the size of organic agricultural land in Sweden (Lindström, Lundberg and Marklund, 2020), and providing product-specific information (actionable labelling) increases consumer willingness to purchase organic food (Aitken *et al.*, 2020), which might have an indirect effect on the area of organically managed land. Generally, though, the supply-side instrument of area support payments is considered the major driver behind the increase in land area devoted to organic farming (Pietola and Lansink, 2001; Sanders, Stolze and Padel, 2011; Chabé-Ferret and Subervie, 2013). This might explain why policy efforts tend to be directed at conversion subsidies for organic farming, despite some authors stressing the importance of a mix of measures (Daugbjerg and Sønderskov, 2012; Sanders, Stolze and Padel, 2011).

The Bavarian organic flagship region programme attempts to respond to calls for a mix of supply-side and demand-side measures by targeting suppliers, farmers, processers, retailers, consumers and authorities alike. However, to achieve the overall programme goal, farmers are the ones who primarily need to adopt a new type of behaviour. Our evaluation study therefore explores whether the programme has encouraged farmers to switch to organic production. This would result in increased organic output irrespective of productivity growth, given that both conventional and organic farmers display similar growth patterns in terms of agricultural land (StMELF, 2018). We measure both actual and intended behavioural change using survey data from inside and outside the organic flagship regions before/at the start of the programme and two years after its implementation. Before applying this difference-in-difference (DiD) method, a well-established policy evaluation tool (see for example Bertoni *et al.* (2020), Petrick and Zier (2011), Pufahl and Weiss (2009)), we identify factors that influence the decision of Bavarian farmers to adopt organic farming, to assess whether they have been taken into consideration by the organic flagship region programme. Our analysis provides empirical evidence of the success of this innovative policy tool and may help decision-makers in adapting their promotion of organic farming. It is, to the best of our knowledge, the first in-depth study of this type of policy measure.

The remainder of this article is structured as follows: Section 2 outlines the theoretical concept underlying the uptake of organic farming, Section 3 gives a brief overview of the organic sector in Bavaria and of the organic flagship region programme. Section 4 describes the dataset and empirical methodology, followed by a presentation and discussion of the results in Section 5. Finally, Section 6 presents some concluding remarks.

V.3 Theoretical framework

The transition to organic farming can be challenging for a farmer and depends on the site and pre-conversion market conditions, the farm structure and the level of intensity of the farming system. It requires a lot of learning, involves financial investments and necessitates overcoming bureaucratic obstacles. Theory suggests that a farmer will accept these challenges if the expected utility to be had from organic farming (U_O) is greater than the expected utility of non-adoption (U_C), i.e. sticking to conventional practices. Formally and following Läpple and Kelley (2015), this relation can be expressed by the following expected utility function for a utility-maximising farmer, including financial and non-financial factors:

$$E\big[U_O\big((\pi_O - G + S_O) + A + SN + PBC\big)\big] - E[U_C(\pi_C + A + SN + PBC)] > 0, \qquad (5.1)$$

where $\pi_k(k = O, C)$ is the farm profit from organic or conventional production respectively, G represents the cost of converting to organic farming, which is linked to the farm structure, farm management and exogenous parameters, and includes additional investment, learning-related costs and income losses resulting from lower yields (Lampkin and Padel, 1994). S_O are organic farming subsidies, which in Europe are higher during the conversion period, when organic production methods need to be used but the resulting product cannot be sold as organic until after transition. A, SN and PBC represent attitude, subjective norm and perceived behavioural control, the psychological constructs underlying the intention to adopt a specific behaviour according to the theory of planned behaviour (Ajzen, 1991). This theory will be explained in more detail in the next paragraph. Farm profit π_k in equation (5.1) can be further analysed as follows:

$$\pi_k = p_k q(f_k, F) - c_k f_k + s, \tag{5.2}$$

where p_k represents the output prices depending on farm type, q refers to the output quantity, a function of input factors f_k, and F stands for production relevant factors, such as quality of land or distance to markets. c_k are the farm-type-specific input prices and s are subsidies received by each farmer. Hence, profit is directly linked to management practices and the type of management. As it hinges on factors like prices, the uptake of organic farming is also influenced by these external parameters. Further parameters that influence utility and, consequently, a farmer's decision-making process are, as mentioned earlier, attitude, subjective norm and perceived behavioural control.

These three constructs form the main building blocks of the theory of planned behaviour (TPB), which evolved from Ajzen's and Fishbein's theory of reasoned action (1980; 1975). It assumes that intention is an appropriate predictor of actual human behaviour. Intention, in turn, is based on beliefs concerning attitude, subjective norm and perceived behavioural control held by people towards a specific behaviour (Ajzen, 1991). Attitude refers to an individual's positive or negative evaluation of the behaviour of interest and is linked to the idea he or she has about how good or bad the outcome is. Subjective norm describes the perceived social pressure or influence from others on carrying out the behaviour, while perceived behavioural control refers to the perceived ability to perform the behaviour. These three constructs have been used extensively in social-psychology research to explain and understand human behaviour. Studies analysing the intentions and behaviour of farmers applying the TPB include those by Hansson, Ferguson and Olofsson (2012), Sutherland (2010), Daxini *et al.* (2018) and Despotović, Rodić and Caracciolo (2019). There are four reasons why the theory is well-suited to examining the adoption of organic farming: First, it enables the study of decisions that involve intensive planning (Krueger, Reilly and Carsrud, 2000), such as the conversion from conventional to organic farming. Second, it controls for difficulties that farmers might face before and during the adoption process (Läpple and Kelley, 2013: 12), third, the TPB has a high explanatory value (Fielding, McDonald and Louis, 2008) and fourth, it provides the possibility of studying internal and external factors as well as the flexibility to include additional variables (van Dijk *et al.*, 2016).

While the TPB is applied to assess factors driving the adoption of organic farming in Bavaria, a combination of two other theories comes into play when measuring the success of the organic flagship region programme in terms of changes to farm practices. One intended effect of the programme is that it should increase the number/share of organic farms inside the flagship regions after a certain time. In our DiD setting, we therefore consider outcome variables not only in relation to farm type, but also to the likelihood of a farmer switching to organic production. We estimated this likelihood in a discrete choice experiment (DCE), in which farmers had the chance to choose a farm type that promises the highest overall utility from a set of alternatives. Discrete choice experiments are based on Lancaster's consumer theory (Lancaster, 1966) and the random utility theory proposed by Luce and McFadden (Luce, 1959; McFadden, 1974). Lancaster's consumer theory suggests that individuals derive utility not directly from goods but from the characteristics, or attributes, of these goods. Assuming that the decision-makers operate rationally, each individual then maximises utility relatively to his or her choices. According to random utility theory, decision-maker i, when making such choices, considers m_i alternatives, which form a choice set I^i. Each alternative j is assigned a perceived utility U_j^i. When trying to model choices of decision-makers, external observers cannot predict this utility with any certainty, which is why U_j^i is represented by a random variable. However, it is possible to estimate the probability p^i that decision-makers will choose a certain alternative given a set of choices:

$$p^i(j|I^i) = \Pr[U_j^i > U_k^i \; \forall k \neq j, k \in I^i] \tag{5.3}$$

Perceived utility U_j^i, which explains the probability of an alternative being selected, consists of two terms: systematic utility V_j^i and a random residual ε_j^i. The systematic utility describes the mean utility derived by all individuals facing the same choice situation as decision-maker i. The random residual on the other hand represents the (unknown) deviation of the utility of a specific decision-maker from this mean value. It captures different personal and situational elements of uncertainty. Perceived utility can therefore be formulated as follows:

$$U_j^i = V_j^i + \varepsilon_j^i, \forall j \in I^i \tag{5.4}$$

For the purpose of this paper, it is sufficient that systematic utility, perceived utility and the probability of a particular alternative being chosen can be estimated econometrically. The latter, which in our case refers to the probability of a farmer choosing an organic farm type, is included in the second stage DiD estimation, which measures the effect of the organic flagship region programme.

V.4 The organic flagship region programme and organic farming in Bavaria

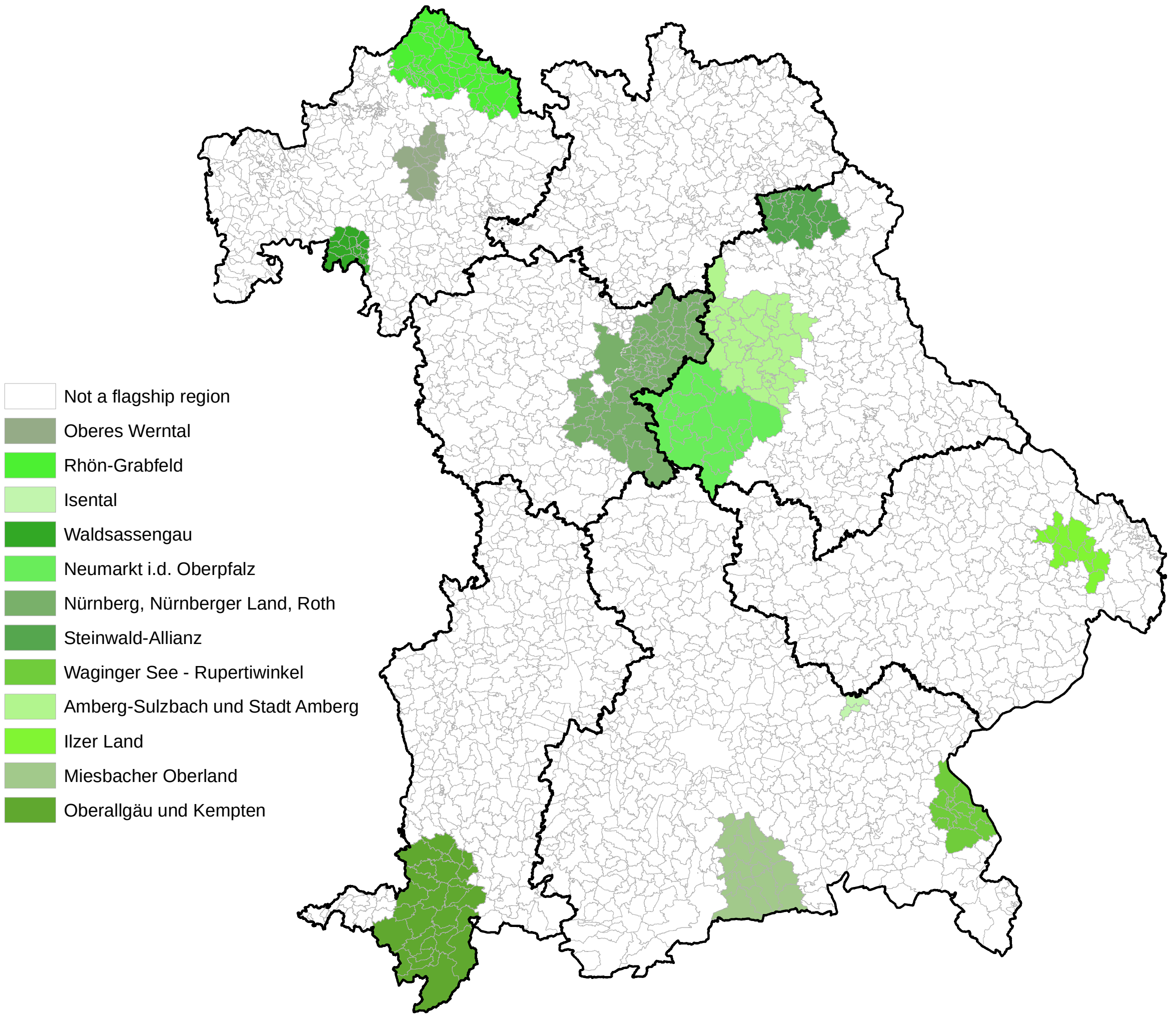
Located in southeast Germany, the federal state of Bavaria is one of Europe's core agricultural and food regions. Its share of gross value added in agriculture, forestry and fishing within the European Union is around 2.3% (Eurostat, 2020a, 2020b), putting it ahead of some important agricultural producers in the EU, such as Denmark, Ireland and Austria. It is especially the well-developed Bavarian dairy sector that contributes to this figure. In 2017, around 1.2 million cows were kept on 30,489 dairy farms, producing roughly 8.2 million tons of milk. This corresponds to 4.8% of the total raw milk production in the EU (Eurostat, 2018: 57; LfL, 2018: 10). In the same year, 6% of all Bavarian milk was produced organically. This share has been increasing steadily over the years, partly as a result of volatile prices for conventional milk and low conversion costs in southern and eastern Bavaria, where extensive and largely grass-based systems are not uncommon. Farm types other than dairy have, however, also been shifting more and more towards organic production. Overall, around 10,500 out of 105,000 Bavarian farms apply organic practices on roughly 11% of the total utilised agricultural area (UAA) (StMELF, 2020).

As was already the case in 2013 and 2014, when the first call for proposals of the organic flagship region programme was made, demand for organic products today continues to exceed domestic production in Bavaria. However, the organic sector has experienced rapid growth in recent years. The societal trend towards organically produced food coupled with the Bavaria-wide policy measures in the fields of education, financial support, marketing and research, advisory services and knowledge transfer is likely to have contributed to this growth. Furthermore, the organic flagship region programme is hypothesised to have stimulated the uptake of organic farming, at least in certain areas, namely within the flagship regions. In two competition rounds (2013 and 2014), the StMELF selected 12 municipal associations on the basis of the quality of their concept notes on ways of strengthening the organic sector within the respective region. Both competitions were open to all Bavarian municipalities. Proposals were typically developed by a team of local players, including municipal decision-makers, activists and actors along the food value chain. Farmers, though, were involved in only a few cases.

The 12 winning municipal associations are presented in Figure V-1. Some of the regions are pioneers in organic farming and wish to reinforce their leading role, while others have a less developed organic sector. Once they had been appointed organic flagship regions, they all began to implement the projects and ideas outlined in their proposals, for the most part in 2016. For this purpose, each flagship region appointed a project manager, who was financed to 75% by the StMELF. Additional consultancy support is granted to all organic flagship regions by various Bavarian authorities and associations working in the areas of agriculture and rural development. They also advise the project manager about projects and initiatives in each region. These vary from one flagship region to another, but the aim is for them to cover aspects relating to production, processing, marketing and consumption in equal measures, as the purpose of the organic flagship region programme is to try to enhance organic production by creating an impact along the food value chain, exploiting existing potential on a local level and raising consumer awareness concerning organic food. Example projects include collaborations between organic producers and restaurants, thematic cooking courses, the creation of regional organic value chains, and the establishment of organic farmer's markets[14].

[14] A complete list of all projects carried out in the flagship regions was not available at the time when our analyses were performed. More detailed information about the overall programme and specific projects can be found on https://www.oekomodellregionen.bayern/. Public direct funds for the whole programme are limited to expenses for the project manager positions for two years.

Figure V-1: Organic flagship regions in Bavaria



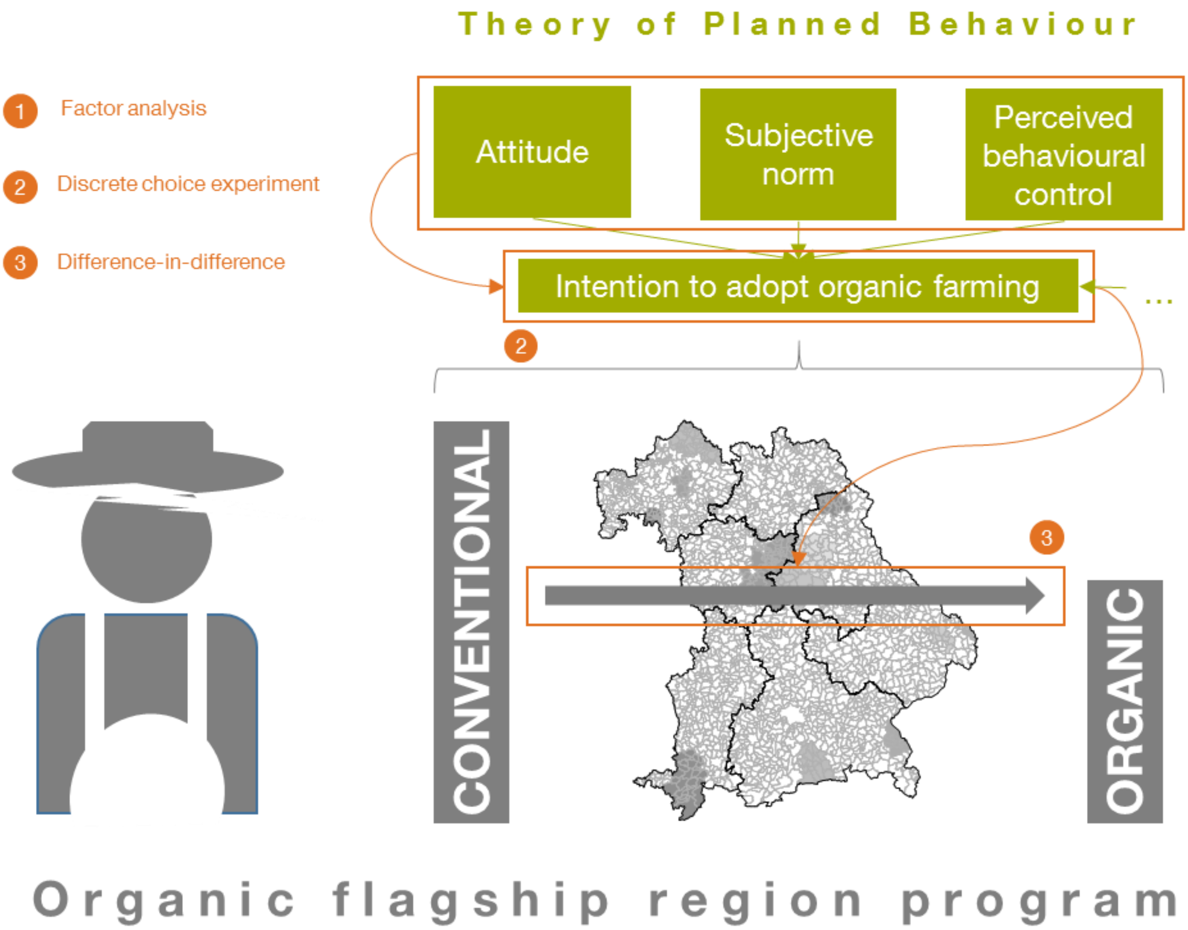
Source: Own depiction

In the next section we describe how we measure the effect of such projects on farmers' intentions of adopting organic farming and how we identify factors that affect their decision-making.

V.5 Materials and methods

Our econometric analysis comprises three parts (see Figure V-2). In part one, we use factor analysis to obtain measures of latent, non-observable constructs that, along with other determinants, are expected to influence the uptake of organic farming. The second part addresses farmer preferences concerning conventional and organic farm types using a DCE, while the third part focuses on DiD-based impact evaluation, making use of estimation results from the choice experiment.

Figure V-2: Conceptual framework used for the purpose of this study



Source: Own depiction

V.5.1 Data and data collection

All of these analyses are based on data from two farm surveys, the first conducted in 2016, when the majority of the organic flagship regions began to operate, and the second one in 2018 (descriptive statistics are reported in the Appendix). Response rates did not vary substantially between both rounds. Repeated surveys including a baseline before or at the programme start as well as a post-intervention period are a key requirement of double-difference methods. Another requirement is the existence of a treatment and a control group. For this reason, both surveys were carried out in nine organic flagship regions (Oberallgäu und Kempten, Miesbacher Oberland, Ilzer Land, Amberg-Sulzbach und Stadt Amberg, Waginger See - Rupertiwinkel, Steinwald-Allianz, Nürnberg - Nürnberger Land - Roth, Neumarkt i.d. Oberpfalz, and Waldsassengau) and in neighbouring, non-treated municipalities in these regions. Since farmers in their capacity as research objects did not considerably influence the proposals each region submitted and as treated and neighbouring non-treated municipalities did not differ significantly in their organic sectors in the pre-treatment period, we treat programme assignment as random, which is of significance to our DiD setting. This setting, together with our interest in farmers' opinions and knowledge of organic agriculture, determined the design of the farm surveys, which were conducted in written form. Farmers in selected municipalities both within and outside the nine organic flagship regions were chosen at random and sent a questionnaire containing questions relating to their farm structure and management, exogenous parameters, socio-economic conditions, the organic flagship region programme (only for farmers located within flagship regions), information provision, collaboration behaviour and social-psychological factors. The DCE indicated the end of the questionnaire. Out of 3,002 questionnaires sent out in May 2016, 423 were completed and returned. In the second round in March/April 2018, the same questionnaire was sent to the same 3,002 farmers, of whom 403 returned a completed questionnaire. Due to data protection regulations, it was not possible to identify farmers who participated in both rounds. Consequently, the data had to be treated as repeated cross-section data.

V.5.2 Factor analysis

For part one of our analysis, we pooled the data from both surveys and used the theory of planned behaviour to explain how underlying psychological constructs influence farmers' decisions to adopt organic farming. While they are not the only factors driving the adoption decision, the TPB constructs of attitude, subjective norm and perceived behavioural control are expected to a great extent to be able to explain farmer behaviour. In order to measure them, several statements were developed for each of the constructs and utilised as indicators. Following related agricultural literature (e.g. Gorton *et al.* (2008), Hansson, Ferguson and Olofsson (2012)), the statements were formulated in a way that made it possible to gauge respondents' implicit beliefs. They were asked to express their opinions and perceptions by indicating on Likert scales the extent to which they agreed with the proposed statements. All statements were carefully formulated, to ensure that every farmer was able to answer them. The questions used in the analysis are given in the Appendix.

In order to summarise the statements into the underlying constructs of interest (attitude, subjective norm, perceived behavioural control), factor analysis, a method of reducing a large number of variables to a small number of factors that adequately describe the variation in the data, was applied. The assumption behind factor analysis is that each observable variable x_{ij}, in our case statements j answered by farmer i, is a linear function of q independent factors p and error terms e_{ij}, which can be written as:

$$x_{ij} = a_{j1}p_{i1} + a_{j2}p_{i2} + \cdots + a_{jq}p_{iq} + e_{ij} \tag{5.5}$$

Both the factor loadings a and the factors (or rather factor scores) were estimated econometrically using principal component analysis (PCA). This method seems better suited in our case than common factor analysis[15], given that we assume that besides common variance, unique and error variance also define the structure of the variables in our dataset. Furthermore, principal component analysis does not suffer from factor indeterminacy concerning the factor scores to be calculated. This fact is crucial to our study, as we use the factor scores in the subsequent statistical analysis. Factor scores are a composite measure of each factor, calculated for each individual. Conceptually, they represent the extent to which each individual scores highly on a group of variables with high loadings on a factor, i.e. on an

[15] There is considerable debate over whether common factor analysis or principal component analysis is the more appropriate method for extracting factors. While common factor analysis is often considered more theoretically sound, it has certain drawbacks concerning the calculation of the estimated communalities used to represent the shared variance and factor score estimation (Hair Jr. *et al.* (2014: 106). Discussions about factor model choice are likely to continue, empirical research, however, shows that in many instances both methods lead to essentially identical results if the number of variables exceeds 30 (Gorsuch (1983) or the communalities are higher than 0.6 for most variables (Hair Jr. *et al.* (2014: 106), which is the case in our study.

underlying construct. The number of such constructs to be retained from our data was based on several considerations, particularly theoretical ones, and the meanings of the factors. In our case, the TPB constructs of attitude, subjective norm and perceived behavioural control were of particular interest.

V.5.3 Discrete choice experiment

The theory of planned behaviour suggests that behavioural intention is the central factor when it comes to human actions, since it is regarded as the direct precursor of any behaviour. In the case of the organic flagship region programme, the behaviour that programme planners intend to influence concerns the choice of farming practices. With our data, this choice and, and given the data structure as repeated cross-sections, possible changes can be observed directly. However, switching from conventional to organic farming is a step which requires careful planning. It can thus be assumed that a period of two years, the interval between both surveys, is rather short for measuring actual changes in farming practices. Indeed, a DiD estimation on actual conversions to organic farming did not show a significant program effect. For this reason, behavioural intention rather than actual choice of farm type was chosen as the outcome variable in the following DiD analysis. It is measured with a DCE, which can be applied for statistically-validated analyses of non-directly-observable, latent preference structures and allows various attributes to be combined in a decision model (Colombo, Hanley and Louviere, 2009). A detailed description of this method can be found in Hensher, Rose and Greene (2005). Just like that of the overall survey, the design of our decision model was preceded by optimisation considerations[16], expert interviews and pre-tests with farmers to ensure the validity and clarity of the questions. The main element of the model was a preference for a farm type (conventional/organic). Respondents were asked to choose hypothetical alternatives from six choice sets. Individual characteristics were assumed to affect the likelihood of an alternative being chosen; however, given the balance of our samples (inside/outside an organic flagship region), we did not include them in our model estimation. The estimation was thus based on the key elements of each DCE. i.e. attributes and their levels.

Following Bateman *et al.* (2002) and Bennet and Blamey (2001), each attribute was chosen on the basis of its relevance to the research questions, the needs of policy makers and its meaningfulness to the respondents. Their selection was further influenced by previous studies on farmers' preferences (e.g. Pröbstl-Haider *et al.* (2016), Jaeck and Lifran (2014)). Ultimately, four attributes were chosen to form a hypothetical farm type (Table V-1). They varied in the choice-sets according to the range of their levels. A more detailed description of the attributes is given in the Appendix.

In the DCE, different combinations of attribute levels were presented to the respondents. They were asked to select their preferred alternative from each choice set. There were three options to choose from in each choice-set: farm type 1, farm type 2 or the alternative 'Neither of the farm types presented'. The choice-sets were preceded by a brief introductory text presenting the hypothetical scenario. In doing this, we tried to avoid hypothetical bias, a type of bias all stated preference techniques are at risk of (Carlsson, Frykblom and Johan Lagerkvist, 2005). Other forms of bias, including attribute non-attendance (Scarpa *et al.*, 2009), anchoring

[16] According to Bliemer and Rose ((2010)) and Huber and Zwerina ((1996)), optimised designs for discrete choice experiments meet the following criteria: (1) orthogonality, i.e. minimum correlation of the attributes, (2) numerical balance of the levels within the choice-sets, (3) minimal overlapping of the expressions in a common choice-set, (4) utility balance, i.e. utility values of the alternatives of a choice-set are as similar as possible and (5) exclusion of dominant alternatives.

(Luisetti, Bateman and Turner, 2011), status quo bias (Boxall, Adamowicz and Moon, 2009) and decoy bias (Bateman, Munro and Poe, 2008) were mitigated by careful pre-testing and by integrating specific design elements.

Table V-1: Attributes and levels in the DCE

Attribute Choice and statement	Level
Profit fluctuation Yearly profit fluctuations compared to current profit fluctuations	-10%, -5%, +5%, +10%
Marketing/distribution of products	0% regional, 50% regional, 100% regional
Farm type	– Conventional – Conventional with participation in agri-environment schemes – Organic (according to EU regulation) – Organic (according to the guidelines of the German organic farming associations Bioland or Naturland) – Organic (according to the guidelines of the German organic farming association Demeter)
Profit Yearly profit compared to current profit	No change, -5%, +5%, +10%

The attribute- and level-dependent farm type choices by the farmers in our sample were analysed on the basis of equation (5.4). Systematic utility V_j^i in this equation is assumed to be a linear function of attributes $\boldsymbol{X}_{kj}^i$ relative to the alternatives and the respondent. Equation (5.4) can thus be rewritten as:

$$U_j^i = \sum_k \beta^i X_{kj}^i + \varepsilon_{kj}^i \tag{5.6}$$

where β^i represents a vector of coefficients[17] capturing the characteristics of farmer i and ε_{kj}^i is an unobserved, independent and identically distributed random term. With the choice attributes from our DCE equation, (5.6) translates into:

$$U_j^i = \beta_0^i + \beta_1^i profit\_fluctuation_j^i + \beta_2^i marketing_j^i + \beta_3^i farm\_type_j^i + \beta_4^i profit_j^i \tag{5.7}$$

[17] β^i is unobserved and, in our model, varies from farmer to farmer in a population with density $f(\beta|\theta)$. The density function is characterised by the parameters θ.

The researcher does not know the β coefficients of an individual farmer. They are estimated based on the unconditional choice probability, i.e. the mixed logit probability, which is represented by the integral of conditional probabilities over all possible values of β:

$$P_j^i = \int \frac{e^{\beta^i x_j^i}}{\sum_k e^{\beta^i x_k^i}} * f(\beta, \theta) d\beta \tag{5.8}$$

In order to obtain the expected value of the random β coefficients, the mean of R draws on its distribution is calculated.

V.5.4 Difference-in-Difference estimation

In the final part of our analysis, we applied a difference-in-difference estimator to assess whether farmers' behavioural intentions of adopting organic farming, measured as the probability of choosing an organic farm type in the DCE, had changed in the organic flagship regions between 2016, defined as the pre-treatment period, and 2018 as a result of the flagship region programme. The DiD methodology suits our research question well, as it addresses the fundamental impact evaluation problem, namely the impossibility of observing the difference between a treated unit's outcome with and without treatment. It involves comparing a treatment group (in our case farmers in organic flagship regions) and a control group, preferably with similar characteristics (farmers in neighbouring regions) before and after an intervention (organic flagship region programme). Estimating the average difference of an outcome variable Y which is related to the intervention (behavioural intention of going organic) separately for the treatment (T) and control group (C) over both periods (time $t = 0$ and $t = 1$) and then taking the difference between the average changes in this variable for both groups gives, under assumptions that we specify hereafter, the programme impact (DiD):

$$DiD = E(Y_1^T - Y_0^T \mid T_1 = 1) - E(Y_1^C - Y_0^C \mid T_1 = 0) \tag{5.9}$$

In this equation, $T_1 = 1$ denotes the presence of the programme in the post-implementation period $t = 1$, $T_1 = 0$ marks untreated areas. Typically, the DiD estimate is calculated within a regression framework. We followed this approach using the subsequent equation:

$$Prob_{org} = \beta_0 + \beta_1 D_{post} + \beta_2 D_{flagship-region} + \beta_3 D_{post} D_{flagship-region} + \gamma X + \varepsilon \tag{5.10}$$

where $Prob_{org}$ is the DCE-based probability that a farmer chooses a given alternative if the farm type is organic, indicating farm type preferences. D_{post} is a dummy variable specifying that the observation comes from 2018, when the organic flagship region programme had already been running for a certain time, $D_{flagship-region}$ is a dummy variable that takes the value of one if the respective farm is located inside a flagship region, X is a vector of control variables with associated vector of parameters γ, and ε is the regression error term. To enhance clarity, we suppressed subscripts that would have referred to each farmer in the regression equation above. Of the parameters to be estimated, β_3 is the one we are particularly interested in, as it represents the DiD estimator.

This estimator is only expected to give valid results if unobserved heterogeneity is time-invariant or follows a similar time trend, if it is uncorrelated with the treatment over time and if the treatment is not related to distributional changes in covariates[18]. Only the latter condition lends itself to meaningful testing. To verify whether the first two assumption hold, we examined the distribution of covariates for farms inside and outside the flagship regions prior to treatment exposure. A comparison shows that the two groups were similar, providing support i) for our assumption that for farmers, the organic flagship region programme is placed randomly and ii) for the notion that unobserved variables are similar as well and follow a parallel trend in both groups in case they are not variables to be influenced by the program.

V.6 Results

V.6.1 Factor analysis

The analysis of Bavarian farmers' views on organic farming as determined by their responses to the Likert scale questions in the survey resulted in a factor solution with three factors, retained on the basis of the TPB. Prior to factor extraction, tests were undertaken to assess the suitability of the data for factor analysis. They showed that the sample size was sufficient[19] and that the set of variables had the conceptual foundation to support factor analysis, with the Kaiser-Meyer-Olkin measure of sampling adequacy (MSA) having a value of 0.814 and the Bartlett Test of Sphericity (p-value 0.000) indicating that the variables were intercorrelated. The MSA was further applied to individual variables. Those with values of less than 0.5 were omitted one at a time, starting with the smallest. It is worth noting that due to the ordinal nature of the Likert statements used, polychoric rather than Pearson correlations were used in the analysis (Holgado–Tello *et al.*, 2010).

The three-factor solution, which is linked to our research objectives, is justified by the interpretation of the Kaiser's criterion and the scree-plot. Table V-2 displays the factors or underlying constructs and the factor loadings acquired via PCA. Since the factors are likely to be correlated with each other, oblique rotation was used to obtain a theoretically more meaningful pattern of underlying constructs (Hair Jr. *et al.*, 2014: 111).

Table V-2: Factor solution of the theory of planned behaviour statements

	Factor 1 *Attitude*	Factor 2 *Subjective norm*	Factor 3 *Perceived behavioural control*
Statement			
I realise new market opportunities very quickly.	0.7148		
I am confident that I will run my farm profitably in the next ten years.	0.7009		
I am always one of the first to adopt new methods of production.	0.6102		

[18] The conditions necessary for the validity of DiD are accurately described in Wing, Simon and Bello-Gomez ((2018)).
[19] In order to perform factor analysis, the sample size should be 100 or larger and the data should contain at least five times as many observations as the number of variables considered in the analysis. Each proposed factor should be assigned at least five variables (Hair Jr. *et al.* (2014).

In ten years, the share of products I sell on regional markets will have changed considerably.	0.4546		
I am actively looking for new information.	0.4767		
Optimising the economic performance of my farm is very important to me.	0.6671		
In ten years, the profitability of my farm will have changed considerably.	0.6785		
I can easily adapt my farm business to new market situations.	0.5048		
In ten years, the amount of goods I produce will have changed considerably.	0.6092		
Enlarging my farm secures the continued existence of my farm.	0.4978		
In ten years, the amount of labour needed on my farm will have changed considerably.	0.5185		
Organic farming is well-accepted in society.		0.6454	
Colleagues doing organic farming convinced me that organic agriculture is beneficial.		0.7255	
Organic products are easier to market than conventional products.		0.6257	
Organic farming is environmentally friendly.		0.8611	
Organic farming promotes animal welfare.		0.8318	
Switching to organic farming is a way to secure the continued existence of my farm.		0.7480	
If I adopt organic farming, I am less vulnerable to changes in prices of the means of production.		0.7373	
I like new challenges like for example adopting organic farming.		0.5369	
Organic farming is less risky in terms of my health and that of my family.		0.8209	
I would adopt organic farming if it were the wish of my farm successor.		0.6318	
Organic production should be increased.		0.7517	
My products should be sold on regional rather than on international markets.		0.5216	
Agricultural policy should strive to improve sales opportunities for organic products.		0.8226	
Public money the agricultural sector receives should always be linked to the provision of ecosystem services.		0.5620	
One argument for going organic is that the CAP greening requirements are easier to fulfil.			0.5669
Direct payments should not be linked to environmental management requirements.			0.6155
Organic production guarantees a higher producer price.			0.5285
I am very often worried about the future of my farm business.			0.4650
It would be good to have more sales opportunities outside Germany and the EU.			0.4509
The organic farming subsidy is a good argument for adopting organic practices.			0.4725
Explained variance	4.3376	7.8640	3.0496
Cronbach's alpha	0.7593	0.8809	0.5785

Notes: Blanks represent loadings of <0.45. Statements that did not load significantly on any factor were excluded from the final analysis. The three factors or components explain 49.2% of the overall variance.

The first factor reflects the attitude construct. It comprises statements about the farmer's sense of himself and his position towards performing a specific behaviour. Factor two, that of subjective norm, is highly loaded by statements relating to the farmer's perception of how others judge his/her behaviour. The perceived behavioural control factor ultimately has a high loading on assertions about the individual farmer's perception of his/her ability to manage and adapt his business. Only this latter component has comparatively low loadings and a Cronbach's alpha value of below 0.7, indicating that the statements or measurement scales might not perfectly capture the perceived behavioural control construct.

The results of the factor analysis were used to obtain factor scores by applying the Regression method to include them along with other explanatory variables in a follow-on organic farming adoption logistic regression. As determinants of behavioural intention, the factors or, rather, the factor scores derived from farmers' beliefs are thought to considerably influence the uptake decision. Table V-3 presents the results of the binomial logistic regression on organic farming adoption, where the dependent variable is assigned a value of 1 for conventional farms and 0 for organic farms. While an interpretation of the coefficients of the psychological constructs is not straightforward due to the complex inter-statement relationships involved, the statistical significance of subjective norm and perceived behavioural control and the almost significance of attitude show that these factors do affect the process of conversion to organic farming. Further significant coefficients were obtained for the variables farm size, grassland share, experience and the dummy variable dairy farm. Their signs indicate that large dairy farms with a high share of grassland are more likely to adopt organic farming, which is largely in line with the findings of previous studies on organic farming in Bavaria (ART, 2013).

Table V-3: Logistic regression for adoption of organic farming

	Estimated coefficient	**z-statistic**
Attitude	0.575	1.24
Subjective norm	2.734***	5.72
Perceived behavioural control	-2.021***	-4.99
Farm size	-0.019*	-1.62
Education	0.678	1.23
Age	-.0060	-1.44
Grassland share	-3.076***	-3.49
Experience	0.066*	1.65
Dairy farm	-1.168***	-1.89
Constant	1.743	0.74
Log likelihood	-58.239	
Pseudo-R^2	0.540	
Observations	203	

Note: *, **, *** represent significance level at 10%, 5% and 1% respectively.

After having identified psychological constructs as critical factors in the adoption of organic farming, the next section presents the results of the DCEs conducted in 2016 and 2018. These give an indication as to whether the TPB components have been addressed by the organic flagship region programme.

V.6.2 Discrete choice experiment

Our core results concerning the DCE are presented in Table V-4 and Table V-5 for the survey years 2016 and 2018. In both years, the whole sample was used to estimate the choice model, i.e. treatment status did not play a role in the first step. The model we chose is a mixed logit model with randomised parameters[20], which allows to account for heterogeneity in farmers' preferences. It was estimated using Stata 15.1 and the *mixlogit* command (Hole, 2018) with 1000 random draws according to the Halton sequence method. In 2016, 2255 choice-sets answered by 397 farmers formed the estimation basis, while two years later the respective figures were 2062 and 357. As expected, results do not vary strongly comparing 2016 with 2018. In both years, the likelihood of a farm type being chosen increases if the profit compared to the farmer's current situation rises. Another factor positively influencing selection probability is regional marketing. Farmers in our sample thus show a clear preference towards selling their products on regional rather than national or international markets. They also seem generally to prefer conventional farm types to organic ones, with all organic farm types showing a negative sign ('conventional' being the reference category). As for the profit fluctuation attribute, the picture is less clear. A negative coefficient in 2016 indicates that farmers appreciate stability, while in 2018, the profit fluctuation coefficient is insignificant.

Overall, the farmers' stated preferences are not surprising, and their attitude especially towards organic farm types seems plausible given that there are more conventional farms than organic ones in the sample. An indication of certain conditions that are necessary for switching from a conventional to an organic farm type is extracted from a willingness-to-accept (WTA) assessment. Assuming profit to be a fixed parameter, we calculated the profit premium that farmers would wish to have in order to adopt organic farming, making use of the convenient results that WTA for any attribute k equals $-\frac{E(\beta^k)}{\beta^{profit}}$. In 2018 for example, farmers would have been willing to adopt organic farming according to EU standards if the profit needed to remunerate the factors of production had been around 11% higher than had they used conventional practices. Adopting organic farming in line with the stricter Demeter regulations would have necessitated a profit premium of 26% compared to conventional farming. These results are in line with the findings on factor costs for conventional and organic farms calculated by the Bavarian State Research Centre for Agriculture (LfL, 2020).

WTA estimations relate preferences to a monetary value and thus give a variable that is easy to interpret. So do the calculations we conducted to understand how the probability of an alternative being chosen changes if the farm type is an organic one. Their estimates were used as outcome variables in the DiD regression in the last part of our analysis. Table V-6 presents these estimates with reference to the 'Conventional' farm type for 2016 and 2018. Choice probabilities seem relatively stable over the years. As with WTA estimates, the results suggest a general preference for conventional farm types, with all organic farm types showing a negative sign. The higher the organic farming standards, the less likely are farmers to select corresponding farm types. In 2018 for example, the probability of an alternative being selected decreased by 3.6% if the farm type was 'Organic (EU regulation)', while it decreased by around 20% if it was 'Organic (Demeter)'.

[20] Significant outcomes of a Hausman test (Hausman and McFadden (1984) showed that the Independence of Irrelevant Alternatives (IIA) assumption, a key concept behind choice models, is violated. In such cases, random coefficient models are a way around the IIA assumption.

Table V-4: Results of the mixed logit model, 2016

Attributes	**Mean**		**Standard deviation**	
	Coefficient	Standard error	Coefficient	Standard error
Profit	0.190***	0.021	0.181***	0.027
Profit fluctuation	-0.025***	0.008	0.030	0.022
Marketing 50% regional	1.496***	0.180	-0.507	0.433
Marketing 100% regional	2.063***	0.217	1.763***	0.296
Farm type ‘Conventional with AES’	0.018	0.233	1.007	0.792
Farm type ‘Organic (EU regulation)’	-1.746***	0.354	2.230***	0.515
Farm type ‘Organic (Bioland or Naturland)’	-1.211***	0.302	3.389***	0.432
Farm type ‘Organic (Demeter)’	-3.498***	0.476	3.984***	0.511
None	1.554***	0.241	2.788***	0.256
Log likelihood	-1772.173			
AIC	3580.346			
BIC	3703.097			
Number of observations	6,765			

Note: *, **, *** represent significance level at 10%, 5% and 1% respectively.

Table V-5: Results of the mixed logit model, 2018

Attributes	**Mean**		**Standard deviation**	
	Coefficient	Standard error	Coefficient	Standard error
Profit	0.136***	0.019	0.126***	0.030
Profit fluctuation	0.014	0.019	-0.106***	0.039
Marketing 50% regional	0.902***	0.198	1.018***	0.334
Marketing 100% regional	1.131***	0.237	2.096***	0.383
Farm type ‘Conventional with AES’	-0.424	0.307	2.774***	0.542
Farm type ‘Organic (EU regulation)’	-1.467***	0.378	2.109***	0.535
Farm type ‘Organic (Bioland or Naturland)’	-1.626***	0.307	2.851***	0.422
Farm type ‘Organic (Demeter)’	-3.542***	0.522	3.042***	0.504
None	1.594***	0.285	3.207***	0.310
Log likelihood	-1556.360			
AIC	3148.719			
BIC	3269.860			
Number of observations	6,186			

Note: *, **, *** represent significance level at 10%, 5% and 1% respectively.

Table V-6: Predicted probabilities of choosing an alternative depending on farm type (reference farm type 'Conventional')

Attribute level	Predicted probability, 2016	Predicted probability, 2018
Farm type 'Conventional with AES'	0.0032	0.0074
Farm type 'Organic (EU regulation)'	-0.0508	-0.0364
Farm type 'Organic (Bioland or Naturland)'	-0.0276	-0.0494
Farm type 'Organic (Demeter)'	-0.1768	-0.1956

V.6.3 Difference-in-Difference estimation

The farm-level probability estimates for choosing an organic farm type that we obtained with the DCE represented the dependent variable in the OLS DiD regression used to assess the impact of the organic flagship region programme. As described in the Methodology section, equation (5.10) is estimated to measure the difference in the probabilities of an alternative being selected for organic farm types during the 2018 post-intervention period between farms inside a flagship region and comparative farms in neighbouring regions relative to the probabilities observed in the 2016 pre-intervention period. The coefficient of interest, the DiD estimate, is the coefficient on $D_{post}D_{flagship-region}$. It is presented together with all the other regression coefficients in Table V-7. Specification (1) was used to perform the basic difference-in-difference estimation without any control variables. In specifications (2) to (6), control variables were added one at a time. These comprised some of the most frequently used variables in the literature on the uptake of sustainable agricultural practices (Foguesatto, Borges and Machado, 2020). Table V-7 shows the results with the probability of choosing an organic farm type according to EU regulations being the dependent variable. Similar results were obtained for the categories 'Bioland or Naturland' and 'Demeter' (see Appendix).

In all specifications, the DiD coefficient is statistically insignificant, indicating that the organic flagship region programme did not have an effect on the probability of farmers choosing an organic farm type. The programme thus did not, as intended, encourage farmers to adopt organic farming practices. As Table V-7 shows, only the post-intervention coefficient is significant in the base specification. Its value of 0.017 implies that there is a general positive trend towards choosing an organic farm type according to EU regulations. Compared to 2016, the likelihood of choosing this farm type increased by 1.7 percentage points in 2018. Unlike the time coefficient, the treatment parameter is insignificant in all but the last specification, where a value of -0.002 implies that the probability of selecting the EU organic farm type was 0.2 percentage points less for farmers in a flagship region than for farmers outside, prior to the intervention.

Table V-7: Difference-in-Difference estimation for the outcome variable *probability organic farm type EU regulation*

	(1)	(2)	(3)	(4)	(5)	(6)
Post-	0.017	0.017	0.017	0.017	0.017	0.017
intervention (PI)	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Organic flagship	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
region (OFR)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)*
PI*OFR	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)

Farm size		-0.000	-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age			-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Education				-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)
Gender					0.000	0.001
					(0.001)	(0.001)
Dairy farm						-0.001
						(0.001)*
Constant	-0.052	-0.051	-0.050	-0.049	-0.049	-0.048
	(0.001)***	(0.001)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
N	711	682	590	525	520	516
R^2	0.463	0.462	0.465	0.469	0.467	0.480

Note: *, **, *** represent significance level at 10%, 5% and 1% respectively.

These results are highly robust to the inclusion of a number of control variables. In fact, the time, treatment and DiD coefficients remain considerably stable. Of all covariates, only the dairy farm dummy variable is (marginally) significant. Its negative sign indicates that dairy farms are less likely to adopt organic farming according to EU standards, which seems plausible given that conventional dairy farms clearly dominate and that around 75% of all Bavarian organic farms follow the guidelines of organic farming associations like Bioland or Naturland in addition to following the EU regulation on organic production (StMELF, 2018).

In the DiD results presented so far, we treated all nine organic flagship regions considered for the analysis and all nine neighbouring regions as one entity, respectively. However, the nine regions and their controls are located in different parts of Bavaria, characterised by different natural and socio-economic conditions. Treating them as one ignores heterogeneity, which might affect DiD estimates. In an extreme case, a positive programme effect in one region could be offset by a negative effect in another region. For this reason, we present the mean values of the DCE probability estimates for each region and year and the corresponding DiD estimate in Table V-8. Due to the limited number of observations for each flagship and control region, no tests of statistical significance could be performed. Still, region-specific calculations seem to confirm the results presented earlier. While compared to a conventional farm type an alternative was less often selected if the farm type as 'Organic (EU regulation)' in 2016 and 2018 inside and outside the flagship regions, this likelihood developed positively from 2016 to 2018.

Table V-8: Region-specific DiD estimates based on predicted probabilities of choosing an alternative with the farm type 'Organic (EU regulation)' (reference farm type 'Conventional')

	2016		**2018**		
	treated	control	treated	control	DiD (percentage points)
Oberallgäu und Kempten / control region	-5.24% (64)	-5.16% (37)	-3.82% (49)	-3.21% (36)	-0.53
Miesbacher Oberland / control region	-5.31% (24)	-5.42% (21)	-3.66% (18)	-3.57% (12)	-0.20

Ilzer Land / control region	-5.96% (10)	-5.03% (6)	-3.40% (9)	-3.61% (10)	1.14
Amberg-Sulzbach und Stadt Amberg / control region	-4.95% (21)	-5.41% (11)	-3.53% (26)	-3.43% (12)	-0.55
Waginger See – Rupertiwinkel / control region	-5.15% (15)	-4.98% (8)	-3.96% (15)	-3.54% (4)	-0.25
Steinwald-Allianz / control region	-5.51% (10)	-7.23% (1)	-3.77% (8)	-4.02% (2)	-1.47
Nürnberg - Nürnberger Land – Roth / control region	-5.22% (39)	-5.04% (34)	-3.82% (43)	-3.54% (30)	-0.10
Neumarkt i.d. Oberpfalz / control region	-5.31% (16)	-5.21% (2)	-3.23% (20)	-3.93% (3)	0.80
Waldsassengau / control region	-5.20% (5)	-5.49% (4)	-3.12% (4)	-3.85% (4)	0.44

Note: Number of observations in parentheses

However, DiD estimates show that there is practically no programme impact over time and between treated and control regions. Only in one region with a reasonable number of observations (Ilzer Land) was a change higher than one percentage point observed.

V.7 Discussion and conclusions

The aim of this study was to investigate the effects of an innovative policy measure promoting the adoption of organic farming. Unlike other organic farming programmes, the measure takes a holistic approach and appoints selected municipal associations as organic flagship regions. Within each region, a project manager organises various events in the areas of organic production, processing, value chain enhancement, marketing, education, administration and awareness raising, in order to reach consumers, producers, processers and public officials alike. As the whole programme is funded by public money, there is also a public interest in its impact.

Using two surveys from 2016 and 2018, each comprising more than 400 farms located inside organic flagship regions and in non-treated neighbouring regions, we investigated the impact against the background of the stated programme goals. To this end, we combined a DiD estimator with the results of a DCE assessing the likelihood of farmers to select organic farm types. Choosing probabilities based on stated preferences as DiD outcome variables rather than the observed conventional/organic variable makes it possible to account for the difficulties of switching to organic production within two years. Moreover, we thereby follow the TPB, which postulates that the intention to perform a specific behaviour is a predictor of actual behaviour. It also states that intention is the outcome of three psychological constructs, namely attitude, social norm and perceived behavioural control. Assuming that these behaviour-governing constructs equally influence Bavarian farmers' decisions to adopt organic farming, we further used a modelling technique combining factor and non-linear regression analysis to explore their importance in going organic. Such an exercise seems crucial given that the organic flagship region programme – with its limited budget and by the way it is designed – can only influence attitudes, opinions and farm management, but not (or only slightly) other factors of adoption, such as farmer characteristics, farm structure and exogenous parameters.

The results of our investigation show that the adoption of organic farming in Bavaria is indeed influenced by psychological constructs, which is in accordance with both theory and findings relating to the adoption of conservation practices reported in previous studies (Cullen *et al.*, 2020; Läpple and Kelley, 2013; Mzoughi, 2011; Sulemana and James, 2014). Programmes promoting organic farming thus need to be designed in a manner that addresses these factors. The results we obtained from the DiD estimation, however, indicate that the organic flagship region programme with its mix of supply-side and demand-side measures did not properly target the psychological constructs underlying farmers' decisions on whether to adopt organic farming. It did though, as preliminary results of a consumer study suggest (Maier, 2020), have the intended effect on the demand-side. One possible avenue in which policymakers might improve the programme could therefore be to approach farmers more directly and to adjust the ratio of events and measures offered inside the flagship regions for farmers and consumers. The measures offered could focus on nudges, which have been shown to influence environmental attitudes in experimental settings (Barnes *et al.*, 2013; Kuhfuss *et al.*, 2016). Given that social norm and perceived behavioural control play an especially important role in the decision to adopt organic farming, nudges related to these constructs can be a powerful tool. Recent studies by Chabé-Ferret *et al.* (2019) and Banerjee (2017) have shown the potential of nudges related to social norm in an agricultural context. Perceived behavioural control, on the other hand, can possibly be influenced by altering constraining beliefs through the provision of specifically targeted information and technical advice (Cullen *et al.*, 2018; Genius, Pantzios and Tzouvelekas, 2006). Of course, ethical issues also have to be considered in this context, as there is a fine line between public authorities acting rationally and being paternalistic (Thaler and Sunstein, 2008).

Looking at the factors affecting the adoption of organic farming, influencing psychological constructs is not the only way of increasing uptake rates, as is also recognised by the organic flagship region programme officials. Programme managers therefore also try to strengthen the organic sector by bringing key actors together to create new market opportunities for organic products inside the flagship regions. It is beyond doubt that such a venture takes longer than two years, the time span between our first and follow-up surveys. While psychological constructs can change within two years, a lack of sales opportunities and/or other farm-specific or external factors might still limit the probability of farmers to switch to organic production. However, considering the farm-structure in Bavaria and the growth of the organic sector in recent years, we believe that non-psychological factors were not an obstacle. However, it is necessary to bear in mind that the TPB and its constructs deal with intentional behaviour only, thus they do not take into account any non-intentional or routine behaviour. This may be relevant in the Bavarian case, where the agricultural practices of many farmers, especially dairy farmers, are already close to the regulations of organic farming, without the farmers being aware of it or planning to adopt organic farming.

In interpreting our results, two further aspects need to be considered. First, we concentrated on a limited number of factors affecting the adoption of organic farming and the likelihood of choosing an organic farm type, respectively, in an attempt to keep the survey questionnaire as short as possible. Second, the approach of choosing controls for a DiD estimation in neighbouring regions might suffer to some extent from spillover effects. Nonetheless, given the EU's focus on sustainable agriculture, our findings are of value to policy makers when it comes to designing agri-environmental policy, as it is essential both to understand the factors that direct farmers' decision-making and to evaluate the effects of new programmes in order to successfully develop agricultural policy. In the case of the organic flagship region programme, follow-up surveys and studies can give further insights into the effects of factors related to the market environment that can influence the adoption of organic farming in the long-run. It would also be worthwhile investigating which of the broad range of measures and events offered inside the flagship regions have the greatest effect on farmers' behaviour.

V.8 Appendix

Table V-9: Descriptive statistics for the pooled sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
Land (hectares)	775	30.7	42.4	0.49	680
Arable land (hectares)	778	12.3	24.4	0	320
Grassland (hectares)	778	17.9	25.2	0	360
Family labour (man-work units)	766	2.1	1.0	0	7
Conventional/organic (1 = conventional, 0 = organic)	763	0.78	0.42	0	1
Farm profit class (1 = no profit, 2 = 1-20k €, 3 = 20k-40k €, 4 = 40k-60k €, 5 = 60k-80k €, 6 = 80k-100k €, 7 = >100k €)	757	2.5	1.4	1	7
Age (years)	679	51.0	10.1	18	80
Experience (years)	758	21.5	11.1	0	68
Gender (1 = male, 0 = female)	775	0.91	0.29	0	1
Participation in agri-environment measures (1 = yes, 0 = no)	622	0,64	0.48	0	1
Dairy farm (1 = yes, 0 = no)	772	0.44	0.50	0	1
Farm successor 'yes'	777	0.28	0.45	0	1
Farm successor 'no'	777	0.18	0.38	0	1
Farm successor 'unsure'	777	0.27	0.44	0	1
Farm successor 'not relevant'	777	0.27	0.45	0	1
Off-farm employment (1 = yes, 0 = no)	788	0.61	0.49	0	1
Agr. education 'vocational training'	695	0.47	0.50	0	1
Agr. education 'master's certificate'	695	0.32	0.47	0	1
Agr. education 'university degree'	695	0.15	0.36	0	1
Agr. education 'other'	695	0.07	0.25	0	1
Flagship region (1 = inside, 0 = outside)	720	0.56	0.50	0	1

Note: The year 2016 was marked by low milk prices, which in combination with the large number of dairy farms and the comparatively small farm sizes in our sample explains low farm profits.

Table V-10: Descriptive statistics, 2016 survey

	Inside flagship region		Outside flagship region	
Variable	**Obs.**	**Mean**	**Obs.**	**Mean**
Land (hectares)	194	28.3	168	30.0
Arable land (hectares)	194	10.5	170	12.3
Grassland (hectares)	195	16.5	170	17.3
Family labour (man-work units)	192	2.1	169	2.1
Conventional/organic (1 = conventional, 0 = organic)	191	0.75	161	0.80
Farm profit class (1 = no profit, 2 = 1-20k €, 3 = 20k-40k €, 4 = 40k-60k €, 5 = 60k-80k €, 6 = 80k-100k €, 7 = >100k €)	192	2.5	165	2.4
Age (years)	170	50.2	157	51.1
Experience (years)	191	20.8	167	21.7
Gender (1 = male, 0 = female)	199	0,90	168	0.92
Dairy farm (1 = yes, 0 = no)	188	0.51	169	0.53
Farm successor 'yes'	197	0.24	169	0.26
Farm successor 'no'	197	0.15	169	0.17
Farm successor 'unsure'	197	0.33	169	0.25*
Farm successor 'not relevant'	197	0.28	169	0.33
Off-farm employment (1 = yes, 0 = no)	199	0.58	173	0.61
Agr. education 'vocational training'	183	0.48	162	0.46
Agr. education 'master's certificate'	183	0.26	162	0.35*
Agr. education 'university degree'	183	0.16	162	0.09**
Agr. education 'other'	183	0.10	162	0.09

Significantly different means between observations inside and outside the flagship regions in a t-test for equality of means at the 10 per cent (*), 5 per cent (**) and 1 per cent (***) level are indicated. The German 'master's certificate' in agriculture is comparable to a university degree in agricultural sciences.

Table V-11: Descriptive statistics, 2018 survey

	Inside flagship region		Outside flagship region	
Variable	**Obs.**	**Mean**	**Obs.**	**Mean**
Land (hectares)	190	31.6	138	34.3
Arable land (hectares)	190	13.5	138	14.8
Grassland (hectares)	190	18.0	138	18.9
Family labour (man-work units)	182	2.0	140	2.1
Conventional/organic (1 = conventional, 0 = organic)	190	0.78	140	0.75
Farm profit class (1 = no profit, 2 = 1-20k €, 3 = 20k-40k €, 4 = 40k-60k €, 5 = 60k-80k €, 6 = 80k-100k €, 7 = >100k €)	187	2.6	135	2.5
Age (years)	166	51.6	125	50.6
Experience (years)	183	22.9	134	20.2
Gender (1 = male, 0 = female)	190	0.92	137	0.88
Dairy farm (1 = yes, 0 = no)	192	0.35	137	0.37
Farm successor ‘yes’	186	0.31	142	0.28
Farm successor ‘no’	186	0.19	142	0.20
Farm successor ‘unsure’	186	0.24	142	0.25
Farm successor ‘not relevant’	186	0.26	142	0.27
Off-farm employment (1 = yes, 0 = no)	190	0.62	142	0.66
Agr. education ‘vocational training’	161	0.40	117	0.50
Agr. education ‘master’s certificate’	161	0.34	117	0.34
Agr. education ‘university degree’	161	0.24	117	0.14
Agr. education ‘other’	161	0.02	117	0.03

Table V-12: Difference-in-Difference estimation for the outcome variable *probability organic farm type Demeter* (no covariates added)

Variable	Coefficient	Std. Err.	t-statistic
Post-intervention (PI)	-0.011***	0.003	-3.16
Organic flagship region (OFR)	-0.004	0.003	-1.23
PI*OFR	-0.000	0.005	-0.06
Constant	-0.178***	0.002	-75.98
R^2	0.037		
Prob > F	0.000		
N	711		

Table V-13: Difference-in-Difference estimation for the outcome variable *probability organic farm type Bioland or Naturland* (no covariates added)

Variable	Coefficient	Std. Err.	t-statistic
Post-intervention (PI)	-0.020***	0.002	-15.05
Organic flagship region (OFR)	-0.002	0.001	-1.15
PI*OFR	0.001	0.002	0.57
Constant	-0.028***	0.001	-25.50
R^2	0.305		
Prob > F	0.000		
N	711		

Table V-14: Difference-in-Difference estimation for the outcome variable *probability organic farm type Conventional with AES* (no covariates added)

Variable	Coefficient	Std. Err.	t-statistic
Post-intervention (PI)	0.004***	0.000	9.88
Organic flagship region (OFR)	-0.000	0.000	-0.10
PI*OFR	0.000	0.001	0.82

Constant	0.003***	0.000	12.12
R^2	0.263		
Prob > F	0.000		
N	711		

VI Revisiting the impact of decoupled subsidies on farm performance: a counterfactual analysis using microdata

VI.1 Abstract

The 2003 reform of the Common Agricultural Policy, which decoupled farm subsidies from production, was expected to increase farmers' market orientation and to positively impact farm productivity. This theoretical effect of decoupling on farm performance has been verified in a few ex-post analyses. However, these studies lack important aspects of farm-level policy impact evaluations. First, they do not use a well-defined counterfactual scenario, second they do not account for farm heterogeneity when measuring performance and third they do not assess farm performance in a comprehensive manner. We address these shortcomings by combining quasi-experimental empirical methods with a latent-class production function. Using UK and French farm-level data, we show that farms indeed operate with distinct production technologies and that decoupling had positive and significant effects on productivity. Our results further show that under decoupling, farmers tend to diversify their businesses while keeping environmental pressure at a similar level as with coupled support.

VI.2 Introduction

Developed countries have a long history of providing farmers with income support (Rude, 2001). It is typically justified by the importance of the agricultural sector in guaranteeing food security and producing safe, healthy and affordable food as well as by the lack of markets for public goods delivered by agriculture (European Commission, 2020b). The way in which this support is granted has been changing over the years and is nowadays largely defined by the World Trade Organization (WTO) Agreement on Agriculture, which classifies domestic agricultural support into different boxes. For developed countries, practically all subsidies need to fall into the "green box", i.e. they must have no, or at most minimal, trade-distorting effects or effects on production (WTO, 1995a). In Europe, this was not the case before the 2003 Fischler Reform of the Common Agricultural Policy (CAP). This reform, a response to WTO requirements, public concerns as regards agricultural development and calls for more flexibility for producers, 'decoupled' agricultural support payments from agricultural production. Previously, subsidies for agriculture in the European Union (EU) were paid depending on the amount and type of production. A large body of literature has documented the functioning and the impacts of such 'coupled' or 'partially coupled' policies on production and choices of farmers (see, for example, Antle and Just, 1991; Dewbre, Antón and Thompton, 2001; Ridier and Jacquet, 2002). It has often criticised coupled subsidies for causing efficiency losses (Chambers, 1995; Serra *et al.*, 2006; Weber and Key, 2012), another reason for policy-makers to advocate lump-sum transfers, i.e. decoupled programmes.

With their growing popularity and use, the number of studies investigating the nature and size of their impact increased rapidly[21]. Researchers showed amongst others that decoupling has significant positive effects on farm productivity and farm specialisation (Kazukauskas, Newman and Sauer, 2014), is likely to let farmers choose off-farm employment (Hennessy and Rehman, 2008), facilitates exiting the sector (Kazukauskas *et al.*, 2013), does not alter farmers'

[21] A detailed discussion of this literature is well beyond the scope of this paper. The interested reader can find a valuable overview in Wagener and Zenker (2020).

land market decisions (O'Neill and Hanrahan, 2012) and may reduce the application of crop protection inputs (Serra *et al.*, 2005). Thus, generally, decoupled farm programme payments seem to properly address major weaknesses related to coupled payments (see for further examples Adams *et al.*, 2001; Goodwin and Mishra, 2005, 2006; Sckokai and Moro, 2006; Urban, Jensen and Brockmeier, 2016). However, their analyses studying the effect of a decoupling policy change suffer from potential bias originating from the lack of a 'what would have happened without' scenario and from not accounting for farm heterogeneity. Furthermore, no consensus has been found yet as regards the claim that decoupled payments do not distort production incentives, neither theoretically (Hennessy, 1998; Chambers and Voica, 2017) nor empirically (Femenia, Gohin and Carpentier, 2010; Weber and Key, 2012). The complexity of this question, which has been recognized by authors such as Moro and Sckokai (2013), also comes from the fact that direct and methodologically sound impact evaluations of decoupled support policies on production decisions are rather scarce and that influencing factors as well as mechanisms behind the impact are numerous and difficult to capture (Antón, 2006). Different farm types facing diverse site conditions are likely to respond in a different way in different categories (economic, environmental, social) to varying levels of support. Consequently, theoretical models that underlie empirical cases and that are used to assess impacts quickly get complex. Furthermore, the nature of decoupling programmes complicates impact evaluation studies in the sense that all farms of a country/region are typically affected equally and at the same time by decoupling. A counterfactual approach is in many cases not feasible. This might – despite big decoupling reforms in the EU and the USA (Federal Agricultural Improvement Reform Act) having happened in the early 2000s and late 1990s respectively – explain the dominance of ex-ante simulation models focusing on aggregate production and the lack of ex-post evaluations and farm-level assessments, the level at which the primary impact of any agricultural policy measure can be expected to occur.

We aim to contribute to the empirics of decoupling by applying counterfactual treatment effect econometric methods (Propensity Score Matching, Difference-in-Difference) to farm-level data, taking into account farm and farm response heterogeneity and assessing the development of a comprehensive set of farm performance indicators as a response to decoupling. Treatment effect tools (Imbens and Wooldridge, 2009) have been used widely in various research areas, our treatment/control group approach to the impact of decoupling, though, is to the best of our knowledge new. Our empirical strategy takes advantage of the fact that the 2003 CAP reform awarded individual member states some flexibility as concerns the way (degree, timing) in which decoupling and the single payment scheme (SPS) were implemented. Unlike previous studies, we do not purely focus on economic performance measures, but include structural and environmental indicators as outcome variables. Against the backdrop of unsolved sustainability issues of the agricultural sector and given that decoupled payments can have some environmental effect by influencing input usage (Bhaskar and Beghin, 2009), including performance indicators from different categories (especially environmental ones) in impact assessment studies is crucial (Moro and Sckokai, 2013).

The quasi-experimental estimation approach mentioned above is applied to the CAP decoupling reform announced in 2003 and established within the EU in the years from 2005 onwards. The impact of this reform on farm production choices and outcomes is assessed on panel data of English[22] and French Farm Accountancy Data Network (FADN) arable farms

[22] In fact, the sample also contained some Welsh farms. However, no matches were found for them in the PSM procedure, which is why in the rest of the text we will speak of English farms only.

observed 2003-2008. Selected English farms are considered as treatment group as the UK introduced a full decoupled payment policy in 2005 already, whereas France started decoupling in 2006 only and kept maximum possible coupling until 2010 (e.g. for cereals and oilseeds 25% of total support (European Commission, 2009)). Control group farms are thus selected from the French sample. By matching English to French farms based on observed farm characteristics and by controlling for general trends, we ensure comparability and the isolation of the decoupling effect. The period under analysis contains two pre-decoupling years, of which we consider the first one (2003) as a pre-treatment year and the second one (2004) as an adjustment year. Decoupling impacts can be expected to be detected in the adjustment year already since farmers take adaptation measures from the point of announcement of future policy changes. In order to contain most, if not all, effects of the 2003 Fischler Reform, we follow the performance of treatment and control group farms until 2008, capturing the partial change from coupled to decoupled subsidies in France in 2006.

In the next section, we describe how a switch from coupled to decoupled agricultural support affects farmer behaviour and farm performance from a theoretical perspective[23]. We then turn to the methodological framework and dataset used, before presenting estimation results and concluding in a final section.

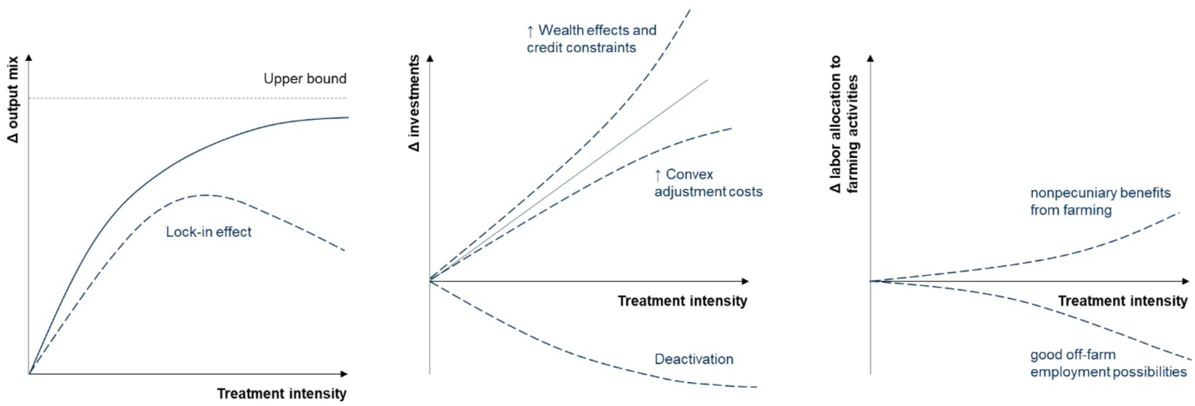
VI.3 Theory and empirics of decoupling

The decoupling of direct payments from production is intended to make production choices more market-oriented as farmers adjust their maximisation goals. While coupled payments motivate farmers to maximise subsidy revenue in consideration of producer prices, decoupled payments trigger demand-oriented profit maximising behaviour. In some instances, they will force farmers to reassess their involvement in agricultural production, accelerating structural change. Profitable farms will be able to expand their production, less profitable ones will exit the sector with farmers allocating their time to more beneficial activities. However, a number of reasons exist why this hypothesis might fall short and why farm-level responses to decoupling might be many. First, payments are basically still coupled, to agricultural land, an incentive to continue farming thus remains (Happe *et al.*, 2008). Second, farmers may not be profit maximisers and choose to continue farming even if other employment possibilities offer higher revenues (Swinbank *et al.*, 2004). Third, other employment possibilities might not exist. Fourth, certain farm assets such as the farmer's own human capital can be regarded as quasi-fixed and typically have a low liquidation value (ibid.). Farmers might consequently face high adjustment costs and prefer to keep on farming. Fifth, agricultural markets might be distorted (e.g. existence of credit constraints, weak financial systems) and these distortions might prevent effects of a decoupling policy to happen. All of these aspects indicate that decoupling might not have a big impact on the decision to farm, but rather on the product mix of a farm and the way of farming. A stronger market-orientation will result in a change in inputs and outputs, which can be measured by total factor productivity. Productivity can further be affected by technological advancements as a result of investments in new machinery or buildings. Such investments can be made possible, especially to credit-constrained farmers, by decoupled payments as land values and available collateral increase (Goodwin, Mishra and Ortalo-Magné, 2003; Roberts, Kirwan and Hopkins, 2003). More productive investment decisions can also arise from risk preferences of farmers that have changed with decoupled subsidies. Decoupled payments are a secure flow of revenue to farmers. They increase a

[23] We will give a brief overview only, as authors such as Guyomard, Le Mouël and Gohin (2004) or O'Donoghue and Whitaker (2010) have examined the topic in detail.

farmer's wealth, which in turn can reduce his or her risk aversion standard (Hennessy, 1998). All in all, the economics of decoupling is complex, not only because the parameters and categories of the response of the farms are numerous, but also because of possible interactions between them and as a result of farm heterogeneity. Still, we hypothesise based on the aforementioned theoretical considerations, which are summarised in Figure VI-1 following Esposti (2017), that decoupling will affect the input and output mix, economies of scale and technical change, and consequently productivity, as well as the intensity of farming and via this intensity the environmental performance of farms.

Figure VI-1: Production, investment and labour allocation response to decoupling under increasing treatment intensity



Source: Own depiction

This hypothesis is tested in an ex post evaluation rather than in a large-scale simulation model. By modelling farm-level response in a production function framework, we focus on the change of the farm input and output mix as the area where a primary impact of decoupling is to be expected. Focusing on inputs and outputs follows the logic behind the response to decoupling in a static environment without uncertainty. In such an environment, decoupling changes the marginal benefit of each farming activity.

As Esposti (2017) we consider a sample of N farms and an exemplary farm i with $i = 1, \dots, N$. The i-th farm shall be represented by an aggregated general multi-input multi-output technology with $F_i \subset \mathbb{R}^m$ being the feasible production set. F_i is assumed to be non-empty, convex and negative monotonic. Combinations of netputs $\boldsymbol{y_i} = (y_{i1}, \dots, y_{im})'$, as $(m \text{ x } 1)$ vector, are possible if $\boldsymbol{y_i} \in F_i$. The netput vector consists of $\boldsymbol{y_{iO}} \geq 0$ as the $(q \text{ x } 1)$ vector of outputs and $\boldsymbol{y_{iI}} \leq 0$ as the $(r \text{ x } 1)$ vector of inputs $(q + r = m)$. Since farms operate in a competitive environment, they all face a market price vector $\boldsymbol{p} = (p_1, \dots, p_m)'$ linked to the netput vector. Furthermore, we assume that inputs can be divided into variable inputs $\boldsymbol{y_{iIv}}$ and quasi-fixed inputs $\boldsymbol{y_{iIf}}$. Variable inputs are those factors farmers can match easily to new production decisions, whereas quasi-fixed inputs are more difficult to adjust to a new production mix (e.g. barns, perennial crops).

A farmer's production choices, assuming profit-maximising behaviour, are a response to price changes between two periods t and s. Under coupled support, profit functions are additionally influenced by the amount of (yield- or crop-dependent) coupled support per unit ($\boldsymbol{S}_{it}$). The sum of market price and unit coupled support $\boldsymbol{p}_t + \boldsymbol{S}_{it}$, which is the marginal value, then decides about production decisions. An indirect profit function can thus be written as:

$$\boldsymbol{\pi}_{it}(\boldsymbol{p}_t, \boldsymbol{S}_{it}) = max_{y_i}\{(\boldsymbol{p_t} + \boldsymbol{S}_{it})'\boldsymbol{y}_{it}: \boldsymbol{y}_{it} \in F\}, \forall i \in N, \forall t \in T \quad (6.1)$$

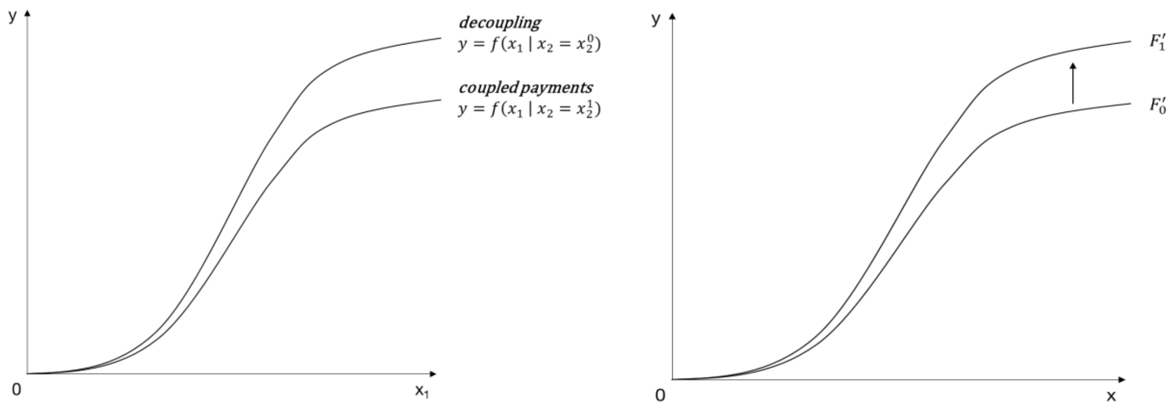
According to Chavas and Cox (1995), the Weak Axiom of Profit Maximisation associated with this function can be formulated as:

$$(\boldsymbol{p}_t, \boldsymbol{S}_{it})'\boldsymbol{y}_{it} \geq \left(\boldsymbol{p}_{t+h}, \boldsymbol{S}_{i(t+h)}\right)'\boldsymbol{y}_{i(t+h)}, \forall i \in N, \forall t, t+h \in T \quad (6.2)$$

$t + h$ indicates a post-reform, t a pre-reform observation. As full decoupling implies $\boldsymbol{S}_{i(t+h)} = 0$, it follows that $(\boldsymbol{p}_t + \boldsymbol{S}_{it}) \neq \left(\boldsymbol{p}_{t+h} + \boldsymbol{S}_{i(t+h)}\right) = \boldsymbol{p}_{t+h}$. We then expect $|\Delta \boldsymbol{y}_i| = \left|\boldsymbol{y}_{it} - \boldsymbol{y}_{i(t+h)}\right| > 0$, i.e. the current year's netputs will be greater than those calculated from the previous year's input and output combination when current prices are used for t and $t+h$ in the profit function.

Although profit maximisation does not necessarily go hand in hand with productivity maximisation/development (Mugera, Langemeier and Ojede, 2016), one of the main farm performance indicators analysed in this paper, the few studies that empirically investigate this association suggest a close relationship between profitability and productivity (Yeager and Langemeier, 2011; Mugera, Langemeier and Ojede, 2016). Consequently, similar implications of decoupling can be expected. From a theoretical perspective and taking into account the aforementioned considerations, decoupling might favour farm-level TFP growth. The decoupling response can be reflected on both the input and output side. Decoupled payments are likely to allocate inputs directly across those production processes that can be immediately activated or quit. It is conceivable that decoupling induces a change in the crop mix with crops being grown that, given market prices, are more favourable for site conditions or that generate higher farm output in terms of revenue. Via this mechanism, decoupling can affect farm technical efficiency as a component of productivity. The underlying assumption is that of perfectly competitive markets where prices serve to allocate resources to their highest valued alternatives, which does not necessarily happen when output prices are influenced by coupled payments. An example is given in Figure VI-2. The two-input production function in the left panel shows for coupling and decoupling how output y (e.g. crop yield) varies with input x_1 (e.g. land) when input x_2 (e.g. pesticides) is altered, where $x_2^1 > x_2^0$. In the scenario where payments are coupled, a farmer might decide to grow crops that are not ideally suited with respect to local natural conditions. Thus, the amount of plant protection products that are applied exceeds the amount needed for a crop that would be cultivated in the absence of coupling. Coupled payments would offset higher costs for pesticides. A reduction of pesticides in the decoupling scenario would result in higher or equally high yields (i.e. productivity growth) as the crop rotation would be optimised with respect to actual demand and site conditions. Another potential effect of decoupling as regards productivity growth is linked to investments in new machinery or buildings enabled by the ease of credit constraints and/or modified risk preferences. Such investments typically involve advances in technology that may be represented by an upward shift in the production frontier. This is depicted in the right panel of Figure VI-2 by the movement of the production frontier from $0F_0'$ in period 0 to $0F_1'$ in period 1. In period 1, all farms can technically produce more output for each level of input, relative to what was possible in period 0.

Figure VI-2: Theoretical link between decoupling and productivity change



Source: Own depiction

The hypothesised relation between farm performance and decoupling as elaborated in this section is assessed empirically by primarily making use of applied production analysis.

VI.4 Methodology

As decoupling aims at encouraging farmers to link their production decisions to market requirements, it can be expected to affect farm performance in various ways (see previous section). We therefore derive several performance measures from a model combining a technology function with a latent class structure.

VI.4.1 Technology model

In order to approximate the production process of a farm, a production function representing the maximum possible output level given production inputs and existing production conditions while still remaining in the production possibility set is estimated. Formally, such a function can be written as $Y = F(\boldsymbol{X}, \boldsymbol{T})$, where Y is the farm's output, $\boldsymbol{X}$ is a vector of production related inputs and $\boldsymbol{T}$ is a vector of shift variables reflecting external production conditions. Production functions are one of several options of modelling production processes. Further approaches include cost, profit or distance functions. The decision about which model and which functional form to choose should be guided by theoretical considerations and behavioural assumptions, however, data availability does set certain limits. From a purely theoretical perspective, (dual) functional representations that include economic variables (e.g. prices, costs, revenues) are desirable. They allow both technical and allocative behaviour of farm managers to be mapped. The data at hand, though, lacked multi-output price-related information[24]. For this reason and in order to avoid endogeneity problems of distance function representations (Paul and Nehring, 2005), a single-output based

[24] The FADN database, from which our data was sourced, does contain information on output prices. However, the FADN Data Committee asked us to limit our data request to 100 variables, which meant that we had to drop certain variables. Given that PSM is quite data-hungry, we needed to make sure to get enough information on farm and farmer characteristics first. In the end, we had to forgo price information and consequently deflate variables measured in monetary terms with Eurostat specific nationwide price indices. This approach is widely applied in the agricultural economics literature (see for example Wimmer and Sauer (2020), Latruffe *et al.* (2017)).

production function with a translog functional form (second-order approximation) is chosen. Translog functional forms have the advantage of being second-order flexible (Diewert, 1974) and easily transformable to their estimable form by imposing linear homogeneity. They can be formulated for production functions with the following equation:

$$lny_{it} = \alpha_0 + \sum_{k=1}^{K} \beta_k \, lnx_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \, lnx_{kit} lnx_{lit} + \sum_{k=1}^{K} \beta_{kt} t lnx_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \varepsilon_{it} \tag{6.3}$$

for farm i in period t with y being total crop output, x referring to inputs, t indicating a time trend as the only component of the external shift vector $\boldsymbol{T}$ and ε representing an independent and identically distributed (iid) random error term. By using such a flexible functional form, observable technology differences among production units are accommodated to a certain extent as derived measures (such as output elasticities). Unobservable technology heterogeneity is partly captured by the error term ε. However, not all factors underlying technology heterogeneity between farms are directly accounted for by estimating (3) alone. Consequently, parameter estimates might be biased (Griliches, 1957) and derived policy recommendations might lack specificity. Acknowledging and evaluating heterogeneity among production systems and exploring differences in the development of performance indicators requires a more explicit approach. Indeed, several methods are available to account for technological heterogeneity in farm level production (Bravo-Ureta, 1986; Tauer, 1998; Newman and Matthews, 2006; Kumbhakar, Tsionas and Sipiläinen, 2009). They range from simply creating a sample that satisfies certain homogeneity criteria (e.g. arable vs. dairy farms, conventional vs. organic farms) to applying random coefficient estimators to model each farm as a unique technology (Alvarez *et al.*, 2008; Greene, 2005). We use a latent class model (LCM) that separates the data into multiple technological classes based on estimated probabilities of class memberships considering multiple pre-specified criteria. The estimation of the production technology as outlined in (3) is thus combined with a probabilistic latent class structure (see for example Greene, 2002, 2005; Orea and Kumbhakar, 2004; Sauer and Paul, 2013) that allows multiple characteristics of farms operating in a specific production system to be considered simultaneously.

VI.4.2 Class identification model

In our LCM, each farm is assigned to a specific class based on indicators capturing aforementioned farm characteristics. Using this model, both the estimated technological as well as the estimated probability relationships are considered (Balcombe *et al.*, 2007; Sauer and Paul, 2013). Such a latent class modelling approach overcomes possible estimation bias due to omitted variables with respect to the class identification vector. It further effectively addresses possible endogeneity problems by estimating the technology model and the class identification model simultaneously. Formally, the latent class model can be denoted as the technology model for class c:

$$lny_{it} = \alpha_0 + \sum_{k=1}^{K} \beta_k \, lnx_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \, lnx_{kit} lnx_{lit} + \sum_{k=1}^{K} \beta_{kt} t lnx_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \varepsilon_{it} \mid c \tag{6.4}$$

where the technology class includes farm i implying a different technology function for each class. Assuming a normal distribution for the error term, the likelihood function (LF) for farm i at time t for class c, $LF_{ict} = f(y_{it} \mid x_{it}, \beta_c)$, takes on an OLS form. The unconditional likelihood function for farm i in class c is obtained as the product of the likelihood functions in each period t:

$$LF_{ic} = \prod_{t=1}^{T} LF_{ict} \tag{6.5}$$

The likelihood function for each farm is the weighted average of its likelihood function for each class c (with the prior probabilities of class c membership as the weights):

$$LF_i = \sum_{c=1}^{C} P_{ic} LF_{ic} \tag{6.6}$$

These prior probabilities P_{ic} are parameterised using a multinomial logit model (MNL) estimated with indicators (separating variables q_i). The MNL parameters θ_c are estimated for each technology class (relative to one class serving as numeraire) with the following equation:

$$P_{ic} = \frac{\exp(\theta_c q_i)}{\sum_{c=1}^{C} \exp(\theta_c q_i)} = \frac{\exp(\theta_{0c} + \sum_{n=1}^{N} \theta_{nc} q_{nit})}{\sum_{i=1}^{N} \exp(\theta_{0c} + \sum_{n=1}^{N} \theta_{nc} q_{nit})} \tag{6.7}$$

where the q_{nit} denote the N q variables/indicators for farm i in time period t. In our case, these indicators are multi-dimensional indices that are obtained using principal component analysis (PCA) for each farm related dimension (e.g. production structure). The factor loadings obtained were used to calculate the index score for each observation via an optimally-weighted linear combination of the factor scores for the individual components. The indices characterise farms according to factors such as production structure, environmental impact and sustainability, innovation behaviour, commercialisation focus, openness towards cooperation, input intensity and capital endowment, diversity of production, individual characteristics such as age or education, as well as locational conditions. In total, eight (France) and nine (England) different farm indices are defined, estimated and standardised for each observation of the respective sample. They are chosen for their potential to contribute to robustly identify and distinguish individual farms in the combined model of technology and class.

VI.4.3 Full model specification

The combined model with the class-specific coefficients to be estimated can be specified in its panel form as follows:

$$
\begin{aligned}
lny_{it} = \alpha_{0|c} + \sum_{k=1}^{K} \beta_{k|c}\, lnx_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl|c}\, lnx_{kit} lnx_{lit} + \sum_{k=1}^{K} \beta_{kt|c} t lnx_{kit} + \beta_{t|c} t \\
+ \frac{1}{2}\beta_{tt|c} t^2 + \varepsilon_{it|c}
\end{aligned}
\tag{6.8}
$$

Alternatively, each observation is considered as a separate entity and the model is estimated as a cross-sectional specification. In both cases, the probabilities P_{ic} are functions of the parameters of the MNL model and the log-likelihoods LF_{ic} are functions of the technology parameters for class c farms. The log-likelihood function for the complete model can then be written as:

$$
\log LF = \sum_{i=1}^{N} \log LF_i = \sum_{i=1}^{N} \log \sum_{c=1}^{C} P_{ic} \prod_{t=1}^{T} LF_{ict} \tag{6.9}
$$

This log-likelihood function can be maximised with respect to the parameter set $\delta_c = (\beta_c, \theta_c)$ using maximum likelihood estimation.

For both countries, the estimations are performed on panel data covering a time horizon of 24 years for France (1990-2013) and 23 years for England (1995-2017). Such long periods are vital for verifying assumptions underlying the Difference-in-Difference (DID) method applied at a later stage. They allow the development of the class-defining indices and economic performance measures to be mapped over time. The latter are derived from the technology-related component of the combined model and encompass productivity, technical change, first-order elasticities and returns to scale. Productivity, more precisely relative levels of productivity, is estimated for the identified farm classes based on the predicted output levels for a given number of inputs at the sample means (Alvarez and Corral, 2010). Technical change as a measure of productivity dynamics is calculated using the output elasticity ϵ with respect to t for the translog functional form:

$$
\epsilon_{y,t|c} = \frac{\partial \ln y}{\partial t} \mid c = \beta_{t|c} + \beta_{tt|c} t + \sum_{k=1}^{K} \beta_{kt|c} lnx_{kit} \tag{6.10}
$$

The third analytical performance measure are first-order elasticities with respect to crop output for each class c, given by:

$$\epsilon_{y,k|c} = \frac{\partial \ln y}{\partial \ln x_k} | \, c = \beta_{k|c} + \beta_{kk|c} lnx_{kit} + \sum_{l=k+1}^{K} \beta_{kl|c} lnx_{lit} + \beta_{kt|c} t \tag{6.11}$$

The estimated output elasticity with respect to input k would be expected to be positive, with its magnitude representing the (proportional) marginal productivity of x_k. Lastly, returns to scale are estimated as a linear combination of the input elasticities with respect to crop output. These are simply defined as the sum of the input elasticities as follows:

$$s\epsilon_{y,\boldsymbol{X}|c} = \sum_{k=1}^{K} (\beta_{k|c} + \beta_{kk|c} lnx_{kit} + \sum_{l=k+1}^{K} \beta_{kl|c} lnx_{lit} + \beta_{kt|c} t) \tag{6.12}$$

Returns to scale provide the basis for inferences about the “cost of scale” with respect to a type of production at farm and sectoral level.

The estimation of the aforementioned farm performance measures and indicators is the first step of our analysis. In step number two, we use the quasi-experimental approach described in the next section to measure potential differences in the development of the indicators for French and English farms after decoupling. A figure showing the interplay of the various methods applied can be found in the Appendix.

VI.4.4 Propensity Score Matching and Difference-in-Difference

As outlined earlier, studying the effect of the 2003 CAP decoupling reform is hampered by the fact that the reform affected all member states equally. It is the temporal and content-related variation in its implementation that still allows us to measure outcomes in a quasi-experimental setting. Certainly, experiments with randomly selected treatment and control groups are the gold standard for impact evaluations. However, in the present case, and generally often in the social sciences, experimental approaches are infeasible, which leads to reliance on quasi-experimental methods (Bravo-Ureta, Greene and Solís, 2012).

Assessing the impact of any intervention requires making an inference about the outcomes that would have been observed for treated units had they not been affected by the programme. In our study, the programme refers to decoupling and consequently English farms are considered treated units[25]. Farm outcomes (here farm performance) conditional on being treated are denoted by O_1 and outcomes conditional on not being treated by O_0. The impact θ of being affected by the programme can then be written as:

[25] In our approach where we compare English and French farms, we make use of the core idea behind matching, which is “to compare treated and control groups that are as similar as possible” (Stuart (2010: 3). More specifically, through matching a “set of subjects all of whom have the same propensity score, the distribution of observed baseline covariates will be the same between the treated and untreated subjects” (Austin (2011: 402). This refers to the notion of Rosenbaum and Rubin (1983) concerning the propensity score as a balancing score. In our setting, treatment equals country affiliation, which means that the propensity score can be interpreted as the probability of being a farm located in England given farm structural variables. This approach is in line with the propensity score theorem, which says that “you need to control for covariates that affect the probability of treatment” (Angrist and Pischke (2009: 81).

$$\theta = O_1 - O_0 \tag{6.13}$$

It is obvious that for all English farms only O_1 can be observed, the size of O_0 remains hypothetical. This fact is the core of the evaluation problem. It is possible, though, to define a group of farms outside of England that share similar characteristics, but are not (or to a different extent) affected by decoupling. Let $D = 1$ mark the group of English farms being affected by decoupling in 2005 and potentially anticipating it in 2004 already. For these farms O_1 is observed. $D = 0$ on the other hand shall denote untreated (French) farms, for which O_0 is observed. Apparently, a simple comparison of outcomes for French and English farms would lead to biased results as farm structures differ in both countries. Farms are thus likely to react differently to decoupling, a fact that previous cross-country studies did not adequately consider. It can be taken into account through matching by in a first step denoting X a vector for observed individual farm and farmer characteristics. The basic idea of matching is then to find in a large group of non-treated units those individuals that are similar to the treated units in all relevant pre-treatment characteristics X. These characteristics are used as conditioning variables. As conditioning on all relevant covariates is not possible in the case of a high dimensional vector X, balancing scores $b(X)$ are proposed by Rosenbaum and Rubin (1983b). They are functions of the relevant observed covariates X such that the conditional distribution of X given $b(X)$ is independent of assignment into treatment. One popular balancing score is the propensity score, which typically measures the probability of participating in a programme given observed characteristics X. In PSM, this probability is used for matching participants to non-participants. We apply it to guarantee that (treated) English and (non-treated) French farms are comparable when evaluating decoupling.

The evaluation parameter of interest in the study at hand is the average treatment effect on the treated (ATT):

$$ATT = E(\theta \mid X, D = 1) = E(O_1 - O_0 \mid X, D = 1) = E(O_1 \mid X, D = 1) - E(O_0 \mid X, D = 1) \tag{6.14}$$

which estimates the average impact of decoupling among those affected by it. In experimental studies, the naturally unobservable treatment-on-the-treated parameter is estimated by comparing the mean outcome in the treated state to that of an untreated randomised control group. The non-experimental approach taken here econometrically (through PSM) creates a control group whose outcomes can then be compared to those of the treatment group[26]. It thus helps to estimate a missing counterfactual mean. In order to identify the counterfactual situation with matching methods, two basic assumptions must be satisfied: the conditional independence assumption and the common support condition. The conditional independence or unconfoundedness assumption "implies that systematic differences in outcomes between treated and comparison individuals with the same values for covariates are attributable to treatment" (Caliendo and Kopeinig, 2008: 35). This in turn implies that selection is based on observable characteristics only and that all variables influencing treatment and outcomes simultaneously can be observed by the researcher. As this is a strong assumption, it must be backed up by the data quality at hand. The data used in this study covers a broad set of farm characteristics and can thus be considered suitable for

[26] A detailed description of the theoretical background of PSM can be found in Smith and Todd (2005).

matching[27]. The second assumption, the common support condition, "rules out the phenomenon of perfect predictability of D given X" (ibid.) and ensures that individuals with the same X values have a positive probability of being both part of the treatment and control group (Heckman, Lalonde and Smith, 1999).

As just stated, PSM matches individuals based on observed characteristics only. It cannot account for unobserved factors, which is why even after matching certain differences might remain between the treatment and the control group. If these unobserved factors (e.g. attitude of the farmer) influence potential outcomes, treatment effects for a single cross-section can be over or underestimated. The availability of panel data and the application of a DID estimator can help to overcome this problem. Let $t \in \{0,1\}$ denote time in two periods. Period zero refers to a pre-treatment period, period one indicates a post-treatment period. The difference-in-difference estimator measures the impact of a programme as the difference between treated and non-treated units taking into account before-after difference outcomes. Assuming that a potential effect of an unobservable variable is constant over time (but may vary across treatment status), taking differences enables this effect to disappear. We make use of this assumption and combine PSM with DID to account for both observable and unobservable sources of bias. Following Heckman, Lalonde and Smith (1999) and Smith and Todd (2005), the ATT can then be defined as follows:

$$ATT_{PSM\ DID} = \frac{1}{N_1} \sum_{i \in I_1 \cap SP} \left[\left(O_{it_1}^1 - O_{it_0}^0 \right) - \sum_{j \in I_0 \cap SP} W(i,j) \left(O_{it_1}^0 - O_{it_0}^0 \right) \right] \tag{6.15}$$

where I_{1t_1}, I_{1t_0}, I_{0t_1}, I_{0t_0} denote the treatment I_1 and comparison group I_0 datasets in each time period, SP the region of common support, $i \in I_1$ are treated farms, $j \in I_0$ are untreated farms and N_1 the number of farms in the respective group and region of common support. $W(i,j)$ are weights that depend on the choice of the matching algorithm.

The PSM DID model can be estimated within a regression framework as follows:

$$O_{it} W_i = \beta_0 + \beta_1 t_i + \beta_2 D_i + \beta_3 t_i D_i + \varepsilon_i \tag{6.16}$$

β_0, β_1, β_2, β_3 are parameters to be estimated, O, W, t, i and D are variables as previously defined and ε_i is an error term. The ATT as the parameter of interest is represented by $\widehat{\beta_3}$, the coefficient on the interaction between post-treatment variable and time. In our study, it is obtained in a two-step procedure. First, PSM is performed to create a counterfactual scenario. In a second step the DID regression is run on the matched sample.

VI.5 Data and estimation

For the latent class estimation, we used unbalanced panel data from the EU's Farm Accountancy Data Network (FADN) on English, Welsh and French farms for the years 1995-

[27] Some debate exists as regards variable choice and model specification. Caliendo and Kopeinig (2008) provide valuable practical guidance concerning this aspect.

2017 and 1990-2013 respectively. The PSM-DID analyses were performed with the same dataset, however, for these estimations the sample was balanced for the years 2003-2008. Prior to all estimations, the sample was restricted to specialised arable farms, which are expected to be affected stronger by decoupling than other farm types, by only selecting farms that obtained at least two-thirds of total revenue from crop sales. Outliers were detected using the BACON algorithm (Billor, Hadi and Velleman, 2000) and dismissed from the sample. The resulting panel dataset consisted of 9,986 farms and a total of 64,981 observations, with an average of 6.5 observations per farm.

In order to realistically model the farm's production processes, we distinguished one output (y), crop production, and five inputs (four for France), land (x_1), labour (x_2), capital (x_3), materials (x_4) and pesticides (x_5)[28]. The output variable is defined as the revenue generated from plant production. Input 'land' refers to the amount of land used in production, 'labour' covers the number of annual work units (AWU), 'capital' is proxied by depreciation costs and 'materials' captures expenditures for crop-specific inputs (e.g. fertiliser, pesticides, seed) and other inputs such as fuel or electricity. All variables measured in monetary terms are deflated by suitable price indices available on Eurostat's online database. By doing so, we obtain implicit quantities, however, a certain price bias might remain as deflating does not possibly account for all changes in prices.

Descriptive statistics of the variables used for the latent class estimation are given in Table VI-7 and Table VI-8 in the Appendix.

VI.6 Results

In the first part of this section, we provide evidence on the economic performance in terms of total factor productivity and technical change of English and French farms in different technology classes as well as on the development of the multi-dimensional indices used to define technology classes. The second part presents results of the counterfactual analysis based on Propensity Score Matching and Difference-in-Difference.

The LCM in equation (6.8) was estimated by maximum likelihood using Limdep 11. Due to degrees-of-freedom problems related to the parameter intensive LCM specification (Sauer and Paul, 2013), it was estimated as a constrained form approximation to the underlying translog functional form. Results of the estimation can be seen in Table VI-1 and Table VI-2. The decision about the number of classes was based on information criteria, namely the AIC and SBIC[29]. For France, four technology groups were identified, for England three. While two of the classes estimated for France show comparably negative technical change rates (-2.39%, -2.43%) and three a similarly high level of productivity, the English classes vary considerably in both technical progress (-2.39%, 1.11%, 3.29%) and productivity Figure VI-12 and Figure VI-13 in the Appendix). The results obtained for both performance measures and countries are largely in line with findings reported in earlier works. Between the main period of interest, 2003-2008, TFP changed annually on average by 0.87% for English farms and by 0.49% for French farms. Similar growth patterns were identified by Rizov, Pokrivcak and Ciaian (2013) (0.18% for UK farms, 0.24% for French farms, all farm types, 1990-2008), Bokusheva and Čechura (2017) (1.7% for English farms, 1.1% for French farms, all farm types,

[28] In the English sample, the variable 'pesticides' was given separately, which is why we include it as an important extra input and deduct it from the 'materials' variable that also includes expenses for pesticides.

[29] The SBIC can be written as: $SBIC = -2 * log\ LF(J) + m * log\ (n)$, the AIC as: $AIC = -2 * log\ LF(J) = 2 * m$, where $LF(J)$ represents the value of the likelihood function for J groups, m gives the number of model parameters and n is the number of observations. The model with the lowest test statistic value is the preferred one.

2004-2013) and Dakpo *et al.* (2019) (TFP increase of 24.5% for French crop farms between 2002 and 2015). Contrary to our results, Latruffe and Desjeux (2016) reported negative productivity change rates for French field crop farms for various periods (1990-1994, 1995-1999, 2000-2005). Their technological change estimates, however, show a similar positive trend like the ones presented here (Figure VI-4) and by Dakpo *et al.* (2019).

Table VI-1: Estimation of the reduced latent class model for French arable farms

	Class 1		Class 2		Class 3		Class 4	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	9.257***	0.097	6.524***	0.145	5.873***	0.204	11.723***	0.248
Land	0.244***	0.029	0.670***	0.061	0.012	0.032	0.837***	0.069
Capital	-0.077***	0.013	-0.038***	0.011	0.229***	0.032	-0.428***	0.022
Labour	0.177***	0.013	0.389***	0.022	0.037	0.025	-0.306***	0.057
Materials	-0.331***	0.012	-0.154***	0.020	0.238***	0.031	-0.365***	0.029
Land*Land	-0.0291***	0.003	-0.062***	0.007	0.033***	0.005	-0.016***	0.005
Capital*Capital	0.012***	0.000	0.007***	0.001	0.006***	0.001	0.011***	0.001
Labour*Labour	0.060***	0.006	-0.260***	0.018	0.052***	0.009	0.119***	0.010
Materials*Materials	0.048***	0.001	0.046***	0.001	0.002	0.002	0.035***	0.001
Time	0.064***	0.004	0.003	0.005	0.070***	0.007	-0.150***	0.010
Time*Time	0.003***	0.000	0.003***	0.000	-0.000*	0.000	0.002***	0.000
Time*Land	0.011***	0.001	-0.001	0.001	-0.009***	0.001	-0.014***	0.002
Time*Capital	-0.001***	0.000	0.000*	0.000	-0.010***	0.001	0.012***	0.001
Time*Labour	0.006***	0.001	-0.003**	0.001	0.011***	0.001	0.018***	0.002
Time*Materials	-0.016***	0.001	-0.008***	0.001	0.006***	0.001	0.002	0.001
Sigma	0.243***	0.001	0.268***	0.002	0.328***	0.002	0.233***	0.004
Probabilities								
Constant	3.106***	0.125	0.768***	0.164	-2.346***	0.191	---	
Index 1 - Structure	2.583***	0.108	2.305***	0.111	3.286***	0.141	---	
Index 2 - Environmental sustainability	0.155***	0.027	0.011	0.031	-7.308***	0.550	---	
Index 3 - Innovation-cooperation-commerc.	0.411***	0.047	-1.606***	0.078	1.128***	0.067	---	
Index 4 - Technology	0.154	0.151	-2.849***	0.207	6.771***	0.151	---	
Index 5 - Diversity	-0.103***	0.038	-0.415***	0.043	1.064***	0.049	---	
Index 6 - Individual	-1.485***	0.065	-1.706***	0.071	-1.741***	0.098	---	
Index 7 - Location	-0.287***	0.029	0.192***	0.033	-0.711***	0.054	---	
Index 8 - Household	-0.239***	0.036	0.089**	0.039	0.039	0.039	---	
Index 9 - Financial	2.259***	0.102	1.241***	0.111	1.694***	0.110	---	
Log-Likelihood Function	-9010.976							
AIC	18210.0							
Observations	50785							

Note: *significant at 10%, **significant at 5%, ***significant at 1%

Table VI-2: Estimation of the reduced latent class model for English arable farms

	Class 1		Class 2		Class 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	8.305***	0.161	7.425***	0.346	8.431***	0.225
Land	0.963***	0.041	0.487***	0.126	1.081***	0.072
Capital	-0.080***	0.012	-0.201***	0.042	-0.151***	0.017
Labour	0.236***	0.018	0.389***	0.037	0.239***	0.016
Pesticides	-0.293***	0.021	0.028	0.048	-0.324***	0.035
Materials	-0.043***	0.005	-0.094***	0.027	-0.037***	0.007
Land*Land	-0.062***	0.003	-0.068***	0.017	-0.083***	0.007
Capital*Capital	0.011***	0.001	0.023***	0.003	0.014***	0.001
Labour*Labour	0.040***	0.001	0.047***	0.006	0.061***	0.003
Pesticides*Pesticides	0.024***	0.001	0.026***	0.003	0.032***	0.002
Materials*Materials	0.005***	0.000	0.012***	0.003	0.005***	0.001
Time	0.024***	0.008	0.166***	0.023	-0.210***	0.016
Time*Time	-0.002***	0.000	0.000	0.001	0.007***	0.000
Time*Land	0.009***	0.001	0.024***	0.005	0.018***	0.003
Time*Capital	-0.003***	0.001	-0.007***	0.002	-0.002	0.001

Time*Labour	-0.004***	0.001	-0.004*	0.003	-0.009***	0.002
Time*Pesticides	0.003***	0.001	-0.018***	0.002	0.005***	0.001
Time*Materials	-0.000	0.000	0.000	0.001	-0.001	0.000
Sigma	0.241***	0.002	0.545***	0.003	0.324***	0.001
Probabilities						
Constant	1.959***	0.194	-3.511***	0.283	---	
Index 1 - Structure	0.136	0.101	0.898***	0.180	---	
Index 2 - Environmental sustainability	-1.198***	0.100	-1.676***	0.136	---	
Index 3 - Innovation-cooperation-commerc.	0.003***	0.000	0.002**	0.001	---	
Index 4 - Technology	0.831***	0.162	4.569***	0.178	---	
Index 5 - Diversity	0.520***	0.074	-0.919***	0.127	---	
Index 6 - Individual	0.408***	0.147	1.402***	0.272	---	
Index 7 - Location	2.125***	0.163	1.047***	0.259	---	
Index 8 - Household	-0.105	0.087	0.834***	0.084	---	
Index 9 - Financial	0.011	0.054	-0.062	0.252	---	
Log-Likelihood Function	-2684.178					
AIC	5522.4					
Observations	14196					

Note: *significant at 10%, **significant at 5%, ***significant at 1%

For both countries, the individual farms are distributed unevenly across the three technology classes with one class capturing around one half of all sample farms. Such an uneven distribution is not uncommon in farm-level latent class models and is linked to the degree of variation in farming conditions. Differing conditions are to a great extent mirrored by farms operating with different production systems as identified by the LCM. Relevant descriptive statistics already indicate that structural differences do exist between the groups that have been found. Farms also vary in terms of first-order elasticities, which with the exception of the ‘materials’ variable for England all show the expected sign and returns to scale. For France, Class 1 and Class 2 farms exhibit increasing returns to scale of about 1.024 and 1.148, respectively (Table VI-10 in the Appendix). Those farms in Class 3 and Class 4, however, show slightly decreasing returns to scale. English farms operate at slightly increasing returns to scale in all classes (Table VI-11 in the Appendix).

As outlined earlier, multi-dimensional indices capturing a broad variety of farm characteristics were used as elements of the class identification vector. In total, eight indices were defined for France and nine for England (see Table VI-1 and Table VI-2), where data availability allowed to additionally account for farm financial structure. The development of the individual indices over time is of interest as decoupling is likely not to affect farm economic performance purely. By altering production decisions, it can influence social and environmental dimensions. In order to measure decoupling effects holistically, we therefore present the pathways of the indices ‘innovation’, ‘technology’, ‘environmental sustainability’ and of the Herfindahl index[30] measuring diversity in the next section. For interpretability purposes[31], we recalculated the respective indices based on a normalisation technique proposed by the OECD (2008b). It scales the indices on a range from 0 to 1, with higher values indicating a better performance.

In contrast to evaluation studies where matching is used to account for bias originating from self-selection into treatment, we apply the method in order to ensure that the farms to be compared in the cross-country DID-setting share similar characteristics before decoupling

[30] The Herfindahl index is a measure of concentration and can be used to determine whether specific farm outputs dominate across all farm outputs. It is calculated per farm and year as follows: $H = \sum_{i=1}^{n}(\frac{y_i}{Y})^2$, where y_i refers to farm outputs.

[31] In the PCA procedure, scaling issues between different components (e.g. share of family labour versus fertiliser useor acreage) were addressed by calculating z-score based deviations, which complicates interpretation.

was implemented differently in France and the UK. Taking a look at descriptive statistics in the pre-treatment year 2003 suffices to understand the necessity of this approach. English arable farms are on average larger than French ones (259 ha to 147 ha) and operate with a different capital and material structure (e.g. depreciation costs per ha: 162 US $ to 271 US $[32]). Such differences are considered to be the result of factors like past farm structure (Neuenfeldt *et al.*, 2019), regional and natural characteristics (Chau and Gorter, 2005; Neuenfeldt *et al.*, 2019), productivity growth (Harrington and Reinsel, 1995), farm household and path dependency (Zimmermann and Heckelei, 2012) or agricultural policies (Ben Arfa *et al.*, 2015). After matching, significant differences of covariates expected to affect the DID outcome variable for French and English arable farms are removed by balancing variables on the propensity score. In our case, the propensity score is the conditional probability for a farm being located either in France or England. It is estimated using a logit model[33]. Table VI-3 reports the parameter estimates for the model. It is statistically significant at the 1 per cent level or higher as measured by the likelihood ratio test. Around 97 per cent of all observations are correctly classified (98.60 per cent for France, 89.27 per cent for England).

Table VI-3: Parameter estimates of logit model explaining country affiliation

Variables	Country (1=England, 0=France)		
	Coefficient	Std. Err.	z-statistic
Farm characteristics			
Utilised agricultural area	0.012***	0.002	4.99
Labour	-0.337	0.239	-1.41
Total assets per ha	0.001***	0.000	8.01
Total output per ha	0.001***	0.000	2.96
Depreciation costs per ha	-0.023***	0.004	-6.46
Expenditures for fertilisers and pesticides per ha	-0.019***	0.003	-5.74
Energy expenditures per ha	0.050***	0.006	8.69
Expenditures for other materials per ha	-0.001	0.003	-0.44
Net investment per ha	-0.002**	0.001	-2.22
Expenditures for contract work and machinery hire per ha	0.005**	0.002	2.17
Environmental subsidies per ha	0.008	0.007	1.05
Intercept	-2.518***	0.815	-3.09
Regression statistics			
Number of observations	1055		
LR Chi-squared	847.08		
Prob > Chi-squared	0.000		
Pseudo R-squared	0.815		
% correct predictions	96.78		

Asterisks denote statistical significance at 1 per cent (***), 5 per cent (**) or 10 per cent (*) level.

The model's parameter estimates provide the basis for calculating the propensity score for each farm, which is then used for balancing observations. Different PSM estimators are available for this step. Caliendo and Kopeinig (2008: 45) state that when it comes to choosing an estimator, "there is no 'winner' for all situations and that the choice of the estimator crucially depends on the situation at hand". As the performance of different matching algorithms largely depends on the data structure and involves a trade-off between bias and efficiency, we tested different matching estimators (nearest neighbour matching with and without replacement, radius matching, kernel matching). They all give similar results (Table

[32] In order to equalise the purchasing power of the different currencies of England and France and to eliminate the differences in price levels between the two countries, purchasing power parities (PPPs) (OECD (2021) were used for estimating the PSM model. Variables measured in monetary terms are thus given in US$ for both countries.
[33] More information on the rationale of estimating the underlying model with a dummy for country affiliation is given in the Appendix.

VI-4), however, in terms of overall matching quality, nearest neighbour matching without replacement, random ordering and a calliper of (0.1), performed best. As comparing the incomparable must be avoided, we checked the overlap and the region of common support between farms in both countries prior to matching, Results confirmed structural differences already detected descriptively. Based on the logit model's explanatory variables, the likelihood of a farm being located in England differs considerably for almost all observations (Figure VI-11 in the Appendix). However, certain farms in both countries share similar propensity scores. To identify these farms with the matching algorithm, we used the calliper and trimmed the sample by ignoring all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group. Consequently, a large share of all observations is dropped. The remaining sample size is further shaped by the choice of 1:1 nearest neighbour matching. Given that many individuals of our sample fall outside the region of common support, treatment effect estimations must be interpreted with caution. According to Bryson (2002), concerns about whether the estimated effect on the remaining individuals can be viewed as representative may arise in such a situation.

Table VI-4: Performance of different matching algorithms in terms of standardised bias and likelihood-ratio test

	Standardised bias (median after matching)	P-value of the likelihood-ratio test of joint insignificance of all regressors after matching
NN matching (1) without replacement (cal. 0.10)	3.6	0.864
NN matching (1) with replacement (cal. 0.10)	7.8	0.004
NN matching (1) without replacement (cal. 0.15)	4.5	0.769
NN matching (5) with replacement (cal. 0.10)	6.1	0.211
Radius matching (cal. 0.10)	5.4	0.273
Kernel matching (bwidth. 0.10)	6.5	0.343

In total, 33 English farms were matched to 33 French farms. Since conditioning was not performed on all covariates but on the propensity score, it must be assessed whether the matching procedure satisfactorily balances the distribution of the underlying variables in both groups. Table VI-5 reports unadjusted (columns 1 and 2) and adjusted (columns 3 and 4) means of covariates among English and French farms for the pre-treatment year 2003. After matching, the differences between farms in both countries are much smaller and in only a few cases significantly different from zero at the 5 per cent level. The standardised bias (SB) indicator, suggested by Rosenbaum and Rubin (1985) and used in many evaluation studies (Guo *et al.*, 2018; Mayne, Lee and Auchincloss, 2015; Sianesi, 2004a), also points towards a successful matching procedure with a value of 3.6% after matching. A SB value below 3% or 5% after matching is generally seen as sufficient in empirical studies (Caliendo and Kopeinig, 2008: 48).

Table VI-5: Means and standardised bias of covariates before and after matching for the pre-treatment year 2003

Variables	(1) Potential comparison farms ENG	(2) Potential comparison farms FR	(3) Selected comparison farms ENG	(4) Selected comparison farms FR	(5) Bias before	(6) Bias after

Utilised agricultural area	258.7	146.7***	156.5	171.3	49.8	-6.6
Labour	3.2	1.9***	1.9	2.1	37.5	-4.1
Total assets per ha	7429.1	2830.6***	3437.9	3313.1	115.8	3.1
Total output per ha	1334.1	1393.3	1268.3	1181.5	-2.8	4.0
Depreciation costs per ha	162.0	271.4***	173.3	153.2	-38.5	7.1
Expenditures for fertilisers and pesticides per ha	215.1	294.9***	228.4	234.3	-49.4	-3.6
Energy expenditures per ha	126.1	59.2***	93.0	93.3	94.2	-0.4
Expenditures for other materials per ha	16.5	17.3	13.6	12.4	-0.6	1.1
Net investment per ha	234.0	550.2***	340.3	329.8	-63.0	2.1
Expenditures for contract work and machinery hire per ha	73.8	66.0	85.1	82.7	8.7	2.7
Environmental subsidies per ha	16.8	7.8***	9.3	2.9	22.6	16.2
Number of observations	850	205	33	33		

Significantly different means between observations from the potential (selected) group in England and from the potential (selected) control group in France in a t-test for equality of means at the 10% (*), 5% (**) and 1% (***) level are indicated.

(5) and (6): Following Rosenbaum and Rubin (1985), for a given covariate X, the standardised difference before matching is the difference of the sample means in the full treated and nontreated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups. The standardised difference after matching is the difference of the sample means in the matched treated (that is, falling within the common support) and matched non-treated subsamples as a percentage of the square root of the average of the sample variances in the full treated and non-treated groups:

$$SB_{before}(X) = 100 * \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{\frac{[V_1(X) + V_0(X)]}{2}}}, \qquad SB_{after}(X) = 100 * \frac{\bar{X}_{1M} - \bar{X}_{0M}}{\sqrt{\frac{[V_{1M}(X) + V_{0M}(X)]}{2}}}$$

In a next step, it is tested whether there is a significant difference in the economic performance over time as well as in the development of farm technology defining indices (especially concerning environmental sustainability, technology, innovation and diversity) between arable farms in England where comparatively strong decoupling occurred and their French counterparts facing a higher share of remaining coupled support. The impact of these differences in putting the policy into practice is measured on the basis of the matching results for observables from the baseline data. However, farmers in England and France may also differ in unobserved dimensions like environmental awareness or managerial attitude and ability. If these characteristics are not taken into account, the comparison between farms in both countries will lead to biased estimates for the treatment effect. Yet, variables like environmental preferences or managerial ability are not measured in our dataset and thus cannot be controlled for. In order to solve this problem, we assume that the effect of these unobservable factors on farm practices is constant through time. Subtracting the difference in practices estimated by matching before implementation of the decoupling policy from the difference estimated after implementation gives the difference-in-difference estimate. Assuming that selection bias on unobservables is constant over time implies assuming that the average English arable farmer and his average French twin would have behaved in the same manner in the absence of decoupling (*common trend assumption*). According to Boninger, Krosnick and Berent (1995), Deary *et al.* (2000) and our own experiences in farm-level analyses, the *common trend assumption* is plausible, because unobserved determinants like important attitudes and individual differences in measures of mental ability especially are usually stable over time. Furthermore, the general CAP framework affects the English and French agricultural sector equally and both countries follow similar macroeconomic trends in the study period 2003-2008, which additionally bolsters support for the *common trend assumption*. Some more thoughts on and arguments for why we think the *common trend* *assumption* holds but also on potential adaptation behavior of French farms are given in the Appendix.

Assuming parallel trends, Table VI-6 shows results of the DID estimation for the matched sample as regards the outcome variable TFP. The table's columns represent different regression specifications. First estimations were performed using a pure DID setting before a number of control variables were added step by step in order to check the robustness of the results[34]. In all scenarios, the DID estimator is positive and significant, pointing towards decoupling having a positive effect on farm-level productivity growth. This effect is also reflected graphically, with English farms experiencing rapid TFP growth in 2005 when the decoupling reform was implemented in the UK (Figure VI-3). French arable farms, on the other hand, show high growth rates in 2007, one year after decoupling with maximum possible coupling was put into practice in France. While French farms lag behind in productivity growth between 2003 and 2008, their technical change rates increased significantly stronger than those of their English counterparts (see Table VI-12 in the Appendix and Figure VI-4). As technical change is a major driver of productivity growth, this finding is somewhat surprising. It could mean that English farms used new technology more efficiently. As a result of decoupling, English farms also got more diverse. Diversity was actually the only multi-dimensional index – some of which are presented in Figure VI-5 – whose development in the period 2003-2008 differed significantly between English and French arable farms. One possible explanation behind this difference could be related to the fact that increased market orientation through decoupling is associated with higher price risk, which lets farmers diversify their businesses. Another interpretation can be linked to farmers generating more off-farm income if subsidies are tied to land rather than products. As concerns the development of the class-defining indices, one last point worth mentioning before concluding is the parallel evolution of environmental sustainability, which indicates that productivity growth does not come at the expense of the environment.

Table VI-6: Difference-in-Difference estimation for the outcome variable productivity, fixed effects regression

Treat = ENG	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DID estimator	0.253***	0.269***	0.245***	0.224***	0.189***	0.187***	0.180***
	(0.044)	(0.044)	(0.043)	(0.041)	(0.044)	(0.044)	(0.044)
Year2003	-0.349***	-0.353***	-0.347***	-0.352***	-0.346***	-0.345***	-0.346***
	(0.036)	(0.035)	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)
Year2004	-0.436***	-.0443***	-0.413***	-0.403***	-0.381***	-0.380***	-0.375***
	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.029)	(0.029)
Year2005	-0.210***	-0.213***	-0.212***	-0.202***	-0.188***	-0.188***	-0.184***
	(0.028)	(0.028)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)
Year2006	-0.194***	-.0199***	-0.199***	-0.196***	-0.182***	-0.182***	-0.178***
	(0.028)	(0.028)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)
Year2007	-0.077***	-0.080***	-0.080***	-0.078***	-0.068**	-0.068**	-0.067**
	(0.028)	(0.028)	(0.027)	(0.026)	(0.027)	(0.026)	(0.026)
Share arable land		0.458***	0.498***	0.488***	0.491***	0.494***	0.492***
		(0.176)	(0.172)	(0.164)	(0.163)	(0.163)	(0.163)
Share off-farm income			-0.342***	-0.339***	-0.311***	-0.313***	-0.312***
			(0.081)	(0.077)	(0.078)	(0.078)	(0.077)
Ratio hired labour – family labour				0.149***	0.148***	0.147***	0.148***
				(0.026)	(0.026)	(0.026)	(0.026)
Subsidies per ha					-0.000**	-0.000**	-0.000**
					(0.000)	(0.000)	(0.000)

[34] Additionally, robustness was checked by performing DID estimations for a period prior to decoupling and for a period some years after decoupling was implemented. Results of these tests are presented in the Appendix.

Environmental subsidies per ha						0.000	0.000
						(0.000)	(0.000)
Organic farming							-0.179*
							(0.094)
Constant	11.858***	11.436***	11.412***	11.357***	11.418***	11.411***	11.419***
	(0.029)	(0.165)	(0.161)	(0.154)	(0.155)	(0.156)	(0.156)
N	396	396	396	396	396	396	396
Within R^2	0.603	0.611	0.632	0.665	0.671	0.671	0.674
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure VI-3: Farm-level productivity level for English and French arable farms, 2003-2008

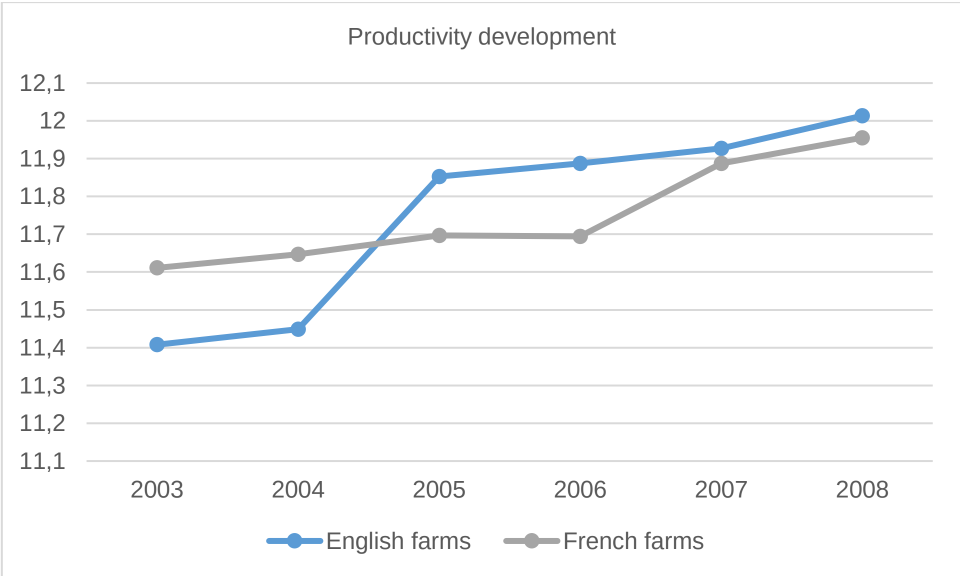


Figure VI-4: Technical change rates for English and French crop farms, 2003-2008

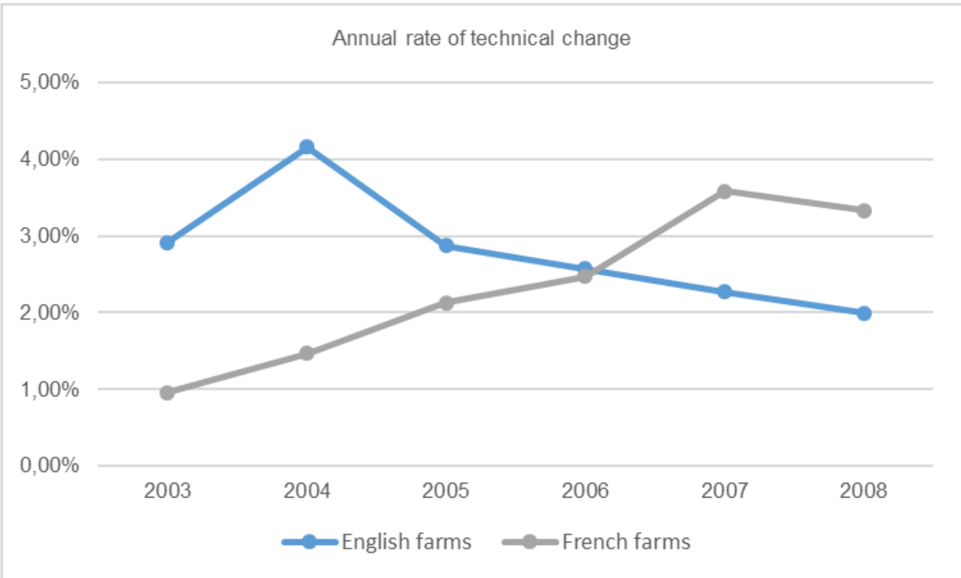


Figure VI-5: Scores of selected multi-dimensional indices

VI.7 Discussion and conclusions

In this article, we examined the effects of the 2003 CAP decoupling reform on the performance of arable farms in England and France. We studied the effect of this policy change, which decoupled direct farm payments from production from 2005 onwards and introduced the Single Payment Scheme using a quasi-experimental design. In doing so, we made use of regional and temporal variation in implementing the reform. Unlike previous decoupling studies, our evaluation tries to be comprehensive in a sense that it measures farm performance in several categories. Additionally, we account for technological heterogeneity among farms when assessing performance improvements through technology choice and change. The importance of considering farm heterogeneity when analysing performance has been pointed out by authors such as Renner, Sauer and El Benni (2021) and Kumbhakar, Lien and Hardaker (2014).

Our results show that both English and French arable farms indeed operate with distinct production technologies. Three technology classes were identified among the sample of

English crop farms, four for French farms. The classes varied mainly with respect to environmental sustainability, diversity and, naturally, the use of technology. In both countries, long-run class-based productivity estimates indicate TFP progress (English farms: 0.25% per year, French farms: 0.16%). Technical change rates are slightly negative over the whole observation period (English farms: -0.02% per year, French farms: -0.17%), however, the 2000s are marked by comparatively high growth rates. Productivity change is thus partly driven by technological advancements. Its rates as well as technical change rates are in a range that has also been reported by Baráth and Fertő (2017), Bokusheva and Čechura (2017) and Latruffe and Fogarasi (2009). However, not all of these authors explicitly focus on arable farms. Much stronger TFP growth for European and French agriculture respectively was found by the USDA (2021) for the period 2001-2010 and by Boussemart, Butault and Ojo (2012) for a period of 52 years until 2011. Differences in the size of TFP change between our estimates and those of authors such as the USDA (2021) might be explained by differing methodological approaches (e.g. the use of indices). A general note that needs to be taken account of relates to the consideration of weather in TFP analysis. Like arguably no other economic sector, agriculture is influenced by climatic conditions. Temperature, sunshine and precipitation affect agricultural production processes, droughts or frost periods can have dramatic consequences, especially for crop growing farms. Bad weather conditions may result in poor outputs in some years for some farms. Good conditions on the other hand may lead to exceptionally high yields. Not accounting for weather conditions can thus result in biased estimates. And given that weather can vary on a regional scale, comparing farms in different countries is not free from the risk of over or underestimating potential effects. Controlling for weather effects, however, requires information on farm location, which was not available for the present study.

Concerning our main research question whether decoupling has affected farm-level productivity, we find evidence that the decoupling policy had positive and significant effects on productivity – a result which has also been reported by Kazukauskas, Newman and Sauer (2014), one of the few papers studying productivity effects of decoupling in an ex-post manner. Improvements of another farm performance indicator, namely technical efficiency, as a consequence of decoupling have been found by Carroll, Newman and Thorne (2008) for the Irish cattle rearing, cattle finishing and sheep sectors. The productivity effect we detected seems to be strongest in the year decoupling was implemented, but also a certain anticipation effect can be observed. Interestingly, the effect is not driven by technical change. Productivity gains can thus be expected to be strongly affected by scale efficiency change or differences in technical efficiency development, which in turn can point towards adjustments of the farm-level product mix. In fact, technological change frequently goes in the opposite direction to the change in technical efficiency, as not all farmers are equally able to instantly adjust to new technology (Brümmer, Glauben and Thijssen, 2002). Our results further show that under decoupling, farmers tend to diversify their businesses while keeping environmental pressure at a similar level as with coupled support.

It needs to be stated that all results presented must be interpreted with care. While our matching approach guarantees comparability, it narrows the sample. The comparatively small area of common support excludes many farms from the analysis. Consequently, it remains somewhat unclear whether these farms would show a similar decoupling response. It is also not clear how exactly the gradual implementation of decoupling in France with different payment levels to be kept for different crops affected individual farm responses. We are still confident that our study can assist policymakers when it comes to future agricultural policy reforms. Until today, EU countries may continue to couple a limited amount of income support payments to certain sectors or products. This procedure is justified by preventing escalation if certain agricultural sectors or sub-sectors undergo difficulties. Still, it can cause market distortions. Against the background of our results, policy measures other than coupling support might be more suitable. Farmers seem to be well capable of identifying best strategies for their businesses. This should also be kept in mind when further refining the CAP towards more sustainable farming. While the eco-schemes that will be part of the CAP's first pillar from 2023 onwards are a first step towards reducing the environmental footprint of agriculture, they might not unfold their full potential as they are largely framed in an action-based manner. This means that payments are coupled to certain production practices. Farmers are thus not incentivised to respond to real market demands for environmental goods, but will allocate their resources according to a market demand defined, but not known with certainty by government bodies. Our results suggest that flexibility in terms of market-oriented production decisions is key to efficient resource allocation. However, more research is needed as concerns the development of markets for environmental goods.

VI.8 Appendix I

VI.8.1 Descriptive statistics

Table VI-7: Summary statistics used for estimating the latent class model (France)

Variable	Unit	Mean	Std.Dev.	Minimum	Maximum
Technology model					
Crop output	Euros	136025.5	129026.4	5103.2	4023170.0
Land	Hectares	122.1	79.4	1.4	794.53
Labour	Annual work units	1.7	1.3	0.1	41.3
Capital (depreciation)	Euros	25286.8	25248.7	0	335675.0
Materials	Euros	38137.5	30903.0	0	478955.0
Class identification model (additional)					
Hired/family labour	Ratio	0.323	1.031	0	50
Organisational form	0=family farms, 1=partnerships, 2=other	0.356	0.479	0	2
Organic production	1=yes, 0=no	0.012	0.108	0	1
Energy use	Euros per hectare	80.1	605.0	0	74804.6
Pillar II subsidies	Euros per hectare	552.7	2509.1	0	71143
Tillage area	Hectares	117.3	76.6	1.4	794.47
Net investment	Euros	56257.5	71129.1	0	1287697.0
Costs contract farming/variable costs	Ratio	0.217	0.658	0	1
Share rented land	Ratio	0.823	0.256	0	1
Miscellaneous income	Euros	10024.7	20077.9	0	1107689
Insurance expenses	Euros	5846.8	4632.9	0	94910.0
Forest area	Hectares	0.3	2.9	0	149
Age of the farmer	Years	53.5	22.6	17	95
Total farm output	Euros	155124.5	138977.7	5103.2	4063431.0
Total assets	Euros	334914.6	271170.7	4125.7	6344058.0
Number of observations	50785				

Table VI-8: Summary statistics for variables used for estimating the latent class model (England)

Variable	Unit	Mean	Std.Dev.	Minimum	Maximum
Technology model					
Crop output	GBP	223114.2	400390.5	1032.7	10264243.0
Land	Hectares	246.0	266.6	5.44	4624.0
Labour	Annual work units	3.2	5.3	0.005	135.4
Capital (depreciation)	GBP	36668.3	50208.2	0	739067.0
Materials	GBP	3522.0	8362.6	0	170192.0
Pesticides	GBP	53673.8	75495.5	0	1950462.0
Class identification model (additional)					
Hired/family labour	Ratio	18.1	271.4	0	11000.0
Organisational form	1=Sole trader, 2=Partnership (family only), 3=Partnership (other), 4=Farming company, 5=Farm company subsidiary	1.868	0.962	1	5
Organic production share (land)	Ratio	0.018	0.126	0	1
Energy use	GBP per hectare	83.5	70.5	0	1331.5
Environmental subsidies	GBP per hectare	21.7	49.8	0	2523.7
Tillage area	Hectares	203.1	233.4	5.44	4206.6
Net investment	GBP	69901.9	192624.3	0	7405222.0
Costs contract farming/variable costs	Ratio	0.240	0.510	0	1
Share rented land	Ratio	0.014	0.075	0	1
Miscellaneous income	GBP	70596.9	132091.9	0	2105571.0
Off-farm income share	Ratio	0.046	0.322	0	0.951
Insurance expenses	GBP	5436.3	5712.8	0	126408.0
Professional fees	GBP	5301.7	8901.0	0	354763.0
Forest area	Hectares	6.6	20.0	0	396.0
Age of the farmer	Years	55.1	41.5	22	97
Gender of the farmer	1=male, 2=female, 0=not specified	0.479	0.522	0	2
Education of the farmer	[1)]	1.2	1.6	0	5

Number of holdings	Number	1.3	0.9	1	18
Altitude	2)	0.5	0.5	0	4
Less favoured area	3)	1.1	0.6	1	7
Rural-urban classification	4)	3.4	3.6	0	8
Total farm output	GBP	306784.9	493818.1	1152.4	11569591.0
Total assets	GBP	1895239.0	2847236.0	5423.4	53841267.0
Debt/equity	Ratio	0.851	0.238	0	1.9
Total subsidies	GBP per hectare	123.8	118.9	0	1061.6
Number of observations	14196				

1) 0=School only, 1=GCSE or equivalent, 2=A level or equivalent, 3=College/National Diploma/certificate, 4=Professional Degree, 5=Postgraduate qualification
2) 1=Most of holding below 300m, 2=Most of holding at 300m to 600m, 3=Most of holding at 600m or above, 4=Data not available
3) 1=All land outside LFA, 2=All land inside SDA, 3=All land inside DA, 4=50% + in LFA of which 50% + in SDA, 5=50% + in LFA of which 50% + in DA, 6=<50% in LFA of which 50% + in SDA, 7=<50% in LFA of which 50% + in DA
4) 1=Urban > 10k - sparse, 2=Town and fringe - sparse, 3=Village – sparse, 4=Hamlet & isolated dwellings – sparse, 5=Urban > 10k - less sparse, 6=Town & fringe - less sparse, 7=Village - less sparse, 8=Hamlet & isolated dwellings - less sparse

VI.8.2 Long-run productivity and technical change estimates*

Table VI-9: TFP change and technical change for English and French arable farms, 1996-2013

	England		France	
	ΔTFP	TC	ΔTFP	TC
1996	-0.0019	-0.0640	0.0083	-0.0217
1997	-0.0062	-0.0508	0.0024	-0.0161
1998	-0.0074	-0.0328	0.0037	-0.0121
1999	-0.0045	-0.0189	-0.0001	-0.0075
2000	-0.0003	-0.0056	0.0008	-0.0024
2001	-0.0013	0.0090	0.0021	0.0001
2002	-0.0012	0.0188	0.0007	0.0062
2003	0.0041	0.0315	-0.0040	0.0092
2004	0.0104	0.0421	0.0071	0.0138
2005	0.0314	0.0296	0.0009	0.0170
2006	0.0029	0.0267	0.0040	0.0226
2007	0.0040	0.0238	0.0119	0.0307
2008	0.0075	0.0207	0.0065	0.0321
2009	0.0047	0.0184	0.0018	0.0324
2010	0.0089	0.0172	0.0004	0.0427
2011	0.0024	0.0140	0.0086	0.0467
2012	0.0056	0.0113	0.0056	0.0502
2013	-0.0005	0.0056	0.0002	0.0495

*whole sample

VI.8.3 Elasticities by class

Table VI-10: Elasticities for French arable farms by class, Wald procedure based on delta method at sample means

	Class 1	Class 2	Class 3	Class 4
Land	0.128***	0.132***	0.148***	0.340***
Capital	0.137***	0.087***	0.218***	-0.039***
Labour	0.309***	0.280***	0.252***	0.240***
Materials	0.451***	0.649***	0.354***	0.423***
Returns-to-scale	1.024***	1.148***	0.972***	0.964***

Note: *significant at 10%, **significant at 5%, ***significant at 1%

Table VI-11: Elasticities for English arable farms by class, Wald procedure based on delta method at sample means

	Class 1	Class 2	Class 3
Land	0.470***	0.160***	0.316***
Capital	0.102***	0.153***	0.113***
Labour	0.219***	0.432***	0.279***
Pesticides	0.251***	0.324***	0.354***
Materials	-0.007***	-0.023**	-0.002

Returns-to-scale	1.036***	1.046***	1.060***

Note: *significant at 10%, **significant at 5%, ***significant at 1%

VI.8.4 PSM-DID technical change

Table VI-12: Difference-in-Difference estimation for the outcome variable technical change, fixed effects regression

Treat = ENG	Coefficient	Std.err.	t
DID estimator	-0.009	0.003	-3.08
Year2003	-0.019	0.002	-8.88
Year2004	-0.005	0.002	-2.71
Year2005	-0.004	0.002	-2.62
Year2006	-0.004	0.002	-2.39
Year2007	0.001	0.002	0.30
Share arable land	0.006	0.010	0.60
Share off-farm income	0.014	0.005	2.72
Ratio hired labour – family labour	0.002	0.002	1.33
Subsidies per ha	0.000	0.000	5.89
Environmental subsidies per ha	-0.000	0.000	-3.73
Organic farming	-0.010	0.006	-1.65
Constant	-0.009	0.010	1.90
N	396		
Within R^2	0.352		
Sigma_u	0.016		
Sigma_e	0.009		
Rho	0.738		
F(12,318)	14.41		
Prob > F	0.000		

VI.8.5 Decoupling in England and France

Table VI-13: National implementation policies

Member State	**Year**	**Model**	**Coupled payments**
Treatment Group			
United Kingdom, England	2005	SPS dynamic hybrid	Full decoupling
Control Group			
France	2006	SPS historical	Maximum possible coupling

Source: European Commission (2008)

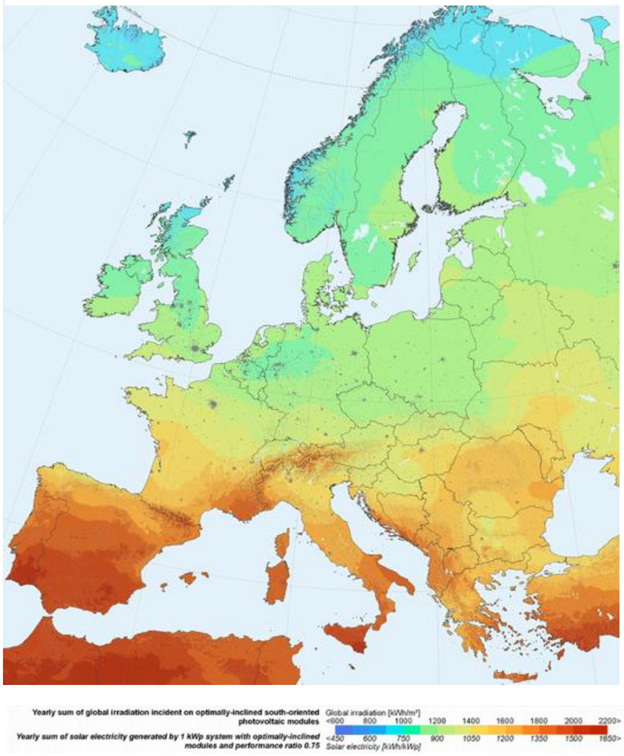
VI.9 Appendix II

VI.9.1 Common trend assumption and comparability

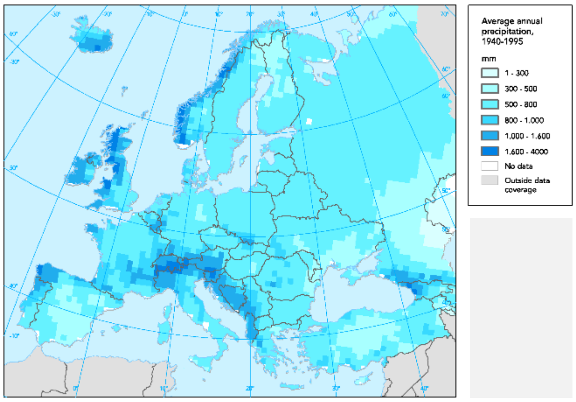
A key underlying concept of the difference-in-difference method is the parallel trends assumption. This assumption states that the untreated units (in our case for later years less treated units) represent the appropriate counterfactual in terms of the general trend that the treated units would have followed had they not been treated. More simply put, the two groups would have followed a common trend. In situations where the treatment and control group are locally close and face the same regulations and socioeconomic context, the common trend assumption is more plausible than when comparing groups in two different countries. For this reason, both comparability and common trend assumption must be checked for the selected countries England and France. While similar natural conditions (soil quality, precipitation, temperature etc.) in combination with PSM are one prerequisite of avoiding comparing the incomparable, similar macroeconomic and policy trends can be considered as the second. We therefore present a series of maps and graphs to descriptively support our claim of comparability and test the common trend assumption econometrically using pre and post-intervention data.

Map 1 shows solar radiation in Europe, expressed as photovoltaic solar electricity potential (European Commission, Photovoltaic Geographical Information System), Map 2 presents average annual precipitation (European Environment Agency) and Map 3 depicts a statistical stratification of the European environment based on twenty environmental variables (Metzger, 2005). All maps indicate that southern England and northern France, where most of our sample farms are located, share similar climatic, geomorphological and soil properties. It can thus be expected that farmers in both areas face similar site conditions. They were further affected by comparable macroeconomic trends as demonstrated by Figures 6-8, which show long-term developments of the indicators GDP, adjusted net savings and value added in agriculture, forestry and fishing (World Bank). Additionally, trends in the agricultural production related indicators fertiliser consumption (Figure VI-9) and cereal yield (Figure VI-10) point towards a similar development of the agricultural sectors in France and England (World Bank). Given these similarities, observed pre-matching structural differences between farms in both countries are assumed to be the result of historical and cultural developments.

Map 1: Solar radiation in Europe



Map 2: Average annual precipitation in Europe, 1940-1995



Map 3: Environmental stratification of Europe

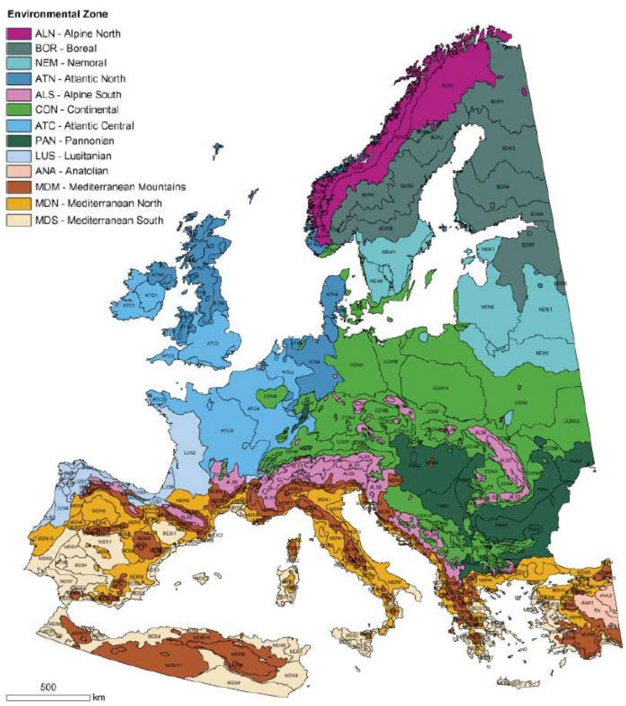


Figure VI-6: GDP development in France and the United Kingdom, 1985-2019

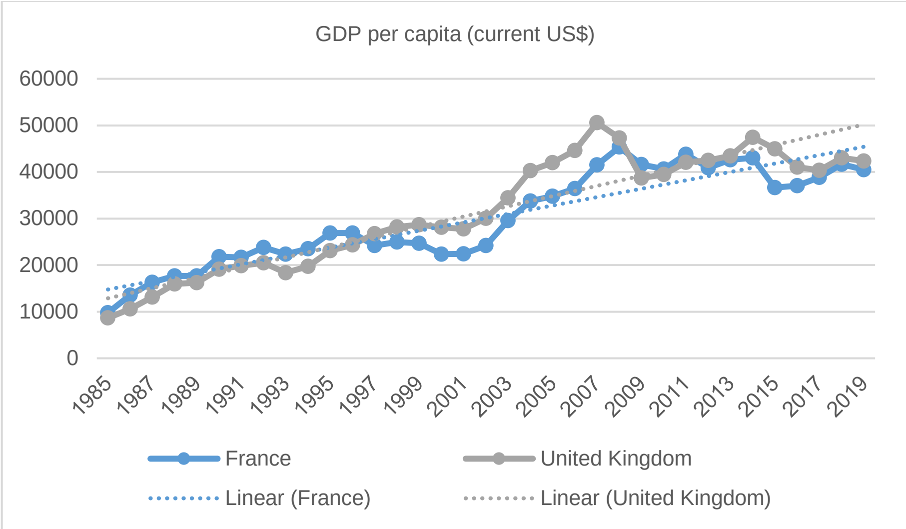


Figure VI-7: Development of the adjusted net savings indicator in France and the United Kingdom, 1990-2018

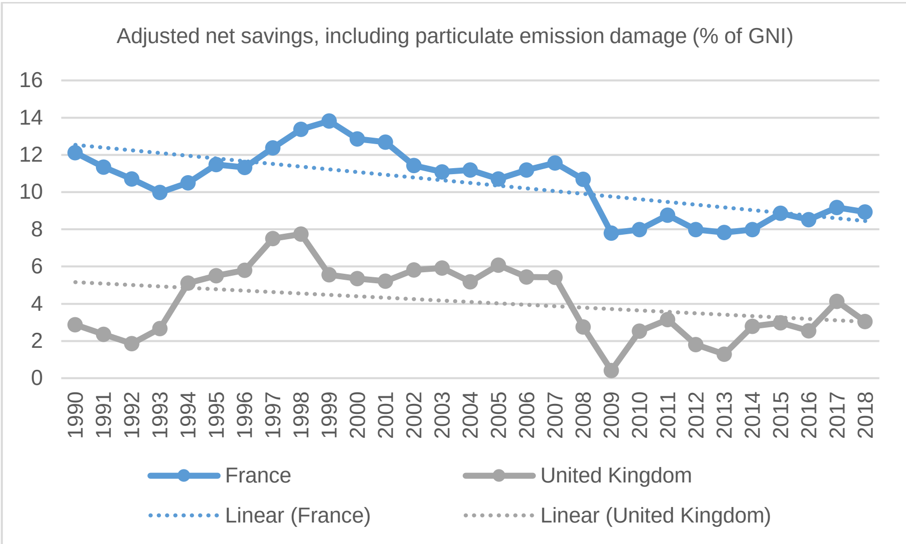


Figure VI-8: Development of the share of the value added in agriculture, forestry and fishing of total GDP in France and the United Kingdom, 1990-2019

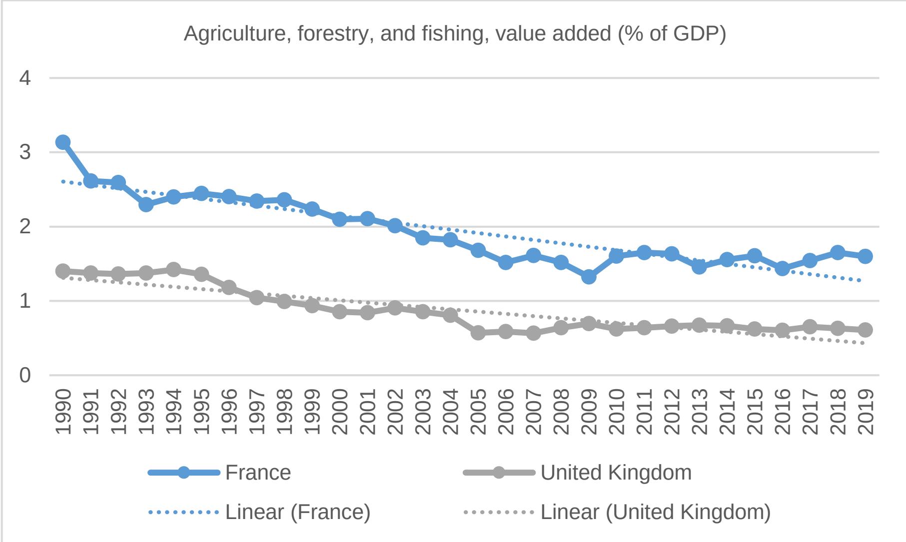


Figure VI-9: Development of fertiliser consumption in France and the United Kingdom, 2002-2016

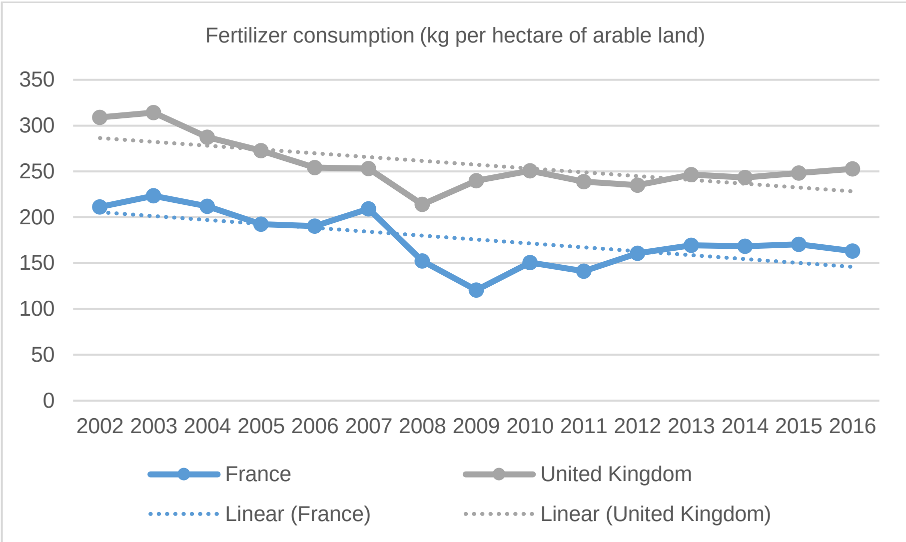


Figure VI-10: Development of cereal yield in France and the United Kingdom, 1995-2017

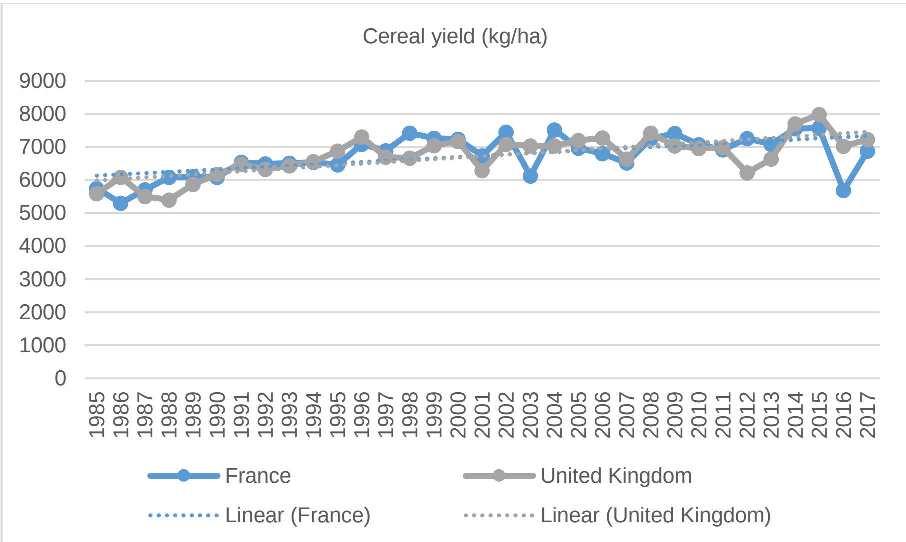


Table VI-14: PSM-DID 'productivity level', 1999-2004, fixed effects regression

Treat = ENG	Coefficient	Std.err.	t
DID estimator	0.010	0.049	0.21
Year1999	-0.029	0.040	-0.72
Year2000	-0.035	0.032	-1.08
Year2001	-0.023	0.033	-0.70
Year2002	-0.022	0.032	-0.69
Year2003	-0.029	0.032	-0.90
Share arable land	0.050	0.047	1.05
Share off-farm income	-0.181	0.128	-1.41
Ratio hired labour – family labour	0.011	0.013	0.86
Subsidies per ha	0.000	0.000	1.16
Environmental subsidies per ha	0.000	0.001	0.15
Organic farming	0.027	0.142	0.19
Constant	11.390	0.063	180.51
N	384		
Within R^2	0.019		
Sigma_u	0.739		
Sigma_e	0.176		
Rho	0.946		

Table VI-15: PSM-DID 'productivity level', 2007-2012, fixed effects regression

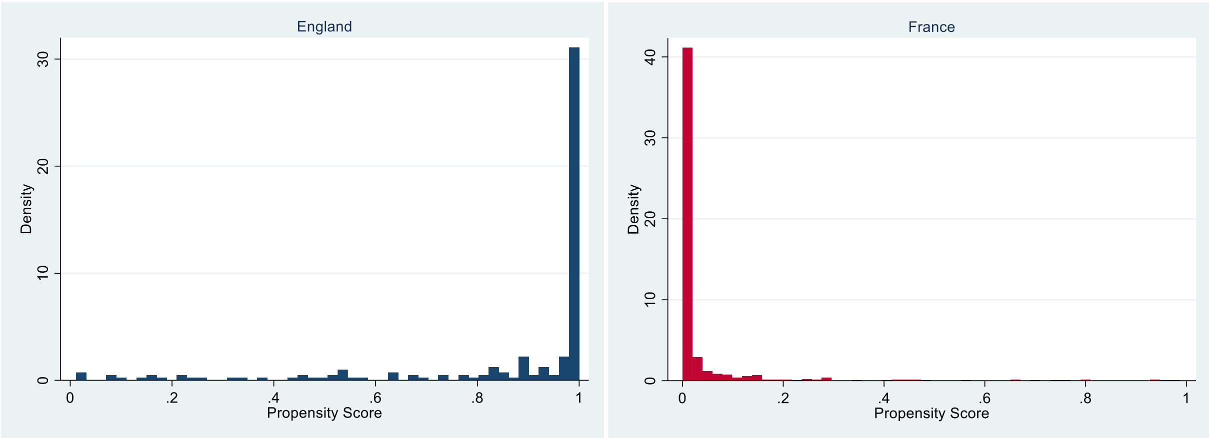
Treat = ENG	Coefficient	Std.err.	t
DID estimator	-0.043	0.035	-1.21
Year2007	-0.384	0.028	-13.88
Year2008	-0.235	0.021	-11.21
Year2009	-0.174	0.021	-8.27
Year2010	-0.196	0.026	-7.46
Year2011	-0.103	0.021	-4.93
Share arable land	-0.051	0.037	-1.39
Share off-farm income	-0.632	1.335	-0.47
Ratio hired labour – family labour	0.097	0.023	4.25
Subsidies per ha	-0.000	0.000	-0.10
Environmental subsidies per ha	0.000	0.000	0.21
Organic farming	-0.005	0.082	-0.06
Constant	12.375	0.053	234.39
N	540		
Within R^2	0.459		
Sigma_u	0.589		
Sigma_e	0.140		
Rho	0.947		

Thinking of classical matching applications, it might seem unusual to estimate the underlying model with a dummy for country affiliation as treatment variable where we might expect a kind of self-selection into treatment. However, in our approach we made use of the core idea behind matching, which is "to compare treated and control groups that are as similar as possible" (Stuart, 2010: 3). More specifically, through matching a "set of subjects all of whom have the same propensity score, the distribution of observed baseline covariates will be the same between the treated and untreated subjects" (Austin, 2011: 402). This refers to the notion of Rosenbaum and Rubin (1983) concerning the propensity score as a balancing score. In our setting, treatment equals country affiliation, which means that the propensity score can be interpreted as the probability of being a farm located in England given farm structural variables. From our understanding, this approach is in line with the propensity score theorem, which says that "you need to control for covariates that affect the probability of treatment" (Angrist and Pischke, 2009: 81), i.e. if $\{Y_{0i}, Y_{1i}\} \perp\!\!\!\perp D_i \mid \boldsymbol{X_i}$ then $\{Y_{0i}, Y_{1i}\} \perp\!\!\!\perp D_i \mid p(\boldsymbol{X_i})$, where Y defines the outcome of individual i, D refers to treatment and $\boldsymbol{X_i}$ is a covariate vector.

If structural differences between farms in different countries are not taken into account when comparing effects of decoupling in ex post studies (as for example in the papers by Kazukauskas *et al.*, 2013 or Rizov, Pokrivcak and Ciaian, 2013), potential effects might be biased as farm structures might interfere with decoupling.

VI.9.2 Propensity Score distribution

Figure VI-11: Propensity score by country



VI.9.3 Potential adaptation behavior of French farms

It can be considered as unlikely that French farms behave exactly as non-treated farms given that all EU15 member states had to decouple (a proportion of) subsidies before January 2007. This major policy shift was announced in broad lines on the EU level in 2003 already. All European farmers were thus aware of the changes to come and can be expected to have shown a certain preparation or adaptation behavior. The permanent need of farmers to adapt to production risk, mostly due to climate and pest conditions, to market risk that impact input and output prices and institutional risk through agricultural, environmental, and sanitary regulations is well-documented (Hardaker, 2004; Darnhofer *et al.*, 2010). So is farmer adaptation behaviour as either a reactive or a proactive process depending on farmer flexibility and expectation capabilities (Robert, Thomas and Bergez, 2016). There are even theories and concepts about the adaptive capacity of farmers, such as the theory of the “farmer’s adaptive behavior” (Petit, 1978) or the concept of adaptive capacity or capability (Darnhofer, 2014).

We can thus expect French farms to adapt to a certain extent to the incoming new regime. However, they still had to deal with stronger coupling until 2010 and a later implementation of the reform. It is consequently also unlikely that they behave just as their English counterparts. This notion is supported by current findings and discussions about the ability of farms to provide farm functions (i.e. the delivery of public and private goods) while facing economic, social, environmental, and institutional shocks and stresses by exploiting resilience capacities (Meuwissen *et al.*, 2019; Slijper *et al.*, 2022). Farm-level responses can be expected to follow short-term (robustness) and long-term (adaptability and transformability) strategical decisions, which supports the assumption that French farms would not totally change their current farming practices in the pure anticipation of the reform to be implemented ignoring current market situations and regulations.

VI.9.4 Productivity and technical change by class

Figure VI-12: Productivity and technical change for French arable farms by class

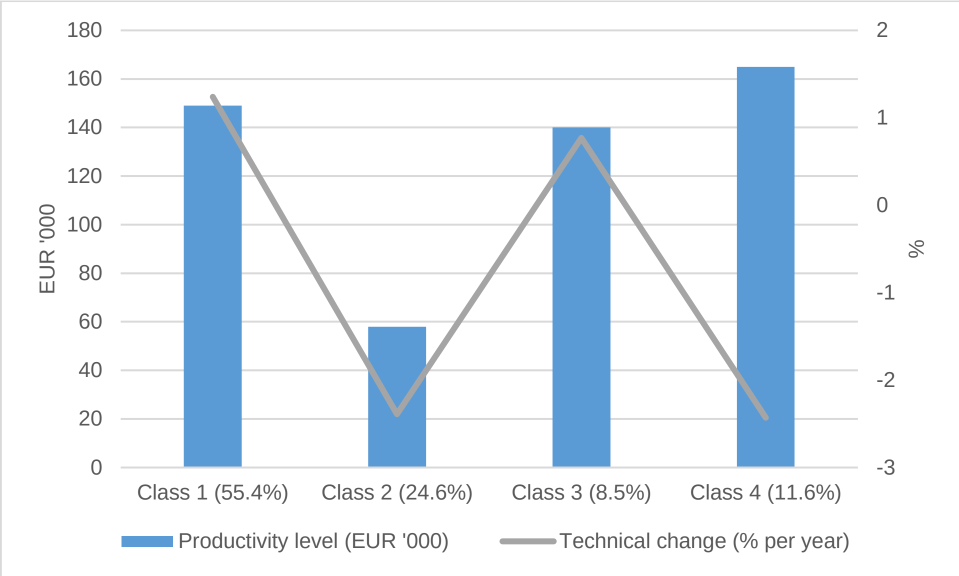
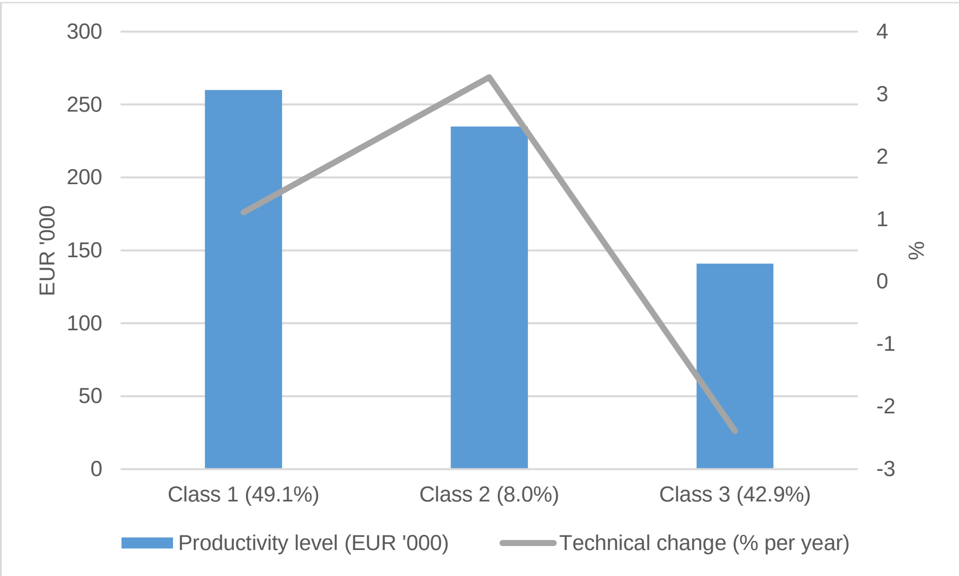
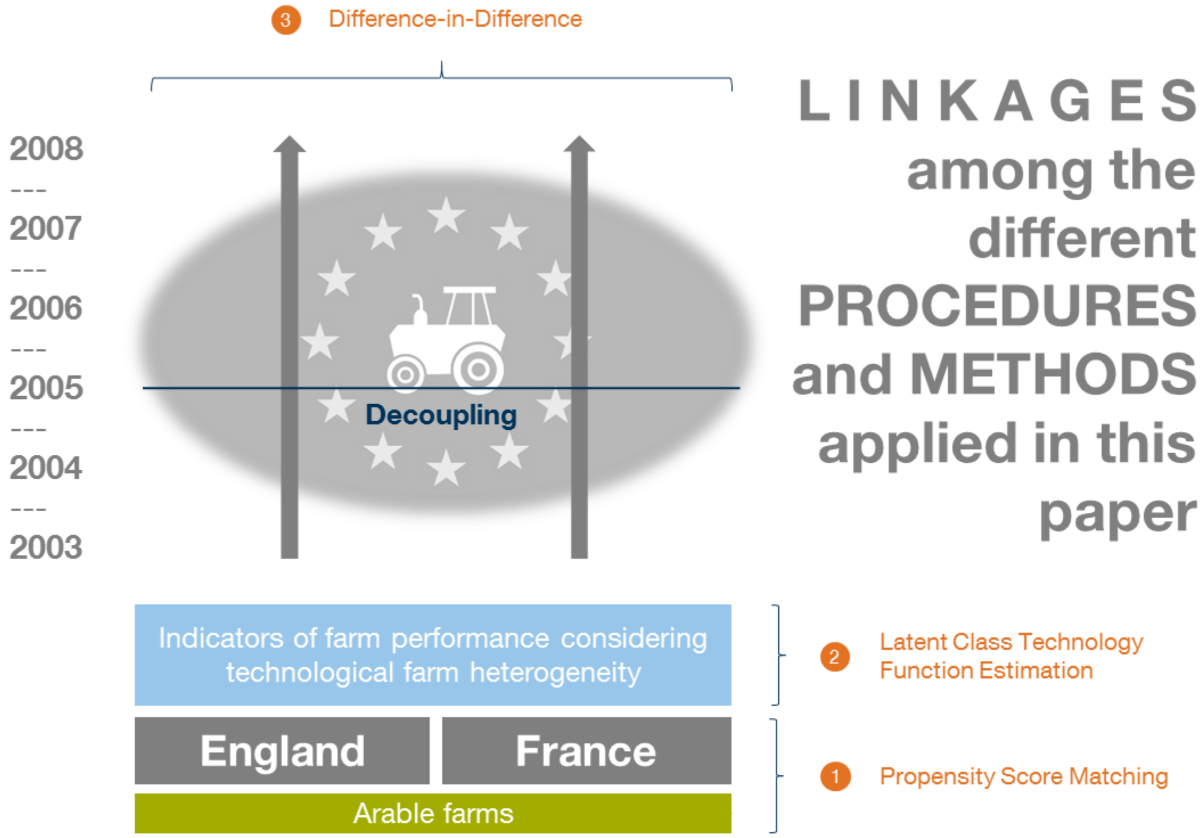


Figure VI-13: Productivity and technical change for English arable farms by class



VI.9.5 Link between latent class technology model and quasi-experimental approach



Source: Own depiction

Part 3: Conclusions

VII Summaries, Author's Contributions and Discussion

This chapter summarises the four studies embedded in this dissertation as well as two additional studies that are co-authored by the author of the dissertation and supplementary to the embedded articles. Table VII-1 gives an overview of all studies, including the main research questions and core findings from a theoretical and/or empirical and/or methodological perspective. In addition, the summaries in the subchapters following the table contain detailed descriptions of authors' contributions to each study.

Table VII-1: Overview of the individual studies of this dissertation and their findings

Title	Main research question	Core findings (theoretical and/or empirical and/or methodological)
a) Studies embedded in this dissertation		
1. The integration of ecology and bioeconomy based on the example of agri-environment schemes (Chapter 3)	Why do agri-environment schemes perform poorly given our knowledge of economic theory that should guide policy-makers when designing AES?	A poor implementation of the economic theory underlying agri-environment schemes can be seen as an explanation for their lack of effectiveness.
2. The impact of agri-environment schemes on farm productivity: a DID-matching approach (Chapter 4)	How does participation in AES affect farm productivity? Is AES design in line with WTO requirements?	AES designed for arable land overcompensate farmers and thus do fail to comply with WTO rules. For dairy farms, we find that AES participation reduces farm productivity (thus having an unintended effect on production), implying that action-based scheme design not considering changing market and production situations might be too restrictive, potentially preventing farmers from participating. The mixed-methods approach (production frontier and impact evaluation) proves to allow for the study of AES effects that go beyond traditional outcomes such as fertiliser intensity or earnings.
3. Promoting organic food production in flagship regions – A policy evaluation study for Southeast Germany (Chapter 5)	Is the policy measure of appointing organic flagship regions an effective tool to promote the uptake of organic farming?	Our results suggest that the organic flagship region programme fails to motivate farmers to switch to organic production and that there is a need to more effectively target decision-influencing factors as identified in the conceptual framework, which is based on the Theory of Planned Behaviour. As for the method, the study shows that choice experiments can be combined with classical impact evaluation methods in cases where the time period between the start of the treatment and the identification of a potential effect is rather short.
4. Revisiting the impact of decoupled subsidies on farm performance: a counterfactual analysis using microdata	Which effect did the 2003 reform of the Common Agricultural Policy, which decoupled farm subsidies	We show that farms operate with distinct production technologies and that decoupling had positive and significant effects on productivity. Our results further indicate that under decoupling, farmers tend to diversify their businesses while

(Chapter 6)	from production, have on farm performance?	keeping environmental pressure at a similar level as with coupled support. Methodologically, we demonstrate why technological heterogeneity is important for evaluating farm performance and how the use of quasi-experimental methods can improve the evaluation of decoupling.
b) Additional co-authored articles cited in the dissertation		
5. Using machine learning to identify heterogeneous impacts of agri-environment schemes in the EU: A case study (Summary in Chapter 7)	How effective are agri-environment schemes? How heterogeneous are the identified effects?	Our results suggest the existence of heterogeneous, but limited effects of agri-environment measures in several environmental dimensions such as climate change mitigation, clean water and soil health. We demonstrate the importance of considering the individual farming context in agricultural policy evaluation and provide important insights into the improved targeting of AES along several domains. When it comes to the method, the study combines economic theory with a novel machine learning approach to identify individualised AES treatment effects. Existing studies were only able to estimate average effects on the basis of traditional statistical methods.
6. Do agri-environment measures help to improve environmental and economic efficiency? Evidence from Bavarian dairy farmers (Summary in Chapter 7)	Which effect do agri-environment schemes have on farm-level environmental and economic efficiency?	Our findings indicate that participation in agri-environment schemes does neither alter farms' economic efficiency nor environmental efficiency. While existing research on schemes effectiveness has primarily focused on either ecological or economic aspects, we methodologically add to the literature by assessing environmental and economic effects simultaneously.

VII.1 The integration of ecology and bioeconomy based on the example of agri-environment schemes

This introductory and theoretical contribution takes a look at the development of economic thinking about the environment and questions the current implementation of an agricultural policy measure, namely agri-environment schemes, as a tool to reconcile ecology and economy. It puts the schemes in the context of the bioeconomy concept, which is considered an important element in the transition to a more sustainable future. Primarily characterized by its special emphasis on renewable resources and their efficient, innovative use, it is also oriented towards natural cycles and links resource use to environmental conservation. More and more products will need to be based on renewable resources in the future, fostering the importance of agriculture and forestry. However, the environmental burdens of the agricultural production process that generates these biological alternatives remain problematic and counteract the bioeconomic idea of sustainability. From an economic point of view, market failure is the cause of excessive environmental pollution. In order to counter environmental degradation resulting from market failure, European policymakers introduced, among other things, agri-environment measures as an integral part of the European agricultural policy in the early 1990s. Though, the fact that agriculture still puts tremendous pressure on the environment casts doubt on the effectiveness of the introduced measures. A poor implementation of the economic theory underlying the measures is hypothesised to explain their lack of effectiveness (keeping in mind other challenges of designing and implementing AES such as top-down vs. participatory approaches).

The descriptive analysis suggests that there is indeed a mismatch between economic theory and its implementation when it comes to agri-environment schemes. Theoretical underpinnings ranging from the Coarse theorem to the internalisation of external effects via subsidies are poorly put into practice. This finding can be assumed to (partly) explain unsatisfactory results in terms of environmental sustainability of farming. A return to economic theories may serve as a beacon on the path to the desired sustainability in the sub-sector of ecology. Of course, the complexity of reality only permits a 1:1 implementation of the economic theory of a model world to a limited extent. Furthermore, the success of agri-environment schemes is not only affected by the implementation of economic theory. The diverse and often competing agricultural policy goals in combination with the broad range of agricultural, environmental and social conditions across Europe have led some researchers and analysts to characterize the EU's agri-environmental policy challenges as a "wicked" problem where any newly proposed measure tends to generate a cascade of new problems (Kuhmonen, 2018). Nonetheless, economic concepts should remain guiding principles. The use of modern technology (such as remote sensing) cuts transaction costs for result-oriented agri-environmental measures, enabling payments to be made to the amount of the services actually provided. Moreover, improved monitoring programmes on individual farms can be used to record all measurable ecosystem services, based on a holistic approach. On the basis of the Coase theorem, payments for ecosystem services could consequently result from a negotiation process between action planners and service providers, provided the "provider gets principle" is adhered to. Different site conditions and opportunity costs would be explicitly considered in this case. Even in a "polluter pays" scenario, Coase's negotiating solution offers a solid foundation. Certainly, the economic efficiency of any new measures would have to be examined in greater detail.

This work has been published as a chapter in an edited book by the Bavarian Academy of Sciences (Mennig and Sauer, 2019). Philipp Mennig developed the research framework and question in consultation with Johannes Sauer. Both Philipp Mennig and Johannes Sauer selected agri-environment schemes as an exemplary agricultural policy tool. Reading several studies about their mixed success, Philipp Mennig developed the hypothesis that a poor implementation of the economic theory underlying the measures may explain their lack of effectiveness. Having set out this working hypothesis, Philipp Mennig carried out the literature review and the descriptive policy analysis. Johannes Sauer supervised the process and both authors interpreted the finding. Philipp Mennig wrote the manuscript while Johannes Sauer provided feedback and further advice.

VII.2 The impact of agri-environment schemes on farm productivity: a DID-matching approach

Improving the environmental sustainability of agriculture is a major challenge that both farmers and policymakers face. Among the policy measures aiming at a reduction of the environmental footprint of farming, agri-environment schemes have gained a prominent position, not least as being key elements of the Common Agricultural Policy of the EU. While quite a number of studies have assessed their impact in terms of environmental outcome as well as participation behaviour of farmers, only a few studies have analysed their impact on farm economic performance and their compliance with rules of the World Trade Organisation. According to WTO standards, payments for agri-environmental schemes should distort neither trade nor production but instead only compensate for income forgone and costs incurred. At the same time, contract design shall give farmers enough flexibility to react to changing market and production conditions. Using accountancy data from conventional Bavarian dairy and arable farms that are observed over the period 2006 to 2011 as well as scheme participation data and secondary data on regional structural characteristics, we apply a difference-in-difference propensity score matching estimator to test if AES have an unintended effect on farm productivity (being measured with the Malmquist index and decomposed following Kumbhakar and Lovell (2000)).

Our results suggest that schemes designed for arable land overcompensate farmers and thus do fail to comply with WTO rules. For dairy farms, we find that AES participation reduces farm productivity, implying production distortions and that action-based scheme design not considering changing market and production situations might be too restrictive, potentially preventing farmers from participating. It thus needs to be questioned whether “Green box” subsidies are as neutral as they are supposed to be. Non-neutral payments have important implications when it comes to equity and trade (especially with developing countries). One solution to this “Green box” issue might be an orientation towards results-based AES, which link payments to actual environmental outcomes. They have the potential to harness farmers' self-interest in optimizing outcomes, thereby providing incentives for entrepreneurship in the provision of environmental goods and services, and to exhibit no production distorting effects if site conditions and the individual farm context are accounted for. However, further research is needed to identify the conditions under which results-based schemes would be more cost-effective and less distorting than traditional action-based schemes, “to develop appropriate risk-sharing mechanisms, and to develop tools to manage the additional monitoring and verification requirements (without incurring excessive administrative costs)” (Hasler *et al.*, 2022: 122).

The article has been published in the European Review of Agricultural Economics (Mennig and Sauer, 2020). Both authors developed the research question. Philipp Mennig reviewed the literature, developed the theoretical framework and selected the methods, applied for and prepared the data and conducted the empirical analysis. As the estimation of the production function was expected to result in a few regularity violations, Johannes Sauer suggested to check for monotonicity and curvature econometrically. Given the relatively low number of violations as well as the agricultural context allowing for such violations, regularity conditions were not imposed (see for example O'Donnell and Coelli (2005) for a Bayesian estimation framework to impose regularity conditions). Both authors interpreted the results. Philipp Mennig wrote the original draft of the manuscript, which was improved through reviews by Johannes Sauer.

VII.3 Promoting organic food production through flagship regions

Mitigating the environmental impact of agriculture is a major issue in negotiations on the future of the European Union's Common Agricultural Policy. Organic farming is commonly put forward in these discussions as a promising way to reduce the negative environmental impact of agriculture. Consequently, different promotional strategies aiming at the adoption of organic farming practices have been developed. In 2013, the German federal state of Bavaria initiated an innovative programme that resulted in 'organic flagship regions' being appointed in the years that followed. These regions are allocated support with the main goal of motivating farmers to switch to organic production. By applying a difference-in-difference estimator to farm-level data that was collected in two surveys (2016 and 2018), we evaluate whether the programme has achieved its aims, i.e. whether more farmers have adopted or plan to adopt organic farming practices within the flagship regions as compared to farmers outside such regions. Adoption probabilities are estimated on the basis of a discrete choice experiment. The Theory of Planned Behaviour, which postulates that the intention to perform a specific behaviour is a predictor of actual behaviour, provides the conceptual framework to identify the main factors influencing a farmer's decision to go organic.

Our results suggest that the programme with its mix of supply-side and demand-side measures fails to motivate farmers to switch to organic production and that there is a need to more effectively target decision-influencing factors. These factors include psychological constructs. One possible avenue in which policymakers might improve the programme could therefore be to approach farmers more directly and to adjust the ratio of events and measures offered inside the flagship regions for farmers and consumers.

A slightly revised version of this article was published in Q Open (Mennig and Sauer, 2022). The research question and the theoretical framework were developed by Philipp Mennig. Philipp Mennig also reviewed the literature on evaluations of organic farming policies. The survey data was provided by Thomas Venus, who further deserves credit for discussing the research approach. Philipp Mennig cleaned and prepared the data and conducted the empirical analyses. These involved the factor analysis, the estimation of a mixed logit model to calculate the likelihood of choosing organic farm types and the difference-in-difference estimation. Both authors interpreted the results. Philipp Mennig wrote the manuscript, which was continuously improved with feedback and suggestions from Johannes Sauer.

VII.4 Revisiting the impact of decoupled subsidies on farm performance: a counterfactual analysis using microdata

The 2003 reform of the Common Agricultural Policy, which decoupled farm subsidies from production, was expected to increase farmers' market orientation and to positively impact farm productivity, although especially the latter is not uncontested in the economics literature. The theoretical effect of decoupling on farm performance has been verified in a few ex-post analyses. However, these studies lack important aspects of farm-level policy impact evaluations. First, they do not use a well-defined counterfactual scenario, second they do not account for farm heterogeneity when measuring performance and third they do not assess farm performance in a comprehensive manner. We address these shortcomings by combining quasi-experimental empirical methods (Propensity Score Matching, Difference-in-Difference) with a latent-class production function. Our empirical strategy takes advantage of the fact that the 2003 CAP reform awarded individual member states some flexibility as concerns the way (degree, timing) in which decoupling and the single payment scheme were implemented. Unlike previous studies, we do not purely focus on economic performance measures, but include structural and environmental indicators as outcome variables.

Using UK and French farm-level data for crop farms for the years 1995-2017 and 1990-2013 respectively, we show that farms indeed operate with distinct production technologies. Three technology classes were identified among the sample of English crop farms, four for French farms. The classes varied mainly with respect to environmental sustainability, diversity and, naturally, the use of technology. We further demonstrate that decoupling had positive and significant effects on productivity. The productivity effect we detected seems to be strongest in the year decoupling was implemented, but also a certain anticipation effect can be observed. Our results finally show that under decoupling, farmers tend to diversify their businesses while keeping environmental pressure at a similar level as with coupled support. Against the background of our findings, policy measures other than coupling support might be more suitable if income support is to remain a policy goal. Farmers seem to be well capable of identifying best strategies for their businesses.

This article is currently in the second round of review with Agricultural Economics. The research question for this article was jointly developed by Johannes Sauer and Philipp Mennig. Philipp Mennig reviewed the literature on farm-level responses to decoupling and developed the theoretical framework. Johannes Sauer provided cleaned EU FADN data for France and the UK. Philipp Mennig prepared the data, adapted the conceptual framework and conducted the main part of the empirical analyses. Both authors interpreted the results. Philipp Mennig wrote the manuscript, which was continuously improved with feedback and suggestions from Johannes Sauer.

VII.5 Using machine learning to identify heterogeneous impacts of agri-environment schemes in the EU: A case study

Legislators in the European Union have long been concerned with the environmental impact of farming activities and introduced agri-environment schemes (AES) to mitigate adverse environmental effects and foster desirable ecosystem services in agriculture. This study combines economic theory with a novel machine learning method to identify the environmental effectiveness of AES at the farm level. We use accountancy data from conventional Bavarian farms for the year 2014 as well as scheme participation data and secondary data on regional structural characteristics to develop a set of more than 130 contextual predictors that help to assess the individual impact of participating in AES. This approach is based on the conditional average treatment effect (CATE). It uses causal forests, a novel machine learning algorithm based on random forests (Athey and Imbens, 2016; Athey, Tibshirani and Wager, 2019; Wager and Athey, 2018). The use of this algorithm – which in a first step fits a propensity forest to estimate the predicted propensity scores, in a second step estimates a separate regression forest for every environmental indicator and in a third step estimates a causal forest to obtain heterogeneous treatment effects – allows to evaluate the impact of AES at the farm level and thus delivers valuable information regarding the heterogeneity of the effects of agri-environment measures. The approach presented in this study surpasses many limitations of previous attempts to evaluate the efficacy of AES based on more traditional econometric methods.

Results from our empirical application suggest the existence of heterogeneous, but limited effects of agri-environment measures in the environmental dimensions climate change mitigation, clean water, soil health and land-use diversity. We find rather small statistically significant effects of AES on land-use diversity for approximately 55 per cent of all observations. Regarding fertiliser expenditures per hectare, we find modest reduction effects for 30 per cent of the sample, while we barely find any impact on pesticide expenditures. Desirable effects could be found for 7 per cent of the sample. In terms of greenhouse gas emissions, we find mostly insignificant or adverse effects. By making use of Shapley values, a model-agnostic interpretability concept stemming from cooperative game theory (Shapley, 1953), which is well-suited for complex prediction models (Lundberg and Lee, 2017; Molnar, 2019) we demonstrate the importance of considering the individual farming context in agricultural policy evaluation and provide important insights into the improved targeting of AES along the domains location, farm type, yield potential and farm size. Based on our results, we could further explore spatial patterns of the environmental subsidy payments as well as important drivers of heterogeneous treatment effects.

This article has been published in the European Review of Agricultural Economics (Stetter, Mennig and Sauer, 2022). Christian Stetter developed the research idea and came up with the research design based on machine learning. He also reviewed the literature on machine learning applications, while Philipp Mennig contributed to the review of the literature on AES effects. Christian Stetter and Philipp Mennig discussed the selection of variables for the empirical analysis as well as the theoretical and conceptual framework on the basis of suggestions of Christian Stetter. Christian Stetter also performed the empirical analyses. The results were interpreted and discussed by all three authors. Christian Stetter wrote the original draft of the article. Philipp Mennig substantially contributed in terms of writing to the introduction, the results and discussion sections. Johannes Sauer provided suggestions to interpreting the results and reviewed the manuscript.

VII.6 Do agri-environment measures help to improve environmental and economic efficiency? Evidence from Bavarian dairy farmers

Nitrogen pollution from agriculture is recognized as one of the most pressing environmental problems humanity faces. The nitrogen surplus in the environment – mainly a result of the intensive use of mineral fertilizers and livestock production – has already surpassed the planet's boundaries (Rockström *et al.*, 2009; Steffen *et al.*, 2015). In order to reduce this surplus, numerous measures have been implemented by countries, associations of states as well as by private and non-profit players all around the globe. The EU, for example, aims to tackle the problem with a number of environmental directives: the Nitrates Directive, the Habitats Directive, the Water Framework Directive and the National Emissions Ceilings Directive. These directives force member states to act and are accompanied by regional, national and EU-level initiatives, one of which are agri-environment schemes (AES), or agri-environment-climate measures (AECM) as they are lately being referred to, as part of the Common Agricultural Policy. Several authors have investigated whether these schemes show the intended impact on nitrogen pollution reduction. However, they assessed scheme effectiveness primarily based on ecological aspects. It has been shown, though, that the environmental effectiveness of agri-environment policies should not be assessed in isolation from economic objectives of farmers. This study therefore presents an innovative empirical application to the assessment of AES on farm-level environmental and economic efficiency.

Applying a multi-equation representation with a desirable technology and its accompanying undesirable by-production technology on a balanced sample of Bavarian dairy farms surveyed between 2013 and 2018, we analyse micro-level environmental (nitrogen surplus is used in the study as a proxy of the environmental dimension) and economic performance of farms participating in AES and non-participating counterparts. A combination of Propensity Score Matching and a robust Difference-in-Difference approach is used to estimate the policy effect, while the multi-equation representation is developed using Data Envelopment Analysis following Murty, Robert Russell and Levkoff (2012). Our results show that the sample farms have a technical efficiency of 0.882 on average, whereas the environmental performance measures focusing on nitrogen pollution show an average score of 0.713, implying that there is a considerable reduction potential in terms of nitrogen pollution. They further suggest that agri-environment schemes do not alter farms' economic and environmental efficiency, pointing towards scheme design that does not negatively impact farm performance.

The article is currently in the second round of review with the European Review of Agricultural Economics. Amer Ait Sidhoum and Philipp Mennig jointly developed the research idea and came up with the research design. While Amer Ait Sidhoum reviewed the literature on modelling good/bad outputs, Philipp Mennig reviewed the literature on AES effects with a focus on nitrogen pollution. Amer Ait Sidhoum calculated farm-level nitrogen surplus using a methodology proposed by Philipp Mennig. Together they decided on the variables to use for the empirical analysis, which was performed by Amer Ait Sidhoum with some suggestions for adjustments from Philipp Mennig. The results were interpreted and discussed by both authors. Amer Ait Sidhoum wrote the original draft of the article. Philipp Mennig substantially contributed in terms of writing to the introduction, the results and conclusion sections.

VII.7 Discussion and Policy Implications

This section presents a discussion across all dissertation topics in relation to the existing literature. The overarching goal of the preceding studies was mainly to provide empirical insights into the microeconomic behaviour of farms as well as their performance in different categories (e.g. productivity, environmental effort) as a response to agricultural policies. This target was pursued taking into consideration the multifunctionality of modern agriculture and policy goals as well as interrelations of the agricultural sector with other domains. In doing so, we provide the basis for scientifically informed agricultural and environmental policymaking. The included studies are connected by their focus on economic theory and important trends in agricultural policy, from agri-environment schemes to organic farming to decoupling.

The first agricultural policy development that was investigated is the growing importance of agri-environment schemes, which have been introduced as compulsory elements of the Common Agricultural Policy in 1992. While their introduction was deemed to reduce the environmental pressure of agriculture, 30 years of experience with this type of policy measure cast doubt on whether this goal was achieved. Agricultural intensification is still one of the main causes of biodiversity loss (EEA, 2019) and nutrient loads to water (EEA, 2020) in Europe. Agriculture further accounts for around eleven percent of total greenhouse gas emissions in the 27 EU member states (EEA, 2022) as calculated with IPCC guidelines for national greenhouse gas inventories for 2019. They decreased by 25% between the years 1990 and 2010, mainly as a result of a declining use of fertilisers and a reduction of livestock numbers, with the largest decrease between 1990 and 1994. Since 2010, emissions have not declined further (European Court of Auditors, 2021). As long-term studies that would connect scheme enrolment and environmental performance of farms since 1992 are missing, these figures do not allow to conclude that agri-environment measures were ineffective. In fact, quite a number of studies have reported (at least some) positive effects (e.g. Batáry *et al.*, 2015, Jones *et al.*, 2017, Tzemi and Mennig, 2022, Marja, Tscharntke and Batáry, 2022). One might thus speculate that agri-environment schemes have at least prevented further environmental degradations to some extent. Their generally still "limited environmental impact" (Hasler *et al.*, 2022: 121), which we also found in the two co-authored studies of this dissertation (Stetter, Mennig and Sauer, 2022; Ait-Sidhoum and Mennig, 2022), however, indicate that the schemes suffer from design and implementation issues. The main of those are reflected upon in Chapter 3 of this thesis and are linked to questions of cost-effectiveness of AES, for which limited information is available (Zimmermann and Britz, 2016). A main weakness of AES design, as stated in Chapter 3, is connected to the uniform payment based on foregone income and additional costs as well as the voluntary nature of the schemes. While rarely associating this AES feature with economic theory behind subsidies, several authors have identified the "adverse self-selection bias toward 'baseline-complying agents'" (Hasler *et al.*, 2022: 109) and moral hazard (Latacz-Lohmann and van der Hamsvoort, 1998) as major drawbacks of agri-environment measures (Martin Persson and Alpízar, 2013; Moxey, White and Ozanne, 1999). Both aspects are ultimately caused by an asymmetric distribution of information between farmers and the government and can lead to a situation where farmers will receive a remuneration for their environmental stewardship, but their scheme enrolment and payment will not be *additional*. This means that it will not make a difference in the environmental outcome of AES other than keeping the status quo. It is a classical example of windfall effects. Solutions to this problem can be conservation auctions (Latacz-Lohmann and van der Hamsvoort, 1997), targeting of agri-environment payments according to dimensions known by agricultural authorities such as location, size, farm typology and yield potential (Früh-Müller *et al.*, 2019; Langpap, Hascic and Wu, 2008) or – as we suppose and for environmental categories where space is not decisive (e.g. greenhouse gases) – adjusting the payment in a sense that it equals the shadow price which can be estimated when determining the efficient level of pollution.

It needs to be stated that much of the agricultural economics literature assumes profit maximising farmers when investigating effects of uniform AES payments, although authors like Morris and Potter (1995) explore a different understanding of the factors behind scheme participation by adding farmers' motivations and preferences next to profitability. They describe four profiles related to AES participation (active adopters, passive adopters, conditional non-adopters, reluctant farmers). Such profiles are clearly hard to be identified as they are linked to variables that cannot directly be observed by the researcher. In Chapter 5 we did try to uncover them as it has been done by various authors, also in a context of PES (Deng *et al.*, 2016; Schroeder, Chaplin and Isselstein, 2015). As regards the criticism we put forward when it comes to PES (with AES arguably being a type of PES) implementation which does not match their theoretical underpinning, Wunder *et al.* (2020), Ferraro (2018) and James and Sills (2019) have all recently elaborated aspects that cover similar perceived weaknesses of PES, albeit focusing less on the theory-implementation relation. Wunder *et al.* (2020: 227–228) list nine major restrictions of PES establishment to be at play, where especially "paying for (perhaps wrong) proxies, not ES delivery", potential noncompliance and "the limited willingness/organizational capacity to pay for the ES" (humans show a tendency to free-ride) are closely related to our findings. They further identify adverse self-selection, poor administrative targeting of PES, which are often developed with political economy motives that lack environmental goals (Da Rosa Conceição, Börner and Wunder, 2015), leakage effects, credit/rebound effects (to occur if newly introduced schemes create wealth that eases credit access, which in turn results in intensification), motivation crowding and land-tenure insecurity as critical factors that can make PES go wrong. Literature focusing specifically on AES mentions similar drawbacks. Cullen *et al.* (2018) additionally report conflicting objectives of different schemes and an increasing complexity in scheme design and implementation – which ultimately leads to high transaction costs as stated in Chapter 3 – as hurdles, Beckmann, Eggers and Mettepenningen (2009) state the importance of increased stakeholder participation in AES development and McKenzie *et al.* (2013) argue that well-designed landscape-scale schemes are likely to be more beneficial than farm-level schemes. Hodge (2001) list further hurdles including limited knowledge of public demand for environmental goods, a lack of incentives for entrepreneurship, a fallback after program participation, the transparency of regular payments and the definition of property and capturing goodwill of farmers. Many of these known drawbacks of PES or agri-environment schemes have their origin in empirical work, however, evaluations of the environmental and economic performance and impacts of AES are still limited due to the lack of systematic, detailed (farm-level) data on the type of scheme, eligibility, payment levels, environmental quality and agricultural practices or outcomes (Hasler *et al.*, 2022). Thus, a number of hypotheses, some of which were set out in Chapter 3, remain untested and leave room for future research. Future empirical work will also be needed to investigate whether proposals that have been made for innovations to the design of AES – including result-based payments (Burton and Schwarz, 2013), creating incentives for the spatial coordination of conservation activities (Parkhurst *et al.*, 2002), adopting collaborative AES (Emery and Franks, 2012), using nudges to influence social norms and foster landscape-level environmental protection (Kuhfuss *et al.*, 2016), auctions (Latacz-Lohmann and van der Hamsvoort, 1997), value chain or combined approaches (Uthes and Matzdorf, 2013).

Regardless of which measures will prove to practically work best and be most cost-effective, one can state today already that the "greening" of agricultural policies is likely to continue. The recent reform of the CAP can be considered another step in this direction with for example the creation of enhanced conditionality, the introduction of eco-schemes in the first pillar and broadening of the scope of AES in terms of environmental goals. To what extent the new green architecture, especially the eco-schemes, really change the agri-environmental situation, has been widely discussed in the literature (e.g. Birkenstock and Röder, 2019), so have design issues of eco-schemes (e.g. Latacz-Lohmann, Termansen and Nguyen, 2022). Considering the list of potential agricultural practices that eco-schemes could support provided by the European Commission (European Commission, 2021), some EU member states might set organic farming as an eco-scheme. This could help the EU in achieving the goal of having at least 25% of the EU's agricultural land under organic farming by 2030 as formulated in the Green Deal. A number of measures promoting organic farming on regional, national and EU levels other than through eco-schemes are already and will be implemented. One of these is the Bavarian organic flagship region programme, which was evaluated in Chapter 5. Like organic farming policies in general, it was developed despite ongoing debate, especially among ecologists and (agricultural) economists, about whether organic farming is an effective way of how to protect nature. It boils down to the question whether humans should be sharing their landscapes with nature by utilising agricultural areas and forests in an eco-friendly manner or whether they should be sparing large parcels of land for the exclusive use of flora and fauna. The latter approach advocates intensive agriculture on productive land whereas the first one favours conservation measures on working lands. In terms of biodiversity, the "sparers" have good arguments demonstrating that locally and in the short run, species do better when segregating conservation from agriculture rather than farming land more wildlife-friendly (e.g. Dotta *et al.*, 2016, Phalan *et al.*, 2011). They can further put forward that all farming is bad for nature and that even wildlife-friendly agricultural land or forests are no good substitutes for natural ones (Phalan, 2018). Proponents of the sharing concept, on the other hand, criticise that studies such as the ones mentioned earlier only assess biodiversity developments in the short term. In the long run, they argue, isolating species in protected areas will lead to a reduction of species (e.g. Kremen and Merenlender, 2018). Furthermore, agricultural intensification will only deliver more land for nature if there are strict rules to protect land not yet used for farming. Otherwise, the Jevons Paradox, named after the British 19th century economist William Jevons, might happen in agriculture. It occurs when for example technological progress increases the efficiency of resource use and thus reduces the amount needed for any one use, but the consumption of that resource rises due to an increased demand as a result of falling costs. According to that paradigm, agricultural intensification might in the end lead to more land being used for agriculture. In fact, land savings from intensification seem far less than what would be expected (Phalan, 2018). What is more, reserving land might only benefit few species given that agriculture and forestry will remain the main users of land, especially with climate change and future needs of the bioeconomy. And even protected areas need a certain type of management in order to remove threats to species (Kearney *et al.*, 2020). Kremen and Merenlender (2018) point out the necessity to provide connectivity between reserved lands if the sparing approach is to work out.

At this stage, the land-sharing versus land-sparing debate has stagnated, suffering not least from missing quantifications of benefits and drawbacks of both concepts and from the inability to generalise findings across locations, measurements and species (Bennett, 2017). Authors like Bennett (2017) and Grass *et al.* (2019) have therefore argued to broaden the question to fully address the challenge of ensuring human well-being. They call for incorporating ecosystem services, "issues of governance, equity, poverty, and the other important social factors that contribute to food security and human well-being for nations and individuals" (Bennett, 2017: 2) in studies on sparing or sharing land. Like other authors when it comes to intensive or extensive agriculture, they conclude that land-sharing and land-sparing are not mutually exclusive and that both are needed to balance management necessities for the multifunctionality of agricultural landscapes. AES or organic farming as ideas of land-sharing can thus be considered as elements of future landscape management systems and researching tools and policy approaches that promote their uptake and effectiveness is likely to remain high on agendas. Especially the question as concerns how the optimal mix of farming system to maximise ecosystem services shall look like will need further research. Being aware today already about which policies or measures can promote different farming systems will be beneficial in the days to come. In this respect, Chapter 5 and the co-authored studies give some hints as to what works in which setting, bearing in mind all limitations discussed in the respective articles.

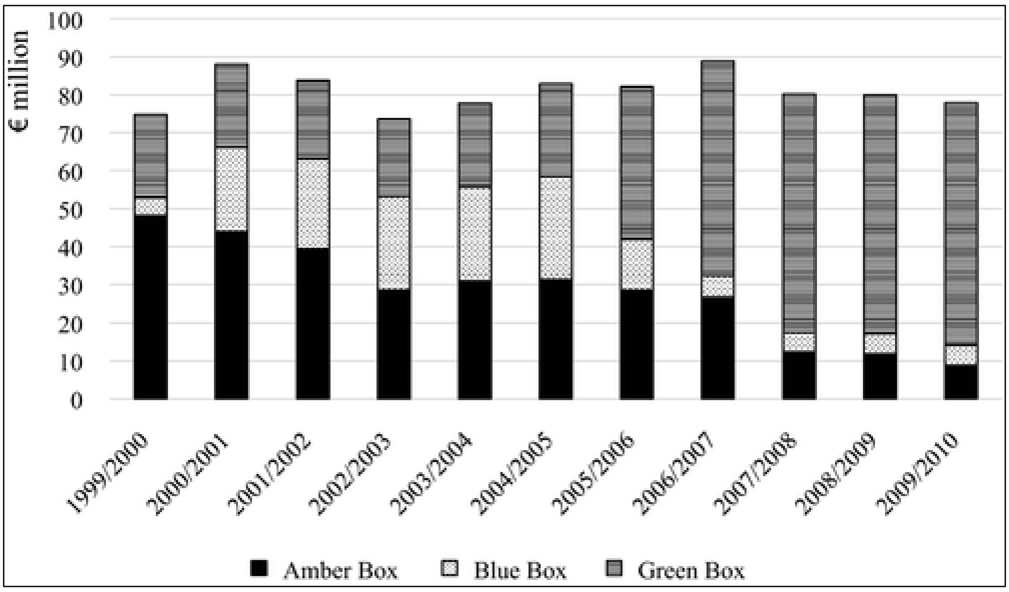
Aspects that look at (green) agricultural policies from another angle are dealt with in Chapter 4 and 6. While in Chapter 4 compliance of AES with WTO rules is the main focus, Chapter 6 investigates one of the most important and arguably most discussed agricultural policy change, namely decoupling. It refers to the generalised tendency to separate subsidies from production levels. In the EU, full decoupling of farm support was established in 2005 with the Fischler Reform. It has been considered an essential policy strategy to reduce international trade distortions associated with support to farmers and the agricultural sector as a whole. Decoupling is further expected to make farms and farmers orient their production towards a fully competitive market. In the EU agricultural policy context where one goal is to guarantee a fair income for farmers, decoupling also helps to maintain the support to farm income. As can be expected, numerous agricultural economists have discussed and justified decoupling or deregulation with a specific interest in investigating the type and size of responses of the farming sector to this new support regime. While over time, empirical and theoretical evidence disproved that such payments were, as claimed by many program developers, production neutral (a good overview on this aspect can be found in Bhaskar and Beghin, 2009), theoretical dispute continues as regards farm-level responses – a dispute which is supported by diverging empirical findings on these responses (Wagener and Zenker, 2020)[35]. According to Esposti (2017: 502), "the economics of decoupling is complex because the determinants and mechanisms of the response of the farms are many, they may interact in many different ways, and this interaction may substantially differ across farms". In a static environment where uncertainty does not exist, the logic behind the response to decoupling is relatively straightforward, as Esposti (2017: 502) notes: Decoupling alters the marginal values associated with each farm activity/production as a change in relative prices. Farms face environmental, technological, financial or other constraints that affect their responsiveness, which evidently depends on the characteristics of individual farms. This already complex situation gets even more complicated when moving to a dynamic environment with uncertainty. Farmers maximise profit or utility over an intertemporal horizon. Consequently, the reaction to decoupling also affects intertemporal decisions (e.g. investments and savings) and by definition involves assumptions and expectations. Nonetheless, a number of authors such as Burfisher and Hopkins (2004) or Antón (2006) argue that comparative static modelling under certainty is still the theoretical foundation of any empirical work on decoupling. This

[35] It is worth stating here that literature on decoupling points out that decoupling analyses cover at least two areas. Esposti (2017) calls the first dimension the economics of decoupling, a mostly theoretical dimension which consists of understanding the mechanisms and determinants with which decoupling affects the farmers' production decisions. The second dimension can be called the empirics of decoupling which concerns the several challenges encountered in actually measuring the size and direction of this production response and of the consequent aggregate effects (trade effects for example).

supports our modelling approach in Chapter 6. It is further backed by the lack of well-developed, comprehensive micro-data studies on the topic and the disregard of farm-level heterogeneity. As concerns these aspects, Chapter 6 contributes both methodologically and empirically to the existing literature. Future studies could, instead of focusing on the overall change of input use or output produced, investigate the exact input or output mix change, i.e. measure allocative efficiency as an expected impact of stronger market orientation. Another important, though slightly different aspect of the decoupling debate that seems to be unsolved is the issue of capitalisation of subsidies, i.e. the question to what extent farm subsidies are capitalised into land rental, but also other input prices. In the EU, high capitalisation rates would contradict the objective of the CAP to direct its "support exclusively to active farmers" (European Commission, 2010: 3) and can cause distortions in income, competitiveness and the economic performance of farm businesses. In fact, a certain capitalisation has been found by many authors (e.g. Guastella *et al.*, 2018; Kilian *et al.*, 2012; Salhofer and Feichtinger, 2020), however, the extent of the capitalisation rate varies considerably across member states and regions (Salhofer and Streicher, 2005; Varacca *et al.*, 2022).

As discussed above, decoupled payments are still controversial as they do create production effects. These effects can be expected to have trade implications and thus to potentially violate key pillars of the WTO Agreement on Agriculture, which shall limit trade-distorting agricultural domestic support. While there is some uncertainty about the degree to which decoupled payments distort trade, Matthews (2008) argues that they remain significant for individual commodities. In a more recent study, Boysen-Urban *et al.* (2020) show a decrease in trade distortion resulting from the implementation of decoupled support in the EU in 2005, but also reveal "that payments assigned to the green box other than the SFP [Single Farm Payments] have a clear effect on trade" (Boysen-Urban *et al.*, 2020: 41). This finding is in line with our results from Chapter 4, which show that action-based AES fail to comply with WTO rules and thus have trade distorting potential. Clearly, our approach does not measure trade distorting effects directly as can be done with various indicators such as the Producer Support Estimate (PSE) from the OECD (OECD, 2010), the Aggregate Measurement of Support (AMS) and the overall base level of all trade-distorting domestic support (OTDS) of the WTO (WTO, 2004) or the Trade Restrictiveness Index (TRI) and the Mercantilist Trade Restrictiveness Index (MTRI) developed by Anderson and Neary (2005). However, it disproves the claim of the WTO that green box payments do not have or at most minimal effects on production (and consequently likely on trade). This is crucial as in Europe more and more decoupled support and other direct payments of domestic support are classified into the green box of the WTO (Figure VII-1). Furthermore, not least after the current food price spikes and the COVID-19 pandemic, governments partly reorient their domestic agricultural policies in an attempt to guarantee food security. One can thus expect a slowdown in the conversion to less trade-distorting policy measures or even a turnaround. A slight trend towards less trade-friendly measures could already be observed in the 2010s with the 2014 reform of the US farm bill and the recent CAP reform which include insurance and risk management programmes as well as safety net instruments (Matthews, 2016; Shields, 2014). The question of trade distortion is ultimately linked to the sector's importance in terms of national food security and ecosystem services provision and the dependence of agricultural production on natural and site conditions, which vary considerably between countries and regions. This in turn has notable implications on competitiveness if goods are traded on a global scale. In Europe, the support scheme for less-favoured areas, established in 1975 with the aim of preventing land abandonment, preserving farmers in constrained rural areas and maintaining cultural landscapes, could also be regarded as a measure to strengthen the competitiveness of farms facing natural disadvantages. In the long term and given the drawbacks of classical agricultural support, less-favoured area payments and payments for actual nature conservation might be the main support instruments to remain.

Figure VII-1: Development of EU domestic support according to the WTO classification scheme (in € million)



Source: Boysen-Urban *et al.* (2020: 33)

VII.7.1 Concluding remarks

In summary, the empirical studies in this dissertation (co-authored studies included) provide empirical evidence that a) action-based agri-environment schemes have unintended production effects and fail to compensate for income forgone and costs incurred only, thus violating WTO rules; b) decoupling direct payments to farmers from production has a positive effect on agricultural productivity, which does not come at the expense of the environment; c) the appointment of organic flagship regions with the aim of promoting organic farming does not guarantee that farmers switch to organic production; d) the effects of agri-environment schemes in several environmental dimensions such as climate change mitigation, clean water and soil health are heterogeneous, but limited; e) agri-environment schemes do not seem to be successful in reducing nitrogen pollution and that considerable reduction potential exists in terms of nitrogen surplus. Our findings underline that sectoral characteristics, farm heterogeneity, the individual farming context as well as the environment in which farms operate are crucial aspects to be taken into account when it comes to evaluating agricultural policy measures. As it remains challenging to *ex ante* consider all factors that possibly influence farm-level responses to policy measures, *ex post* studies – as provided in this dissertation – are vital to guide policymakers when adjusting existing and designing new agricultural policies, especially as regards the increasing complexity of the agricultural production context described in the introduction of this dissertation.

Methodologically, this dissertation contributes with the empirical application of economic theory (in particular production theory) and impact evaluation using state-of-the-art econometric techniques. All embedded empirical studies model farming technologies and farmer behaviour with sound methods, stress the importance of theoretical consistency and try to build counterfactual scenarios that capture the "what would have happened without situation" as best as possible. As discussed and illustrated by Angrist and Pischke (2009), well-controlled comparisons and/or natural quasi-experiments are essential to detect causal relationships.

Despite all efforts to obtain unbiased and theoretically-consistent estimates, our studies have significant limitations that one needs to be aware of and that offer scope for further research. For example, the study presented in Chapter 5 estimated effects based on repeated surveys with a time span of two years. One can speculate that this time span is too short to assess programme effects and that follow-up surveys would be beneficial. Furthermore, potential spillover effects in border municipalities were not taken into account. Another limitation of our studies is connected to the production function estimations. Authors like Njuki, Bravo-Ureta and O'Donnell (2018) stress the importance of including changing configurations in weather when estimating total factor productivity. Other important factors are related to soil quality or topography. The basic premise is that changes in weather and climate, but also specific site conditions affect agricultural inputs and outputs via realisations and expectations. In the functions we estimated, we did not control for such factors. Furthermore, we did not explicitly address endogeneity issues that can arise when endogenous variables appear on the right-hand side of regression equations. OLS regressions only yield unbiased estimates if the error term is uncorrelated with the independent variables. Correlation between an independent variable and the error term can arise from the dependent and the independent variable being jointly determined (simultaneity), from unobserved variables that affect both the dependent and independent variable (omitted variable bias) or from measurement errors. One prominent remedy to obtain consistent estimates is to use instrumental variables. Two last examples of weaknesses of our studies are linked to the DiD estimations and the use of environmental indicators. Our DiD models are not estimated using clustered standard errors as suggested by for example Bertrand, Duflo and Mullainathan (2004) and our environmental indicators are not able to capture direct environmental effects of agricultural production. The latter point is mainly a result of missing farm-level environmental information, which calls for improving data collection and monitoring.

Finally, it needs to be stated that the external validity of our results can be tested by doing the same or similar analyses in additional locations or for different economic sectors. For example, organic flagship region programmes (Chapter 5) also exist in other German federal states. So do AES in a certain heterogeneity all over Europe. Particularly with regard to their growing importance (eco-schemes in the new CAP) and new designs (e.g. result-based, collective), impact evaluations will also be needed in the future.

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