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Analysing the Feasibility of Counterfactual Methods for Estimating Environmental Effects of the CAP.

Potential Evidence based on FADN data.

Competence Centre on Microeconomic Evaluation (CC-ME)

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Contents

Abstract

The Common Agricultural Policy (CAP) has been one of the main pillars in the construction of the European project. While its fundamental goals remained the same, the policy over the time adapted to evolving needs: since 2014 specifically with and ever-increasing regard also towards environmental objectives. This Report aims to assess the feasibility of estimating a causal relationship between the CAP and environmental outcomes. It offers an assessment of the present state of both data availability and associated obstacles and deficiencies. Different counterfactual impact assessment scenarios based on the FADN survey at the European level are summarised in a set of concise documents, referred to as fiches, which provide details about the databases and variables to be used, the methods to be applied, and give a judgement on the current feasibility at different geographical levels within the EU territory. Where applicable, references to further complementary data sources containing potentially useful information are outlined.

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Executive Summary

Motivation

The European Commission's **Better Regulation Guidelines** emphasize the crucial importance of both continuously monitoring and of evaluating the impact of the policies implemented. This proactive approach empowers Member States and the Commission to make evidence-informed decisions and to improve subsequent future actions. The **Evaluate First** principle, to which the European Commission has been committed for a long time and increasingly since adopting the 2015 **Better Regulation Agenda**, involves conducting rigorous ex-post evaluations of past interventions as an instrument towards the improvement of policy outcomes in subsequent implementations.

Counterfactual Impact Evaluation

Counterfactual Impact Evaluation (CIE) methods are widely recognised as the most suitable tools for policy evaluation, given that they allow for the isolation of **causal link between interventions and outcomes**. In contrast to ex-ante simulation methods, which aim to predict future effects, CIE exercises measure the **actual impacts** of already implemented programs. CIE is a sophisticated statistical engine, powered by rigorous economic modeling and high-quality data.

This Report's ambition is to explore the possibility of establishing the existence of a **causal chain between CAP policy intervention, agricultural practices and environmental outcomes** across European farmland. CIE methodologies applied to linked microdata on European farm characteristics, CAP policy interventions, observed farming practices and environmental measurements are also able to shed light on the **magnitude** of the impacts that CAP policy interventions have been having on outcomes of interest (e.g., the environment in recent years and decades). On the basis of such results, one can estimate **what might have occurred** under **alternative policy scenarios** or **in the absence of any policy intervention**.

Report highlights

- The Report provides arguments for the importance of estimating the impacts of CAP interventions through a CIE framework, that is, uncovering the **causal links** between policy measures and outcomes of interest.

- Throughout the report, special attention is devoted to **environmental variables** as key outcomes of interest when assessing the impact of CAP policies and of their environmentally-targeted components in particular. The **Farm Accountancy Data Network (FADN)** survey is used as the main source of microeconomic data on European farms and their detailed activity.

- The Report provides an overview of the current situation in terms of **data availability and data-related challenges and shortcomings** when it comes to engaging in CIE exercises on environmental outcomes in combination with the FADN survey **at the European level**.

- **Greening Payments** for environmentally-friendly farming practices, such as the maintenance of permanent grassland, crop diversification and the protection of ecological focus areas, represent the main focus of the report in terms of exploring the feasibility of CIE exercises. The specific rules under which Greening Payments have been allocated over the 2014-2022 period are explored as sources of the quasi-experimental variation needed to empower CIE methods.

- The feasibility of a number of different counterfactual impact evaluation scenarios is summarised in **concise Fiches**, that provide details on the databases and variables to be used, CIE methods to be applied, and gives a judgement of the current practicability at different geographical levels within the EU.

This Report originates from an ongoing collaboration between the Competence Centre on Microeconomic Evaluation (CC-ME) at the Joint Research Centre (Unit S3) and the European Commission's Directorate-General for Agriculture and Rural Development (DG AGRI). This feasibility report represents a first step towards the goal of assessing environmental impacts of the past CAP cycle through counterfactual methods, to further enhance the evaluation and aid the design of current and future Policy cycles, primarily at EU but also at Member State level. Rigorous ex-post evaluations based on counterfactual methods constitute the main vocation of the CC-ME, a research team which is committed to providing high-quality, data-driven, and evidence-based support to EU policymaking.

1 Introduction

This Report contributes to answering the following questions: ‘Are counterfactual impact evaluation methods (CIE) applicable when measuring the environmental impacts of the EU Common Agricultural Policy?’ and ’If so: where/when/how are CIE methods applicable?’

Policy evaluation has a large learning potential: lessons learned can guide in balancing and optimising intended outcomes in future policy implementation. This is in line with the “evaluate first principle” put forward in the EU Better Regulation agenda.

The CAP is a central piece of EU policy, aiming to support the economic, social, and environmental dimensions of agriculture in Europe. Increasing the knowledge about positive environmental impacts that the CAP has achieved would bring large value-added to European policy making. This Report aims at evaluating the 2014-2022 cycle in order to inform future policy decisions and promote performance based policy reforms.

CIE methods are a powerful set of tools employed to answer counterfactual questions; they draw their strength from rigorous research designs and detailed data. The ideal CIE research design is the **“randomised experiment”**, in which the policy intervention is randomly assigned to ‘treated’ units: in such cases, causal inference is drawn by comparing the observed outcomes of treated and non-treated units. Recent advances in quantitative methods – also known as **credibility revolution** in Economics – highlight that empirical analyses, based on observational data, should benchmark to randomised experiments as much as possible. Experimental and quasi-experimental studies allow for the isolation of specific sources of variations and offer appropriate tools through which to address the counterfactual question: “What would have happened without that specific policy?”. However, it is rare to encounter such situations in real-life policy scenarios, given that policies are typically not randomly assigned to some unit and not to others and are, instead, assigned according to predefined, deliberate criteria such as e.g. a specific need or merit. In such non-experimental settings, finding differences in the outcomes of units that received the policy treatment and those that did not is not sufficient claiming a causal relationship between the policy intervention and the outcome. In such settings, CIE methods retrieve **quasi-experimental conditions** to estimate the causal impact of the intervention, finding ways to take into account (‘control for’) the range of other factors influencing outcomes of interest. As such, good-quality research designs have to include appropriate definitions of: policy interventions; treated and ‘control’ units; outcomes; all factors inducing variation on the policy allocation and outcomes themselves. The implementation of identification strategies and the availability of good-quality, disaggregated data are fundamental for the elaboration of valuable ex-post causal evaluations.

This Report aims to promote the application of CIE methods at highly relevant EU-level policy areas, such as the CAP, adopting the following specific objectives:

- The focus is on the relevant CAP Regulation in the 2014-2022 period, with a spotlight on targeting sustainable management of natural resources and other environmental outcomes (biodiversity, soil, water, climate change and greenhouse gas emissions).
- FADN is used as the main currently available data source. Further reference is made to additional data sources that will be included in future research.
- Only causal identification strategies for analysis are discussed (CIE methods).
- This report also covers, whenever possible, evaluation at the Member State and the regional levels.

This Report follows a stream of collaboration with DG AGRI A3 on investigating the socio-economic impact of CAP, and represents a first step towards the goal of systematically evaluating the CAP on environmental outcomes using CIE methods i.e. quantifying the net effect of the CAP from an EU perspective. The Report charts feasibility of CIE methods for the CAP, thereby exposing which identification strategies are available for CAP funds targeted at environmental objectives.

At this stage, CIE feasibility is investigated based on the FADN dataset, which is a representative yearly survey which is harmonised at the EU level collecting data from commercial farms above a minimum size, variable across Member States (MS), and represents 50% of the EU farming population, and more than 90% of the production, and of the agricultural area.

The environmental content of FADN variables is mainly of the indirect type. Environmental outcomes (emissions, nutrient balances) are not quantified at the farm level. Still, variables related to farms' activity, such as either the number and the density of livestock, or the quantity of fertilisers and pesticides purchased, may be monitored in FADN as descriptors and drivers of environmental outcomes. Approximating environmental outcomes by farms' input usage has been already exploited by some CIE empirical research, and has been supported theoretically by the agricultural literature,as recently summarised by the Reports of LIFT Horizon 2020 project (Rega et al., 2021). The analysis can be extended by incorporating environmental data from additional sources, thereby providing more comprehensive and robust insights into the correlation between environmental factors and farm-related data.

In-depth analyses are conducted for CAP measures such as Greening, Agri-environmental-climate (M10), Organic (M11), and ANC (M13) referring to 2014-2022 CAP cycle. The following CIE methods are discussed: Regression Discontinuity Design and Difference in Difference for the evaluation of Crop Diversification and Ecological Focus Area; Propensity Score Matching for the evaluation of M10 and M11.

The feasibility of each analysis proposal is associated with the availability of a minimum number of treated and non-treated observations. However, it is essential to acknowledge that the actual implementation of CIE methods might lead to further loss of observations.

The Report is structured as follows: Section 2 presents the institutional framework by describing the CAP green architecture from 2014 onward; the motivations for and the main obstacles to CAP evaluation are then discussed. Section 3 reviews the relevant environmental outcomes and the related data sources; the main environmental-related contents of FADN are then exposed and discussed. Sections 4 and 5 provide detailed descriptions of the relevant elements of policies benefiting the environment included respectively in Pillar 1 and Pillar 2: existing empirical findings are reviewed, key elements for CIE are investigated, and appropriate CIE strategies, which propose feasible evaluation questions using FADN, are presented. Practical feasibility summaries concerning the presented evaluation questions can be found in Section 6 and main conclusions are drawn in Section 7.

2 The CAP and the European Green Deal

This Section presents the main features of the CAP green architecture from 2014 on. The motivations for CAP evaluation and the main obstacles are then discussed.

2.1 The environmental dimension of the CAP

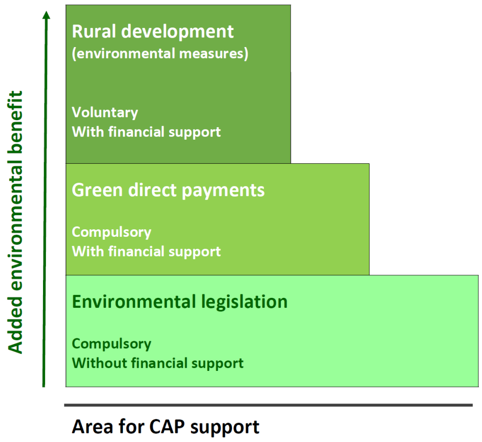
The CAP from 2014 to 2022

The Common Agricultural Policy (CAP) has been one of the most significant policies of the European Union (EU). In 2020, it represented 34.5% of the total EU budget. Since its inception, the CAP has changed considerably, moving from a policy aimed at stabilising prices and markets to a more comprehensive policy characterized by a territorial approach. In particular, during the recent programming periods, there has been an increasing effort to integrate environmental objectives. The CAP has become a multipurpose policy targeted to meeting environmental, social, and economic objectives. It is organised into two pillars. The first pillar is financed by the European Agricultural Guarantee Fund (EAGF) and receives the largest share of the CAP budget, around 75.6% of the total CAP's budget for 2014-2022. Funds under this pillar benefit EU farmers and act via direct payments or market measures like the common organisation of the markets. In particular, traditional forms of income support, as direct payments, have become increasingly greener during the 2014-2022 programming period. This is because of the introduction of cross-compliance (i.e., beneficiaries needing to meet specific standards on environmental management, public, animal and plant health and animal welfare animals in order to receive subsidies).

The second pillar, or Rural Development Policy (RDP), was introduced under the 'Agenda 2000'. It is co-financed by the European Agricultural Fund for Rural Development (EAFRD) and regional or national funds. The RDP aims to achieve three long-term objectives: (i) promoting the competitiveness of agriculture and forestry; (ii) ensuring sustainable management of natural resources and climate action and; (iii) achieving balanced territorial development of rural economies and communities, including the creation and maintenance of employment. RDP is implemented through the rural development programs (RDPs) drawn up by the Member States and regions. These multiannual programs apply a tailor-made strategy that meets the specific needs of the Member States or regions, and is based on a mix of measures selected from a "menu" detailed in the rural development regulation (Regulation (EU) No 1305/2013).

The CAP aims to achieve them in both a socially and economically sustainable way for farmers, rural communities, and the EU. In summary, three lines of intervention, depicted in Figure 1, comprise the CAP Green Architecture of the 2014-2020 programming period, later extended until 2022. The first line concerns obligatory compliance with Community environmental rules. The second row adds compliance with environmental standards and practices as a condition for eligibility for 30% of direct payments under the first pillar of the CAP. The third line rewards farmers who voluntarily sign up for environmental measures for the additional costs of managing their land to produce additional ecological public goods in the second pillar of the CAP. Spending on first pillar, via direct payments, is significantly higher than spending on second pillar environmental measures.

Figure 1: Environmental measures in the CAP architecture. (Source: DG AGRI)



Innovation in CAP 2023 to 2027

A proposal for the CAP reform was presented by the European Commission in 2018. Following extensive negotiations between the European Parliament, the Council of the EU and the European Commission, agreement was reached and the CAP 2023-2027 was formally adopted on 2 December 2021; it entered into force on 1 January 2023. In line with the European Green Deal , the CAP 2023-2027 has three objectives which specifically address environmental issues and reinforce coherence between agricultural and environmental objectives: contributing to climate change mitigation and adaptation; foster sustainable development and management of natural resources; contributing to halting and reversing biodiversity loss, enhance ecosistem services and preserve habitats and landscapes. EU countries are obliged to display a higher ambition on environment and climate action compared to the previous programming period and are required to update the plan whenever climate and environmental legislation is modified. The conditionality aspect relating to environment and climate friendly farming practices and standards is enhanced by imposing a stronger set of mandatory requirements. At least 25% of the budget for direct payments are allocated to (voluntary) eco-schemes, thereby providing stronger incentives for climate-and environment-friendly farming practices and approaches (such as organic farming, agro-ecology, carbon farming, etc.) as well as animal welfare improvements. At least 35% of RDP's funds are allocated to measures to support climate, biodiversity, and environment and animal welfare. The fruit and vegetables sector's operational programmes allocates at least 15% of their expenditure towards the environment (compared to 10% during the 2014-2020 period). Moreover, 40% of the CAP budget needs to be climate-relevant and the general commitment is to dedicate 10% of the EU budget to biodiversity objectives by the end of the EU's multiannual financial framework (MFF) period, something which is strongly supported.

Why evaluate previous CAP cycles?

This subsection is dedicated to explaining the rationale and the motivation behind engaging in CIE of **past** CAP policy cycles. In particular, this Report is focused on assessing the feasibility of applying CIE methods to evaluating the 2014-2022 cycle -which is already closed at the time of writing- so it is worth devoting some paragraphs to highlighting the utility of such an endeavour.

Informing Future Policy Decisions and Future Evaluations. One of the primary reasons for conducting counterfactual impact evaluation is to inform future policy decisions. By examining what might have occurred under alternative CAP policy scenarios, one can gain valuable insights into the potential consequences choices made in the past. Depending on the quality and granularity of the available data, CIE applications may allow the researcher to draw conclusions about **the impacts generated by specific policy components** (e.g., the impact of greening subsidies, the complementary income support for young farmers, coupled direct payments, and so on). Information of this type empowers policy-makers to make wiser decisions, considering the lessons learned from previous policies and building them into the iterative process of policy design. Put otherwise, **feedback extracted from impact evaluation exercises performed on the 2014-2022 CAP cycle** is likely to help to prevent the repetition of any ineffective (or even harmful) policy components and to encourage the continuation or strengthening of those more likely to yield desirable outcomes. Ex post evaluations from the previous CAP cycle also allow for **future evaluation exercises**, as the environmental policies included in the 2014-2022 CAP are also foreseen in the 2023-2027 CAP.

Resource Allocation, Accountability and Transparency. The budget of the European Union is limited, so an efficient allocation of resources is essential. Counterfactual policy impact evaluation aids in resource allocation and optimisation by providing data-driven insights into which policies deliver the most significant benefits for a given cost. Which components of CAP are the most worthwhile pursuing, in a limited-resource scenario? Answers to questions like these rest on cost-benefit analyses and CIE methodologies represent the most rigorous way of assessing such benefits. The final objective is to prioritise policies that are cost-effective and that have the greatest positive impact on society, the environment, and any other dimension deemed valuable. Counterfactual analysis can also play an important role in ensuring accountability for previous policy decisions. By examining CIE results, citizens, stakeholders and policymakers are enabled to check whether the CAP or any other policy met its intended goals or had unintended negative consequences. For instance, the demand for further CAP evaluations has been recently raised from the European Court of Auditors. Indeed, it has been suggested that the CAP measures, as currently implemented, may be unlikely to significantly enhance the environmental and climate performance (See European Court of Auditors, 2017, 2020, 2021a,b). As a conclusion, there is a pressing need for continuing efforts towards high-quality evaluations of the CAP.

2.2 The evaluation of the CAP

CIE for CAP

Ex-post evaluations of the CAP have been systematically carried out with considerable effort. Among various approaches to support evidence-based policy making, CIE, when feasible, is the gold standard for evaluating policy impact.

Generally speaking, the causal analysis aims to identify the effect of the intervention (denoted 'x') on the outcomes of interest (both intended and unintended – denoted 'y'), also taking any **other** factors or policies influencing the outcomes of interest (so-called contextual indicators, denoted 'z') into account. CIE exercises aim to draw **conclusions about the causal effects of an intervention**, leveraging the description of what happened, and going beyond it, thereby delving into the mechanism leading from intervention to observed changes. In other terms, it would like to conclude that "x causes y, after controlling for the effect of other factors z" (i.e. taking 'z' into account).

As an example, one may observe a negative relationship between the outcome of interest and the introduction of the policy in the data. At such a stage, one should not conclude that the intervention was ineffective or detrimental: this is because **"what would have happened without the policy"**, known as **the counterfactual outcome**, could have been even worse. In order to estimate the impact of a programme on outcomes, the chosen impact evaluation method must, therefore, estimate the counterfactual. Isolating the observed changes and attributing them to the intervention is a challenging endeavour, but it is necessary one in order to identify causal effects. The implementation of proper counterfactual methods allows for the identification of the causal impact of specific policy interventions and go beyond simple correlation. In a nutshell, CIE requires the following steps: (i) finding a comparison group to estimate what would have happened to the programme participants without the programme, (ii) making comparisons with the treatment group that has received the programme. Finding such comparison groups is the core of any impact evaluation, regardless of what type of programme is being evaluated. The main challenge is to identify a treatment and a comparison group that are statistically identical, on average, in the absence of the programme. Further, a

clear evaluation question also needs to be accompanied by the specification of which outcome measures will be used to assess results, including in the case of multiple outcomes.
Empirical CIE analyses, however, are made difficult by the pervasive confounding factors that include both contemporaneous factors, which are correlated with the treatment intervention and outcomes, and selection bias, where treated units are selected, or select themselves, to receive the intervention on the basis of characteristics that also affect the outcome. For example, while analysing policies that target the environment, one should expect that changes in weather, as well as in other economic characteristics (such as the geography, the employment and technology opportunities), may affect environmental outcomes. Furthermore, the characteristics that lead programme administrators to target certain farms, plant or animal species, or geographical areas, are frequently correlated with outcomes. Voluntary programmes also suffer from self-selection bias. For example, incentive programmes often reward farms for not engaging in environmentally destructive activities. In order to conduct a rigorous analysis, one must consider the possibility that such (non-)actions would have occurred even in the absence of the programme. Counterfactual thinking is absolutely essential to distinguish between programme effects and hidden biases, but it is still not always used even in ex post evaluation studies. That is why this report emphasises the importance of rigorous CIE analysis wherever possible. The benchmark for scientific quantitative methods is **randomised control trials**, where units are assigned to treatment or to the control group at random. This solves the selection bias issue. When randomised control trials are not possible, one can resort to **quasi-experimental methods** that mimic the experimental design in order to solve the selection bias, under appropriate assumptions. Some of the typical CIE methods, which might be implemented to evaluate the CAP, are briefly listed below. Tool 68 of the Better Regulation Toolbox describes the methods for evaluating policies' causal effects; additional helpful material is available in Annex A.1; full references are given in the following books: Angrist and Pischke (2015), Imbens and Rubin (2015) and Angrist and Pischke (2009).

- Propensity Score Matching (PSM)
  Matching methods use statistical techniques to construct a comparison group even when selection into treatment is not random (non experimental data). Matching estimators look for one (or a set of) nontreated unit(s) that are most similar to a given treated unit in terms of observable characteristics. These methods enable comparisons between treated and control units in a way that facilitates an understanding of causal relationships between interventions and outcomes. The probability that a given unit is treated is the propensity score; a model for the propensity score is usually fitted on the observed characteristics, which serve as explanatory variables. The closest units in terms of fitted propensity score become the comparison group, and they are used to produce an estimate of treatment effect. See Rosenbaum and Rubin (1983). In the context of CAP evaluation, matching methods have been used to evaluate the different impact of organic and conventional farming systems (Cisilino et al., 2019) as well as the impact of

protected areas (Andam et al., 2008), to mention a few. Cisilino et al. (2019), for example, compare the environmental performance of organic farms with respect to conventional farms and they evaluate the impact of Organic Agriculture subsidies. In this case the propensity score is defined as the probability of participation for a farm given a set of characteristics. The basic idea of the matching is to combine each treated with one or more non-treated that is as similar as possible thereto. The pairing (between treated and non-treated) is based on the Propensity Score (PS), which is the conditional probability that a farm is treated given its observable pre-treatment characteristics (covariates).

- Difference-in-Differences (DiD)

  The difference-in-differences (DiD) estimation procedure is helpful when working with treatment effects over time in which panel or longitudinal data (e.g., information on farms are repeated over time (even two time periods)) are available. DiD methods evaluate the difference in mean outcomes between treated area/farm and matched non-treated area/farm after receiving policy support, and the difference in the mean outcome between treated area/farm and matched non-treated area/farm in prior period to the programme implementation. DiD methods compare changes (or growth rates) in outcomes between treated and untreated units where treated and untreated units are selected following a reasoning similar to the matching techniques. See Roth et al. (2023) among others.

- Regression Discontinuity Design (RDD)

  The RDD is an impact evaluation method for programmes that have a discontinuity in the eligibility criterion that sets a threshold, above (or below) which units are (are not) treated. The most important requirement to apply RDD is the existence in the continuously distributed variable (‘running variable’) that contains a clearly defined cutoff. Such a threshold should define which units in the data are assigned to ‘treatment’ and which to ‘control’. RDD estimates impacts around the cutoff and allows for the exploitation of this special assignment mechanism to identify a local treatment effect. Indeed, the main drawback of the design is a potentially low external validity because causal identification is highly local. RDD is often used in agricultural contexts as programmes and policies are often implemented by means of running variables with thresholds. For example, in the implementation of Environmental Focus Areas, a sample of farms receive a treatment result from a deterministic rule assigned by the regulation. In such cases, RDD makes it possible to exploit this special assignment mechanism to identify a local treatment effect. See Cattaneo and Titiunik (2021), Wuepper and Finger (2022), Sauquet (2022), and Varacca et al. (2022).

In principle, by means of those statistical methods, the evaluation of the CAP might concern either the entire CAP or the single measures programmed under Pillars 1 and 2, separately.

However, when addressing the impact of a selection of aggregated CAP funds or of the entire CAP, causal identification might be complicated due to a series of policy traits, as discussed below.
The CAP is not a single programme, but is instead made up of a large set of measures and the beneficiaries might receive numerous interventions in a given period. In statistical terms, this implies that CAP is not a simple treatment, but is a **mix of treatments**.
On one side, an approach that attempts to consider the impact of each of the hundreds of the individual CAP instrument is neither feasible nor desirable. Due to the large scale of this treatment vector, a certain level of aggregation of CAP funds, which might allow comparisons over time and between beneficiaries, is unavoidable. On the other side, the CAP's overall policy assessment requires a characterisation of the policy mix, and, despite the reduction in dimensionality achieved by any significant level of aggregation, implementing an evaluation strategy based on multiple treatments still poses serious challenges; this is because the heterogeneity which arises from a number of different dimensions exacerbates the problem of controlling for pre-treatment variables.

Moreover, in their simplest form, CIE methods are based on comparing the results of the units receiving the treatment with the untreated units, which under the assumption of a random allocation of the treatment constitute the counterfactual scenario. Instead, the CAP is universal and covers almost all farms and areas. When the observation units are regions or farms, then all units are likely beneficiaries. This implies the **absence of a control group** of untreated units to establish counterfactual comparisons with CAP recipients. In this case, a counterfactual scenario might exploit different intensities of the funds.

Existing literature on ex-post effects of the CAP as a whole

As far as the effects of the entire, or highly aggregate, CAP are concerned, Table 1 illustrates a careful selection of published papers investigating the CAP at aggregate level from the ex-post perspective.
For the reasons discussed in the previous paragraph, no contribution exploits CIE methods and only a few seriously take the possible influence of contextual factors on outcomes themselves and on the policy adoption into account. The analyses are mainly based on regression or Input-Output models and, hence, do not provide causal claims. At the regional level, the main findings support a positive effect of the CAP on several socio-economic outcomes, such as employment, per capita household income, agricultural output, and convergence. At the farm level, CAP is found to sustain agricultural income, with detrimental effects on Total Factor Productivity, at least for some crops. In the end, the only study focusing on effect of the CAP on environmental outcomes is the one by Coderoni and Esposti (2018). They investigate the role played by the CAP on agricultural GHG emissions approximated, at the farm level, by Carbon Footprint although they do not implement a causal identification strategy.

Table 1: Selection of Literature on ex-post effects of the CAP at aggregate level

Outcome	Paper	Effect	Level	Coverage
GDP	Crescenzi and Giua (2016)	Positive	Regional	12 EU15
GDP	Bonfiglio et al. (2016)	None/mixed	Regional	EU27-2007
Household income	Loizou et al. (2019)	Positive	Regional	EL
Agricultural Output	Juvancic et al. (2005)	Positive	Regional	SI
Employment	Loizou et al. (2019)	Positive	Regional	EL
Total and Agri labour requirements	Juvancic et al. (2005)	Positive	Regional	SI
Unemployment	Galluzzo (2018)	Negative	Regional	RO
Emigration	Galluzzo (2018)	None/Mixed	Regional	RO
Beta-convergence	Montresor et al. (2011)	Positive	Regional	EU15
Reduction of development disparities	Juvancic et al. (2005)	Positive	Regional	SI
Regional disparities in income	Hansen and Herrmann (2012)	None/Mixed	Regional	DE
Out-farm migration of employment	Tocco et al. (2013)	None/Mixed	Individual	FR, HU, IT, PL
Farm income	Biagini et al. (2020)	Positive	Farm	IT
Cereal Farm TFP	Biagini et al. (2022)	Negative	Farm	FR, DE, IT, PL, ES, UK
Carbon Footprint	Coderoni and Esposti (2018)	Mixed	Farm	IT

Taken together, the listed points and the limited number of studies on the topic emphasize the complexity of implementing a CIE of the CAP at the aggregate level.

In summary, it seems that a minimum level of CAP disaggregation has to be introduced when its causal impacts are being investigated. An example is provided by Dumangane et al. (2021), who evaluate the impact of the CAP on socio-economic outcomes, by considering the CAP in terms of a (limited) number of economically meaningful funds, respectively Market Measures and Direct Payments, in Pillar 1, and the whole of Pillar 2.

The analyses of the CIE's feasibility of the CAP, which will be discussed in this Report will, therefore, concern specific measures, rather than the entire CAP.

3 Environmental outcomes and data sources

This section presents the relevant environmental outcomes of the policy evaluation exercise and the related data sources. The first subsection discusses the expected relations from policy to environmental outcomes, the second subsection describes the outcomes of interest while the related data sources are listed in the third paragraph.

3.1 Expected relations from Policy to Environmental Outcomes

Over the past 30 years, CAP has been increasingly oriented towards improving the environmental and climate performance of the European agriculture, as confirmed by the CAP 2023-2027 programming period. Furthermore, the Green Deal strategy outlined a comprehensive approach to facilitating the transition towards sustainable food systems that links all actors in the system in a holistic approach; this is a path sketched out in the Farm to Fork (F2F) and Biodiversity (BDS) Strategies. The environmental measures that encourage green farming and enforce environmental rules have already been an essential component of CAP 2014-2022.
The sustainable management of natural resources and climate action - with a focus on greenhouse gas emissions, biodiversity, soil and water - is one of the three general objectives for the 2014-2022 CAP. Those objectives are targeted by means of Pillar 1 Direct Payments and Market Measures, and the Pillar 2 Measures. As summarised in the Staff Working Document on Impact of the CAP on biodiversity, soil and water (natural resources) (European Commission (2021a)), the general objectives are related to a number of distinct effects on natural resources. In particular,

1. reduced loads of nutrients, organic wastes and chemicals applied on land, achieving nutrient balance;
2. maintenance of soil organic matters, soil structure and carbon sequestration;
3. decreasing risk of leaching and run off nutrients, organic waste and chemicals;
4. decreased risk of soil and bank erosion;
5. decreased water abstraction in soil or water-body, increase of water retention;
6. decrease/halt biodiversity loss.

The following Sections discuss outcomes and the related data sources.

3.2 Outcomes of interest

Greenhouse gas emissions (GHG)

Agriculture is a driving force behind global warming, accounting for approximately 10.9% greenhouse gas (GHG) emissions worldwide in 2021[1]. Having acknowledged the impact of farming on climate change and vice versa, the EC has identified climate change mitigation as a crucial objective of the CAP 2023-2027. In the CAP 2014-2022 most of the measures have the potential to influence greenhouse gas emissions from agriculture even if they are not directly aimed at GHG mitigation.
GHG inventories are estimated according to internationally agreed methodologies that follow the guidelines of the 2006 Intergovernmental Panel on Climate Change (IPCC), see IPCC (2006). Estimations of GHG emissions and removals are relative to the national territory and offshore areas over which the country has jurisdiction. At a country level, national inventories provide estimates for the calendar year during which emissions to (or removals from) the atmosphere occur.
Data on GHG emissions by source sector and year are publicly available at country level (NUTS0) by the Environmental European Agency. A GHG inventory report includes a set of standard reporting tables covering all relevant gases, categories, and years. In the 2006 Guidelines, the following GHGs are covered: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_{20}), hydrofluorocarbons ($HFCs$), perfluorocarbons ($PFCs$), sulphur hexafluoride (SF_6), nitrogen trifluoride (NF_3), trifluoromethyl sulphur pentafluoride (SF_5CF_3), halogenated ethers, and other halocarbons. Indeed, those gases have Global Warming Potentials (GWPs) where GWP compares the radiative forcing of a tonne of a GHG over a given time period (e.g., 100 years) to a tonne of CO_2.

GHGs emission and removal estimates are classified by main sectors. Agriculture belongs to the Agriculture, Forestry, and Other Land Use (AFOLU) sector and has unique characteristics: many processes lead to emissions and removals of GHGs, which can be widely dispersed in space and are highly variable in time; the factors governing emissions and removals can be both natural and anthropogenic (direct and indirect).

For the AFOLU Sector, anthropogenic GHG emissions and removals by sinks are defined as all those occurring on ‘managed land’, where managed land is a land to which human interventions and practices have been applied to perform production, ecological or social functions. Guidance and methods for estimating GHG emissions and removals for the AFOLU sector now include:

- CO_2 emissions and removals resulting from C stock changes in biomass, dead organic

[1] Gases that trap heat in the atmosphere are called greenhouse gases - GHGs. Data on greenhouse gas emissions and removals, sent by countries to UNFCCC and the EU Greenhouse Gas Monitoring Mechanism (EU Member States), are available at `https://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer`

matter and mineral soils, for all managed lands;

- CO_2 and non-CO_2 emissions from fire on all managed land;
- N_2O emissions from all managed soils;
- CO_2 emissions associated with liming and urea application to managed soils;
- CH_4 emissions from rice cultivation;
- CO_2 and N_2O emissions from cultivated organic soils;
- CO_2 and N_2O emissions from managed wetlands;
- CH_4 emission from livestock (enteric fermentation);
- CH_4 and N_2O emissions from manure management systems; and
- C stock change associated with harvested wood products.

For agriculture, the IPCC method accounts for non-CO_2 GHG emissions (N_2O) and CH_4. The non-CO_2 GHG emissions are calculated using emission factors (EFs) based on such factors as the amount of nitrogen fertiliser applied, or the number of livestock of different categories kept on farms.

As mentioned previously, the IPCC refers to a specific inventory that uses statistics at a national level. Therefore, they are not entirely appropriate for a local or regional scale where detailed information on the structure of the agricultural sector and activities becomes more relevant. However indirect methods to estimate agricultural GHG emissions at a farm level have been proposed in the literature, see Coderoni and Esposti (2018) and Stetter and Sauer (2022) among others.
In this case, emissions are regarded as the outcome of a combination of farm activities and management practices. The IPCC's methodology has been adapted to evaluate the emission intensity of a farm linking GHG emissions to economic indicators. In particular, the simplest approach to estimating GHGs is to combine information about the extent to which a human activity takes place (activity data, AD), with coefficients which quantify the emissions or removals per unit activity (emission factors, EF). The GHG emissions at farm level are, therefore, calculated as follows:

$$EM_i = \sum_{l=1}^{L} (AD_{il} \times EF_{il}) \tag{1}$$

where EM_i describes total GHG emissions of a farm i; AD_{il} refers to some activity data of emission source $l = 1, \dots L$ while EF_i is the emission factors. For example, in the methane emissions from Enteric Fermentation of livestock, AD is the number of head of livestock species/category while EF is the kg CH_4 released per unit and per year of the defined livestock population.

We might notice that, operationally, while *AD* data can be retrieved from FADN survey (i.e., at farm level), data on *EF* are taken from data published at the regional level.

Carbon Sequestration (CS)

Another aspect of GHG is Soil carbon sequestration. CS primarily occurs when atmospheric CO_2 is transferred to soils and plants absorb CO_2 during growth via photosynthesis. Soil organisms transform plant material (such as crop residues and leaf litter) into soil organic matter; this, in turn, retains water and nutrients in the soil, thereby promoting plant growth. Depending on how the land is managed, these processes can lead to a net transfer of carbon from the atmosphere to the soil over time. While large quantities of atmospheric carbon dioxide are consumed by plants during the process of photosynthesis each year at the global scale, much of this is returned to the atmosphere within a short time period by the reverse process of respiration ot through the mineralisation of the soil organic matter. Operationally, net CS is the difference between the uptake and release of CO_2 from a particular environment, see Rees et al. (2005). For convenience, all practices that can increase soil carbon stocks, either by enhancing CS or by preventing losses of soil carbon, are collectively defined as net CS practices.

Land management has a significant impact on soil organic carbon (SOC) stocks with a number of measures clearly leading to carbon emissions, such as the conversion of grasslands to arable cultivation, conventional tillage, the degradation of organic-rich soils through pressures such as erosion, soil sealing and compaction. Conversely, a number of practices can be used to preserve and increase SOC levels (e.g., water management in wetlands, restoring grasslands, reduced tillage, and crop rotations).

In the CAP 2014-2022, several good agri-environmental conditions (GAEC) contribute directly to climate mitigation, with main objectives on the GAEC referring to preserving carbon stock and maintenance of soil organic matter, protection of carbon-rich soils. Other GAECs, even if they do not explicitly mention climate-related objectives, will have beneficial effect on soil organic carbon. GAECs on landscape features will also represent an opportunity to increase storage of carbon in biomass. These are further enhanced by the CAP 2023-2027.

Carbon sequestration is highly difficult to measure at farm level while FADN data might be used to evaluate sustainable management practices. Importantly, the recent EU Staff Working Document (SWD) 2021/450 (European Commission (2021c)) calls for a further effort in combining data from IACS (on the management and control of CAP payments) with satellite data which provide a regular and systematic observation, tracking and assessment of agricultural activities and practices via the Copernicus Sentinels, for example. Following similar lines of reasoning, LUCAS and the related ad hoc modules might also be used to extrapolate useful information on carbon. The LUCAS Topsoil dataset provides information on the chemical and biological properties of topsoil for a subset of points from the LUCAS campaign (ESDAC). These measurement points are geo-referenced. The ability to establish a geographical match with FADN data is of crucial importance to meeting the higher goal of quantifying the environmental impacts of CAP policies with counterfactual methods. This alignment is of paramount significance to attaining causal insights into the connections between CAP policies, farmers' actions, and topsoil quality.

Soil (S)

Soil is one of the most important natural resources and is a key resource for both agriculture and forestry. Activities in agriculture and forestry have a direct impact on soil quality in the EU; this includes soil erosion, compaction, organic matter content, soil biodiversity, soil pollution, and salinisation and the balance of nutrients in soils. Sustainable soil management - referring to activities in agriculture and forestry for soil conservation, amendment, restoration, fertilisation and health, to protect, restore and improve soil quality - is necessary to safeguarding its natural functions and production.

Some of the instruments and measures of the CAP period (2014-2022) are explicitly designed to address soil sustainable management (i.e. the horizontal requirement of minimum soil cover and management practices, the requirement to maintain soil organic carbon in soil, the obligation of crop diversification under greening, the RD support to investments in forests (M08), agri-environment and climate measures (AECM or M10.1) and support for organic farming (M11)).

Those measures aim to diffuse soil sustainable practices such as the maintenance of crop residues, manuring and compost application, tillage on arable land, crop rotation and introduce provisions on the use of both plant protection products and fertilisers. The CAP 2014-2022 also aims to contribute to durable changes in farmers' practices by helping to introduce the use of catch, cover and *N*-fixing crops.

Soil quality is generally analysed on the basis of the effects of the instruments and measures on sustainable soil management practices. FADN data do not record the specific characteristics of soil but they might be used to evaluate sustainable management practices. However, Land Use/Cover Area frame survey (LUCAS) and the ad-hoc modules, as well as the (Land Use-based Integrated Sustainability Assessment) LUISA survey, can be used to extrapolate useful information on soil characteristics.

Biodiversity (BD)

It is clear from numerous studies -reviewed in Stoate (2011) among others - that the key determinant of the richness and abundance of biodiversity associated with agricultural habitats is the degree to which they have been modified from their natural state as a result of agricultural improvements (e.g., the draining, ploughing and reseeding of grass, conversion from grasslands to crops), the intensification or modernisation of management (e.g., cultivation, the use of fertilisers, irrigation, and pesticides), and specialisation in particular intensive systems. Therefore, semi-natural agricultural habitats are of particular value for rare and otherwise threatened species of open habitats because they provide grass and shrub dominated habitats that are similar to previously present natural ecosystems (such as steppic grasslands) and provide the species' specialised ecological requirements. As a result, most natural and semi-natural agricultural habitats in the EU are listed on Annex I of the Habitats Directive (HB), and many associated species are listed in Annex II of the Habitats Directive or listed in Annex I of the Birds Directive (BD), given that they are also highly or exclusively dependent on natural or semi-natural habitats .

The HD and BD form the cornerstone of the EU's biodiversity policy framework. Both Directives have two main approaches (pillars) through which they can achieve their objectives: the protection of sites of particular importance to specific listed habitats and species, through the establishment of the Natura 2000 network, which comprises Special Protection Areas (SPAs) designated under the Birds Directive (for birds listed in Annex I of the Directive and for migratory species) and Special Areas of Conservation (SACs) designated under the Habitats Directive (for habitats listed in Annex I and species listed in Annex II); and protection measures that apply to all birds (with some exceptions) and selected non-bird species.

The CAP 2014-2022 has the potential to positively affect soil biodiversity (i.e., cross-compliance related to landscape features, conservation of wild birds, and conservation of natural habitats and of wild flora and fauna, which protect LF); some eligibility criteria for direct payments might also include local practices important for the conservation of habitats in Annex I of the HD and those covered by the BD (i.e., crop diversification, maintenance of the ratio of permanent grassland, and the EFA's requirements).

As for the measures chosen for the implementation of Pillar 2, those that relate directly biodiversity include the AECM (M10), the organic farming measure (M11), the Natura 2000 measure (M12), the forest-environment measure (M15), the measure to support investments improving the resilience and environmental value of forest ecosystems (M8.5) as well as the physical investments measure (M4), particularly non-productive investments; measures for advice and training (M1 and M2) and the ANC measure (M13).

The MS and regions have programmed those CAP instruments and measures in a rather heterogeneous way, see European Commission, Directorate General for Agriculture and Rural Development and Alliance Environment (2020) for a summary.

At a farm level, FADN does not provide information about habitat biodiversity, but it does provide information about the agricultural practices that have been shown to have the most significant influence on biodiversity. The Streamlining European Biodiversity (SEBI) and the

Sustainable Forest Management (SFM) indicators are reported by MS to Forest Europe and the agri-environmental indicators are compiled by Eurostat. However, this information is only available at the national level. In general, the number of European-wide data sources measuring biodiversity are increasing over time. The European Atlas of Forest Tree Species, the most recent LUCAS Soil wave including soil biodiversity measures (2022 data was not released for research at the time of writing), and the Natura 2000 Network data are examples of attractive datasets with high research potential.

Analysing the impacts of CAP policies on biodiversity can become an even more comprehensive and insightful endeavour when utilising FADN in conjunction with other data sources that provide direct measurements of biodiversity in Europe. An example of such sources is the Pan-European Bird Monitoring Scheme (PECBMS), a collaborative initiative focused on monitoring the population trends of common bird species across Europe. However, the ability to establish a geographical match with FADN data is of crucial importance in order to unlock the full potential of datasets such as the PECBMS for counterfactual analysis on biodiversity. The more detailed the geospatial integration between farms and observed outcomes, such as bird numerosity, the higher quality and precision shall be expected from the CIE exercise.

Landscape features (LF)

Within the CAP terminology, agricultural landscape features (LF) are to be intended as "small fragments of non-productive natural or semi-natural vegetation in agricultural landscape which provide ecosystem services and support for biodiversity" as stated by Czúcz et al. (2022) (p.4). This definition includes several non-productive elements: hedges, ponds, ditches, trees in line or in group or isolated, field margins, terraces, dry-stone or earth walls, planted areas, individual monumental trees, springs or historic canal networks. An in-depth inventory on the existing information on agricultural LF at EU level is provided by Czúcz et al. (2022).

In the CAP period (2014-2022), LF are promoted to achieve the objectives of the sustainable management of natural resources, maintaining rural areas and landscapes across the EU, and tackling climate change, with a focus on biodiversity, habitats, greenhouse gas emissions, soil and water.

The CAP 2014-2022 promotes the retention, maintenance and/or creation of LF in agricultural land in three ways: (i) cross Compliance sets requirements related to landscape features in Good Agricultural and Environmental Condition, and Statutory Management Requirements SMR2 - Conservation of Wild Birds, and SMR3 - Conservation of Natural Habitats and of Wild Flora and Fauna, which protect LF; (ii) Greening measures which include the maintenance of EFA; (iii) Rural Development Programmes in the Sub-measure 4.4.- Support for non-productive investments linked to the achievement of agri-environment-climate objectives and M10 - Agri-environment-climate measures.

It is widely acknowledged at present that LF have a significant beneficial impact on the neighbouring agricultural lands and the entire human economy in the form of ecosystem services. These (direct and indirect) impacts include improved air quality, water quality, water quantity, the reduction of greenhouse gas emissions, carbon sequestration, climate change adaptation, regulation of soil erosion and soil quality, support biodiversity and pollination, as shown in a synthesis of recent metareviews, see Alliance Environment (2017).

At the farm level, FAND data might be used to evaluate sustainable managerial practices promoted by the CAP measures. Moreover, the LUCAS ah-hoc survey on soil, as well as Copernicus data, such as Small Woody Features, might be used to extrapolate useful information on the potential beneficial impact on agricultural lands and on the ecosystem.

Water Quality (WQ)

Intensive agriculture and densely populated areas represent major sources of nutrient pollution for European inland and coastal waters, altering the aquatic ecosystems and affecting their capacity to provide ecosystem services and support economic activities. One of the main challenges with achieving good ecological status for water bodies is reducing the pressures from agriculture. The main pressures are given by pollution (Nitrogen N, phosphorus P, pesticides), water abstraction (irrigation) and hydro-morphological change (drainage, canalisation). Grizzetti et al. (2021) among others stress that nutrient pollution is one of the major pressures on European aquatic ecosystems altering their condition and, in particular, the imbalance of nitrogen and phosphorus over silica.

In 1991, the EU introduced the Nitrates Directive (ND), which aimed to reduce water pollution caused or induced by nitrate from agricultural sources. Under the ND, MS identified polluted and threatened water bodies and designated nitrate vulnerable zones, where action programmes are implemented by farmers on a compulsory basis, thereby respecting a Code of Good Agricultural and Environmental Practice, and taking additional measures, such as manure processing and restricting the application of fertilisers. The implementation of the ND is now an integral part of the Water Framework Directive which, in turn, motivates some of the CAP 2014-2022 instruments and measures.

In the 2014-2022 CAP framework, instruments and measures can all influence water quality by either enforcing or supporting practices that reduce the amount of nutrients, organic wastes and chemicals applied on land; decreasing the risk of transfer of such pollutants into waters by preventing leaching and runoff; decreasing soil and bank erosion. Furthermore, in order to reduce the agricultural pressures on water quantity, the CAP instruments and measures provide a regulatory frame and support to practices that decrease water abstraction for irrigation; improve water retention in soil; and improve bank stabilisation.

In particular, some of the regulatory provisions contained in cross-compliance rules, relate to water issues that stem from the ND. Under Pillar 2, FA 5D and 5E also contribute to addressing water issues, by increasing the organic matter content in soil.

FADN data do not record the water quality but they might be used to evaluate the implementation of sustainable managerial practices improving water quality. On the other hand, both data from the Water Quality (EEA) and the Copernicus data on Water and wetness might be used to extrapolate useful information on water quality and quantity.

Water Management (WM)

Environmental water management has become a global imperative in response to environmental degradation. There is widespread concern that poor water management will be one of the major factors limiting sustainable development. In the 2014-2022 CAP framework, instruments and measures can influence water management. In particular, some of the regulatory provisions contained in cross-compliance rules relate to water issues that stem from the ND. Furthermore, a number of GAECs target water directly. Under Pillar 2, the issues of water preservation and the enhancement of water management are addressed through two Focus Areas: FA 4B - improving water management, including fertiliser and pesticide management and 5A - increasing efficiency in water use by agriculture.

FADN data on the irrigation system, the cost of water, and the share of irrigated agricultural area might be used to evaluate the implementation of sustainable practices concerning water management.

Economic Outcomes

The general objective of the CAP policy's environmental section is to ensure coherence with overarching environmental policy objectives. At a farm level, this translates into the need to ensure coherence between agricultural and environmental policy objectives. A straightforward implication of implementing environmental practices involves undergoing a decrease in the output produced, see also the evidence shown in counterfactual studies by Dakpo et al. (2016), and Dakpo et al. (2020).

Measuring farms' environmental and economic performance can help policy-makers to design more effective policy schemes that internalise environmental considerations.
Farms' economic performance may be monitored by inspecting their technical efficiency (TE) or in terms of other economic indicators, such as value added or income. Pioneering contributions on the estimation of TE from the economic perspective are provided by Shephard (1970), Färe (1988), and Coelli et al. (2005). See Fare et al. (1993) and Daraio et al. (2019) and references therein for a review of the relevant literature; Mechri et al. (2017) for a useful applied guide to the agricultural field, and Battese (1992) and Nandy et al. (2019) for a survey

of empirical applications in agricultural economics.

When considering **both economic and enviromental outcomes**, the production function allows for the measurement of a **global performance ratio**, which accounts for all inputs and outputs of the production processes, together with partial measures of environmental and economic performance.
The literature integrating environmental aspects into productive efficiency is reviewed and discussed in Lauwers (2009), and Dakpo et al. (2016), Dakpo et al. (2020) and in references provided therein.
As far as the existing empirical findings on the economic-environmental trade-off are concerned, several studies have compared yields of organic farms relative to conventional farms, see Tzouvelekas et al. (2001b), Tzouvelekas et al. (2001a), Lansink et al. (2002), and Kumbhakar et al. (2008) among others.
Results documenting the different types of **greening payments on technical efficiency are mixed: negative impacts** are shown by Areal et al. (2012) for English and Welsh dairy farms, Kumbhakar et al. for Norwegian crop farms; Lakner and Breustedt (2017) for organic farms in Germany; Latruffe and Desjeux (2016) for dairy, beef and crop farms in France; and Madau and Madau (2007) for a sample of farms in Sardinia. More generally, Varacca et al. (2022) find **no effect** with the introduction of Ecological Focus Areas on farms economic performance indicators. However, other analyses have found a **positive relationship**: among others, Raimondo et al. (2021) for Italian olive farms with organic certification; Mamardashvili and Schmid (2013) for Swiss dairy farms; Manevska-Tasevska et al. (2016) for dairy, beef and pig farms in Sweden; Lakner and Breustedt (2017) for organic farms in Switzerland; Mayen et al. (2010) organic dairy US farms; and Cillero and Reaños (2022) for Irish beef farms.

There is also a very wide body of literature that investigates the effect of the CAP on other measures of economic performance. Arata and Sckokai (2016) find that the effect of AESs adoption largely depend on the share of the agri-environmental payment on farm revenue. If this share is larger than 5%, then participation in AESs is effective in promoting greener farming practices in all countries but Spain, where a negative effect on farm income is also shown. Cisilino et al. (2019) studied the effect of Organic Farming subsidies under the Rural Development Policy 2007–2013 programming period and they found no effect of income and output in a sample using a panel sample of Italian farms from FADN and also found that the income indicators considered do not differ statistically between treated and untreated groups. Bertoni et al. (2021) analyse the effect of three AES implemented in the Lombardy Region (Italy). Their results suggest that AES are effective in improving the farms' environmental performance. However, their preliminary cost-benefit analysis highlights that the costs of implementing this policy tend to be high, when compared to the additional environmental results obtained.

3.3 Data sources

The main data sources to measure the outcomes of interest are

1. **FADN**. The Farm Accountancy Data Network is a survey carried out each year for farms and is harmonised at the EU level regularly. The environmental content of FADN variables is mainly of the indirect type. It contains variables related to farms' activity that contribute to describe the environmental outcomes, as it will be described in Section 3.5. FADN notably also and mainly contains several economic variables.

2. **The Farm Structure Survey (FSS)**.
   The FSS, also known as Survey on the structure of agricultural holdings, is carried out by all European Union (EU) Member States and processed by Eurostat. The FSS is conducted regularly throughout the EU with a common methodology and it provides comparable and representative statistics across countries and time at regional levels (down to NUTS 3 level).
   Every 3 or 4 years, the FSS is carried out as a sample survey and as a census every ten years. A survey was conducted in 2016, thus providing information on the period pre-Greening. Previously, information on EU farms was collected in 2013, 2010 (census), 2007, 2005, 2003, and 2000 (census).[2] In the post-Greening period, the only source of information is the 2020 census, which is set to be released in 2024.
   It contains information about the legal personality of the holdings; the manager's age; other gainful activities type; animal variables; labor force; standard output; manure production and imports; crop variables; irrigation; tillage; crop rotation; and manure application. Eurostat releases a Scientific Use File (SUF) version of the FSS in which anonymised micro-data are available. The procedure anticipates the recoding of identifying variables, removal of detailed geographical coordinates, merging of products categories, and micro-aggregation of all numerical variables of the highest values.[3] The latter procedure aims to reduce the risk of identification of the biggest units preserving the totals. Contrary to the FADN where smaller holdings are under-represented, the information about the largest farms is not available in the scientific release of the FSS. On one hand, the precise impact of the security protocol on the evaluation exercise is unknown. On the other hand, when released, access to FSS data for the years 2010, 2016, and 2020 would enable the observation of variables related to environmental interest, for instance facilitating the evaluation of green direct payments, such as crop diversification, EFAs, etc. Changes

[2] Some countries always run census (BE, LU, NL), and some may report with one year lag in the pre-Greening period.

[3] Micro-aggregation is a family of masking methods for statistical disclosure control of numerical microdata (although variants for categorical data exist). The rationale behind micro aggregation is that confidentiality rules in use allow the publication of microdata sets if records correspond to groups of k or more individuals, where no individual dominates (i.e., contributes too much to) the group, and k is a threshold value. The strict application of such confidentiality rules replaces individual values with values computed on small aggregates (micro aggregates) before publication.

intervened at the NUTS2 (or NUTS3) level could be computed for the inter-census period. If the NUTS3 code were accessible, then aggregated statistics would be representative at the NUTS3 level for the population of farms, whereas FADN currently guarantees only NUTS2 level representation. Additionally, these changes could be analyzed based on farming typologies or size. Unfortunately, Eurostat makes available as SUF only the micro datasets 2016 and 2020 (this last not yet delivered), making hard to evaluate the CAP 2014-2022 impact based on this dataset.

3. **The Integrated Administration and Control System (IACS)**. IACS consists of a number of digital and interconnected databases, targeted at administering and controlling the payments to farmers, in particular:

    - a system for the identification of all agricultural plots in EU countries, called the Land Parcel Identification System;
    - a system allowing farmers to graphically indicate the agricultural areas for which they apply for aid (the geospatial aid application);
    - a computerised database for animals in EU countries where animal-based aid schemes apply;
    - an integrated control system that ensures systematic checks of aid applications based on computerised cross checks and physical on-farm controls (on-the spot checks).

    The IACS databases are managed by local Managing Payments Authorities. Additional information is available at:
    `https://agriculture.ec.europa.eu/common-agricultural-policy/financing-cap/assurance-and-audit/managing-payments_en`.
    A number of pilot projects, co-financed by Eurostat, and participated in by MS have been conducted on using IACS for agricultural statistics with the aim of preparing countries for the IFS (Integrated Farm Statistics) data collection. The main result of these endeavours is that a general agreement emerged on the opportunity of using administrative data for statistical purposes. A complete integration between IACS and agricultural statistics is not possible, at present, given that some concepts in statistics need to be stabilised. However, deeper alignment of concepts should be pursued in the long-term.

4. **The Land Parcel Identification System (LPIS)**. The purpose of LPIS is to implement the European Union's CAP measures. The reference parcel of LPIS is farmer's block, which is a compact area of agricultural land in agricultural use by one Agricultural Holding.
    The LPIS databases are managed by local Managing Payments Authorities. Additional information is available at:
    `https://data.europa.eu/data/datasets/8c8072f5-2075-49c3-b3e5-56ee58f8db8d?`

`locale=en`.

The LPIS contains all data about most crops for the farms that receive CAP subsidies, and the farmers had to provide this information at an early stage. The use of LPIS may be criticised as not being sufficiently representative for the whole farming sector, due to the fact that not all farmers applied for subsidies. However, the potential data applications remain quite considerable.

5. **Copernicus satellite data**. Pan-European High Resolution Layers (HRL) provide information about specific land cover characteristics and are complementary to land cover/land use mapping as in the CORINE land cover datasets. In particular, the following sources might be of use:

   - The Small Woody Features (SWF) layer captures woody linear structures, such as hedgerows, scrubs or tree rows along field boundaries, riparian and roadside vegetation, patches of trees and scrub. Time coverage 2015 and 2018;
   - The Grassland HRL layer displays information on grassland, non grassland and grassland change 2015-2018. PLOUGH, also, provides thematic information on ploughing events derived from historic data. Time coverage is 2015 and 2018;
   - The Water & wetness HRL product displays water and wetness classes vegetation. The main product is a classified layer, differentiating the classes of permanent water, temporary water, permanent wet, temporary wet, and dry areas, derived from water and wetness. Time coverage is from 2009 to 2018.

6. **LUISA** is an approach to integrating land-use relevant information from the increasingly available sources of geospatial data into a single, consistent and more detailed land use and land cover map for Europe. It is fully compatible with the Corine Land Cover (CLC) nomenclature and aims to increase the detailed information about CLC. The final products are publicly available in two resolutions: 50 metres (native resolution) and 100 metres (generated using a custom resampling method from the original 50 metre version).

7. **LUCAS surveys** (Land Use/Cover Area frame Survey) for 2009, 2015, 2018, and 2022. Information about the Copernicus programme are processed using a common methodology for the whole of the EU territory. The LUCAS survey gathers harmonised information about land use, land cover, and environmental parameters. It also provides territorial information by witch analyse the interactions between agriculture, environment and countryside, such as irrigation and land management.

8. **LUCAS ad hoc modules** on Grassland, Extended Grassland, Landscape Features, Soil and Copernicus (including prediction of Soil Organic Carbon (SOC)). For example, in the LUCAS ad hoc modules on topsoil, data samples have been analysed for: the percentage of coarse fragments; particle size distribution (% clay, silt and sand content); *pH* (in $CaCl_2$ and H_2O); organic carbon; carbonate content; phosphorous content; total nitrogen

content; extractable potassium content; cation exchange capacity; electrical conductivity.

9. **Waterbase** - Water Quality ICM. The dataset contains a time-series of nutrients, organic matter, hazardous substances and other chemicals in rivers, lakes, groundwater, transitional, coastal and marine waters. A list of spatial object identifiers with selected attributes, reported through WFD and WISE Spatial data reporting, is added to dataset as spatial reference. The data is compiled and processed by the EEA.

10. **Case studies** might be used to gather information which is not otherwise available at the EU level. By focusing on one Member State or regions, case studies can be a means of accessing qualitative or quantitative information that would otherwise be difficult or impossible to get.

Table 2 summarises the main data sources to measure the outcomes of interest.

Table 2: Environmental outcomes and relative data sources

Outcomes	*Data Sources*
GHG	National inventories
S	LUISA; LUCAS; Grassland HRL
CS	LUISA; ad-hoc LUCAS; LUCAS
BD	ad-hoc LUCAS,PECBMS
LF	ad-hoc LUCAS; SWF
WQ	EEA; Water & wetness HRL
WM	FADN

3.4 An overview of data-related challenges

In addition to the overview of potential data sources suitable for the quantification of outcomes, provided in the previous subsection, it is also important to highlight a number of challenges that the empirical researcher might face when engaging with CIE exercises in the context of the CAP and in particular the 2014-2022 policy cycle. The following paragraphs will provide a non-exhaustive list of data-related challenges, focusing especially on research centered on environmental outcomes.

Geographical matching

While the array of environmental data available for research, coupled with precise geo-location information, continues to expand — consider LUCAS soil measurements and water quality monitoring stations as notable examples — the task of establishing connections between these environmental outcomes and past agricultural policies, and the possibility to explore the intricate relationship between the two, is impeded by the **scarcity of geo-coded data on European farmland properties** that is available to the researcher.

Surveys such as FADN are released for research purposes with highly imprecise geographical location associated to each surveyed property; this is mostly due to privacy concerns and is done in order to guarantee the anonymity of individual farms. The most common scenario is finding geographical information to be limited to the NUTS2 or, at best, NUTS3 area to which the farm belongs. NUTS3 (Nomenclature of Territorial Units for Statistics, Level 3) areas in Europe can vary significantly in size depending on the country and its geographical characteristics.

The ensuing situation for the researcher lies in having highly precise information about where the specific environmental outcomes were measured. However, there's no way to determine whether these measurements were taken on the land parcels owned by the farms observed in the dataset(s). If such a geographical match was feasible, then highly valuable links between policy incentives, farm behaviour and environmental outcomes could be established at the micro-level. In the absence of such a match, however, the researcher is left to resort to carry out analyses at the aggregate level, typically averaging both environmental outcomes and farm-information at the regional (e.g. NUTS3) level. This operation implies losing - or at best watering-down - important micro-level information with high research potential and therefore obtaining less precise results in terms of policy impact evaluation.

The fact that the size of NUTS3 areas is not standardised throughout across all of Europe, as it depends on national and regional administrative boundaries, brings further complications in terms of unequal representativeness and reliability of research results. Taking the example of soil quality or biodiversity measures being taken on an evenly-distributed 100x100 kilometers grid, the researcher will find that their results will be more reliable for some NUTS areas - as they build on multiple environmental observations within the territory - while for other NUTS areas there will be very few, single or no environmental observations available to match to any agricultural-policy information they may have.

As a final remark on the challenges of geographical matching, one has to also consider that the geographical arrangement of European farms is often complex, in the sense that land parcels belonging to a specific ownership are not necessarily clustered around the farm's headquarters. Another layer of challenge is added to the research that aims at establishing causal relationships between policy, farm behavior and any environmental outcome when some farm parcels are geographically detached from farm headquarters or the farm's main parcel. This is so because, in surveys such as FADN, 'the address' or 'the location' of the farm mostly refers to its headquarters or main parcel only - but does not reveal the location of each single parcel under the same ownership. This means that the hypothetical case of obtaining the geo-location of surveyed farms at a level more precise than NUTS2 or NUTS3 - say, a 10x10km grid of cells, for instance would not necessarily lift **all** of the geographical matching problems, given that farm headquarters may lie in one such 10x10km cell and some of its annexed parcels in the next cell(s), unbeknown to the researcher, leading to wrong matches between environmental outcomes and farm properties. Only having access to the IACS (Integrated Administration and Control System) and in particular to its LPIS (Land Parcel Identification System) component, both described in the previous subsection, allows for this additional, yet relevant, layer of empirical challenge to be overcome. Regrettably, few European Member States make their IACS / LPIS systems available for researchers to explore; this is mostly, again, due to privacy concerns.

In summary, the information necessary to completing the link between policy incentives, farm behaviour and environmental outcomes through precise geographical matching *is* thus available, in separate valuable datasets, but their potential is currently not always exploitable by researchers *at the European level*. The response of research is often to resort to case studies rather than European-wide research -that is, focusing on specific European Member States or NUTS regions, which have in place more research-friendly agricultural data sharing platforms in place.

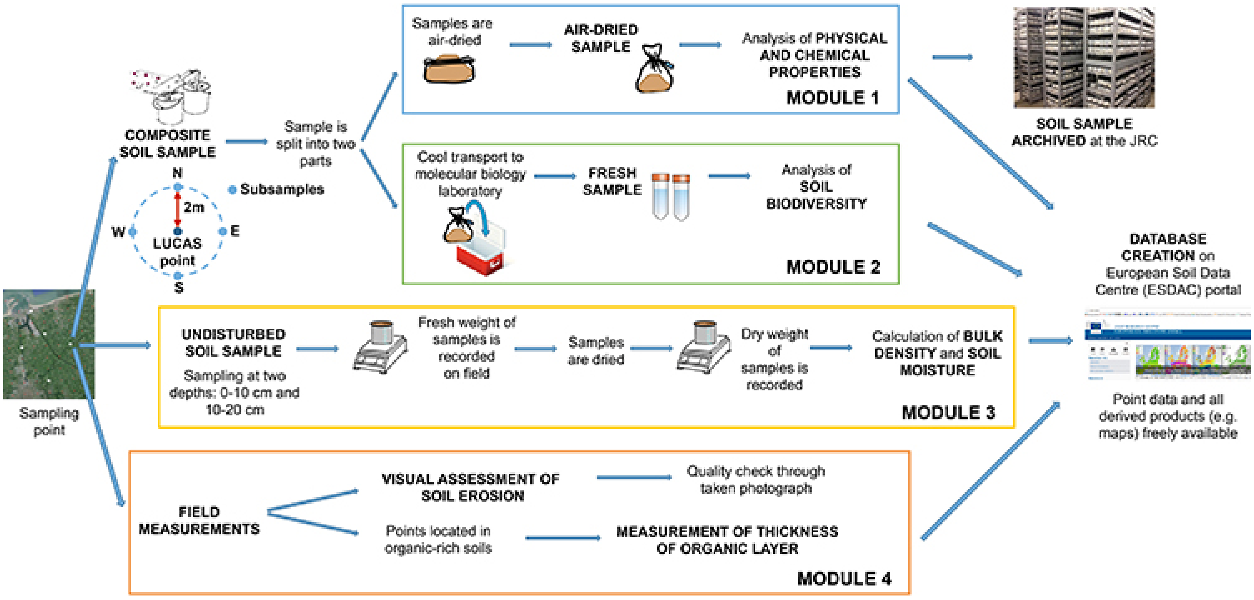
Timing I: data collection and availability for research

The timely availability of data is a key issue in any empirical research endeavour, an indispensable condition for maintaining the relevance of findings, especially if there are specific policy spans to be investigated (e.g. the 2014-2022 CAP cycle) and if such investigations are meant to provide evidence-based advice to the following spans.

Most of the data sources deemed useful to measuring environmental outcomes of interest, listed in the previous subsection, are subject to a staggered collection, elaboration and release procedure by the different agencies in charge of each source. LUCAS soil modules, LUISA land cover statistics, Waterbase at the European Environmental Agency, just to name but a few, involve collecting data in successive waves, spaced over time. After raw data -on soil quality, land use, water quality, and so forth- is collected, the agency in charge elaborates it and creates data products, typically differentiated by internal and external use and, thus, by level of data anonymisation, where research purposes are typically included among the latter. The process from data collection to availability of the final data product for research can be lengthy; it can span over years, thereby representing an obstacle to the chances of producing timely research results. To give a concrete example, at the time of writing (Autumn 2023) the LUCAS Soil Modules, which provide highly valuable soil quality measurements and which are managed by the European Soil Data Centre (ESDAC), have been released in three waves (2009/12, 2015 and 2018). The 2018 wave of soil sampling was followed by laboratory analyses, data processing and data release procedures that resulted in the data being available for researchers in 2022, that is, six years thereafter. Figure 2 illustrates the main stages of the process leading to soil quality data being made available for research.

The 2022 sampling wave has been already been carried out but its results are not yet available

Figure 2: LUCAS Soil workflow from sampling to database generation (Source: ESDAC - JRC)



and may very well follow a similar time horizon to the previous wave, in terms of reaching the empirical researcher. A second, similar, example is given by the WISE WFD database, containing data from the 1st and 2nd River Basin Management Plans reported by EU Members States under the Water Framework Directive (WFD). This database is managed by the European Environmental Agency and constitutes one of the most valuable sources of water quality data at the European level. The results of the 2016 water quality reporting wave collects surface water and underground water quality measurements taken at the Member State level over the period 2011-2016 and were only made available for researchers to analyse only in 2020. This means that even the swiftest empirical investigation, carried out as soon as data is released, will produce results on water quality outcomes will be referring to information from between six or ten years prior thereto.

To conclude this illustrative passage, a researcher aspiring at investigating impacts of CAP policy measures implemented over the 2014-2022 cycle on soil and water quality **at the European level** would, at the time of writing, have to limit their scope to soil measurements taken no later than 2018 (LUCAS) and be at a loss in terms of water quality. In such situations, similarly to what was mentioned for the case of **geographically-precise** and **geographically-linkable** data, the researcher often has to forgo European-wide analyses and resort, instead, to the second-best solution of focusing on **specific subsets** of European Member States or NUTS regions in order to provide **more timely** data on environmental outcomes.

Timing II: long-run effects and gaps between policy action and consequence

The time gap between the implementation of environmental policies and the measurable consequences of those policies can often be significant. This delay arises from various factors, including the complexity of ecosystems, the lengthy processes of environmental change, and the time required for policies to take effect. One major contributing factor to the time gap is the intricate nature of ecosystems. Ecological systems are highly dynamic and can exhibit long response times to changes in environmental conditions. For instance, reforestation initiatives aimed at increasing forest cover and sequestering carbon may take decades or even centuries to manifest their full impact on carbon sequestration and biodiversity restoration. The time it takes for crop diversification or other environmentally-friendly cropping practices to show positive effects on soil quality can vary depending on multiple factors, including the initial state of the soil, specific crop rotations, and local environmental conditions. Several studies have examined the impacts of crop diversification on soil quality over time, finding the shortest-term effects typically not earlier than three years ahead of time. Elements like the risk of soil erosion, organic matter input, and the buildup of pests are assumed to become evident within a few years of implementing diversified cropping systems. Changes in microbial diversity, nutrient cycling, and soil structure need even longer to manifest. The longer the observation time frame available to the researcher is, the wider the array of measurable impacts and the higher the confidence in the robustness of findings.

In summary, the time gap between the implementation of environmental policies and their measurable consequences is a critical consideration in environmental research and, more concretely, in Counterfactual Impact Evaluation applied to the EU Common Agricultural Policy. This consideration emphasises the need for patience, long-term commitment, and robust monitoring programmes to assess the effectiveness of the environmentally-focused elements of CAP policies fully; recognising that environmental change operates on various timescales is crucial for setting realistic expectations and refining policy strategies for sustainable environmental outcomes.

Innate spatial complexity of environmental and biological relationships

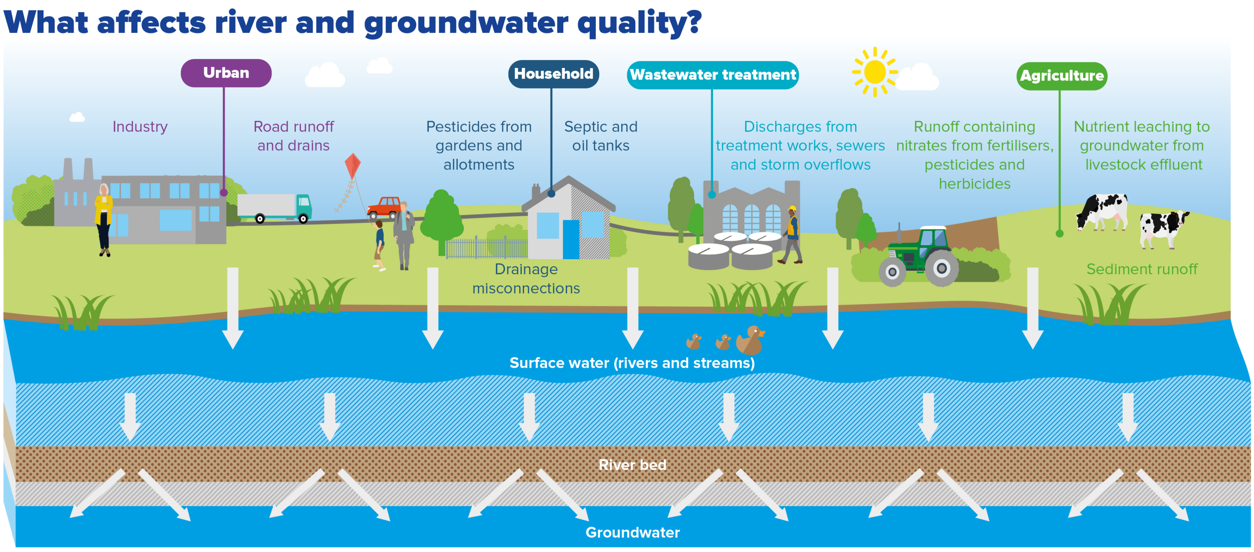
This final item briefly comments on an additional challenge faced by the empirical researcher when engaging in counterfactual impact evaluation of environmental policies.

The difficulty is given by the fact that the specific spatial scale or extension at which the benefits of these policies should be measured often remains unclear. The challenge lies in the diverse ways in which policies affect the environment, and especially in the intricate web of interactions within ecosystems, so that defining the appropriate spatial scale for measuring policy benefits is a far from trivial task.

One factor to consider is **ecosystem interaction**. Ecosystems are characterised by intricate and interconnected relationships among their components. Policies aimed at preserving or restoring biodiversity, for instance, can have far-reaching consequences that extend beyond the immediate geographic area in which they are implemented. Changes in one part of an ecosystem can ripple through others, thereby making it challenging to determine where to draw the boundaries when assessing policy impacts.

Figure 3 illustrates these concepts by showing how results on underground water quality may be attributable to a series of environmental policies affecting different economic actors, ranging from the individual households, to industry, and to farmers. The picture becomes even more complex when one considers that surface and underground water bodies are often connected by an intricate network of upstream-downstream relationships and that elements such as pollutants can travel long distances inside the web, so that their origin is often hard to trace back.

Figure 3: An illustration of the several factors jointly affecting groundwater quality (Source: Water for Life - www.southernwater.co.uk)



A second factor to be mentioned is scale mismatch: environmental policies often operate at regional, national, or even international levels, while the ecological processes they aim to influence may operate at local scales. This scale mismatch can complicate the measurement of benefits, as the effects of a policy may manifest differently at various spatial extents. Other dimensions of challenge are **spatial heterogeneity in policy impacts**, due to variations in baseline conditions, climate, and local ecological dynamics and the action of **cumulative effects** of policy interventions (i.e., effects that accrue in an additive way over time and space, so that a broader time and spatial perspective is needed to capture the full scope of their effects).

The current dynamic of European-level data availability displays a positive trend. The amount of precise, timely, and sophisticated environmental outcome data on a European scale is constantly increasing, thanks to the efforts of institutions such as the European Environmental Agency, the Joint Research Centre, and the European Space Agency, just to mention just a few. This upsurge in data availability is not only a testament to the dedication of these organisations, but also a promising sign for the effective evaluation of the Common Agricultural

Policy's (CAP) impact on the environment.

To ensure the continued effectiveness of CAP impact evaluation, it is imperative that this positive trend in data availability is not only maintained, but is also accelerated. The wealth of data generated by these institutions should be harnessed to provide policymakers, researchers, and stakeholders with the necessary tools to comprehensively assess the environmental consequences of agricultural practices. Furthermore, fostering collaboration between these institutions and Member States can help establish standardized methodologies and metrics for evaluating the CAP's impact, thereby facilitating more robust and consistent assessments.

In conclusion, the current positive trend in European-level data availability represents a valuable asset in the pursuit of effective CAP impact evaluation. Continued investment in data collection, sharing, and analysis is essential to upholding and enhancing this momentum.

3.5 Farm Accountancy Data Network (FADN)

This section discusses the use of FADN dataset to construct environmental outcomes.
The FADN dataset appears to be a suitable source for this Report's research question of the report. Indeed, FADN is the only survey carried out each year and harmonised at the EU level regularly, with a sample of 80 000 farms across Member States (MS) from a population of 9.1 million. The representativeness of its aggregated statistics is guaranteed according to regions (NUTS2), economic size, and farming type. It collects data from commercial farms above a minimum size (variable across Member States), and represents 50% of the EU farming population, more than 90% of the production, and the area.
The FADN contains general data about the farm; type of ownership; type of farming and economic size of holdings; type of land use; quality products; the value of assets; productions quotas and rights; debts; value-added tax; inputs; plant productions; livestock and animal products; other gainful activities; and CAP support in subsidies table.
However, the FADN has however limited content on environmental (and social) outcomes. To bridge this gap, a project was launched in 2020 along the Farm to Fork strategy to transform the FADN (Farm Accountancy Data Network) into the FSDN (Farm Sustainability Data Network). The new FSDN survey will include additional variables related to environmental (and social) dimensions.
The environmental content of FADN variables is mainly of the indirect type.
Indeed, environmental outcomes (emissions, nutrient balances) are not quantified at the farm level. Still, variables related to farms' activity, such as the number and the density of livestock, or the quantity of fertilisers and pesticides purchased, may be monitored in FADN as descriptors and drivers of environmental outcomes. For instance, using high quantities of fertilisers may lead to a large nitrogen surplus, and correspondingly large flows of nitrogen emissions and pollution. Similar transimissions mechanisms apply to the use of pesticides and energy. In

summary, higher expenditures on inputs are expected to result in more pollution and higher environmental damages.

Approximating environmental outcomes by farms' input usage has been already exploited by some CIE empirical researches (see Tables 11 to 12), and supported theoretically by the agricultural literature,as recently summarised by the Reports of LIFT project[4] (Rega et al., 2021).
The LIFT project fine-tuned some "protocols" to quantify the uptake of ecological agriculture in the European Union. The main findings state that:

- Farming systems may display ecological compliance to four (non-disjunctive) dimensions:
  1. Soil conservation;
  2. Overall input intensity;
  3. Internal integration and circularity;
  4. Ecological infrastructures.

  The stronger the intake in these dimensions, the higher the ecological compliance of farming systems will be.
- No information is available within FADN on soil farming practices and the presence of seminatural features. So that only the farms' intake in terms of "Input intensity", and "Integration and circularity" may be quantified based on FADN.

Based on this evidence, a set of FADN activity variables contributing to describing the environmental outcomes of the CAP have been identified as necessary elements for the implemention of CIE.
To this end, different strategies have been leveraged:

1. A literature review of the (few) scientific papers using CIE on environmental outcomes;
2. The list of variables with environmental content declared by AGRI.A2[5];
3. The variables used by the LIFT scoring system (Rega et al., 2021) to identify ecological farming systems of the Low-input farming and Integrated/Circular farming typologies.

The list of collected variables related to environmental outcomes, identified through the strategies mentioned above, are described in Table 3 and 4.
It is worth noticing that FADN variables represent only **indirect measures** of the environmental outcomes. Moreover, they provide only partial descriptions of farm environmental impact in terms of specific aspects, such as, for instance, Animal welfare and Water management.

[4] The LIFT project has been financed by H2020.
[5] Farm Sustainability Data Networkstate of play, FSDN Stakeholders workshop, 22 November 2022.

Table 3: Existing variables in FADN related to Environmental Outcomes

Outcome	FADN variable name	Computation method
Nutrients		
Cost of fertilisers	Total fertilisation costs per ha of UAA	(SE295/SE025)
Quantity of N	Quantity of N used in mineral fertilisers per ha of UAA	H_SC_3031_Q/SE025
Quantity of P	Quantity of P205 used in mineral fertilisers per ha of UAA	H_SC_3032_Q/SE025
Quantity of K in mineral fertilisers	Quantity of K2O used in mineral fertilisers per ha of UAA	H_SC_3033_Q/SE025
Purchased manure	Purchased manure Value per ha of UAA	H_SC_3034_V/SE025
Pesticides		
Cost of crop protection products	Total costs for pest control per ha of UAA	(SE300/SE025)
Energy		
Cost for fuels	Total expenditure in fuels per ha of UAA	((IHFULS_V+ IFULS_V)/SE025)
Cost for electricity	Total expenditure in electricity per ha of UAA	(IELE_V/SE025)
Values of production on renewable energy	Production of renewable energy Sales value per ha of UAA	L_SA_2030_V/SE025
Animal welfare		
Total livestock units (LSU)	Total grazing livestock	(SE085 + SE090 + SE095)
Stocking density (LSU/Agricultural Area)	Total grazing livestock (LU) per ha of forage area	(SE085 + SE090 + SE095) / SE071
Grazing on common land	Total number of LU grazing days by farm animals on common land used by the holding/total grazing livestock (LU)	A_OT_210_C/(SE085+ SE090+ SE095)
Veterinary expenses	Veterinary expenses Value	H_SL_2080_V

Table 4: Existing variables in FADN related to Environmental Outcomes - continued

Outcome	FADN variable name	Computation method
Biodiversity and High-diversity landscape features		
Total agricultural area out of production	Total agricultural area out of production	SE074
Shares of permanent grassland and land lying fallow on agricultural area	(Permanent grassland + Land laying fallow + Land laying fallow for melliferous plants)/UAA	(M_AI_10200[a] +M_AI_10310[a] + M_AI_10322[a])/SE025
Share of protein crops	Areas with nitrogen-fixing crops/UAA	M_AI_10319[a]/SE025
Crop diversification index	No. of crops per farm – Simpson Index Number of arable crops Main arable crops (ha, %) Arable crop heterogeneity Leguminous crops (%)	
Woodland area, forests, poplar plantations (not included in UAA)	Woodland area + Afforested areas + Hectares of agro-forestry	SE075+ M_AI_10317[a] + M_AI_10314[a]
Greening – EFA Areas -Number of basic units (in hectares)	Ecological focus area (no basic units)	M_AI_10300[a]
Stocking density (LSU/Agricultural Area)		
Water management		
Irrigation system	Irrigation system Type	A_OT_210_C
Cost of water	Total expenditure in water per ha of UAA	(IWATR_V/SE025)
Share of Irrigated Agricultural Area	UAA under irrigation per ha of UAA	(IRRA_X[b]/SE025)
LIFT - Integrated/Circular farmings		
Seeds	Total costs for seeds and plantlets for ha of UAA	(SE285/SE025)
Feed for livestock	Value of feed for the predominant farm livestock, including concentrated feeding stuffs and coarse fodder/ total grazing livestock (LU)	SE310/(SE085+SE090+SE095)
Own feed for livestock	Value of own produced feed on total feed value	SE315/SE310
Electricity - own production (if ONRGPRD_SV>0)	Value of sold electricity produced on farm on total value of consumed electricity	ONRGPRD_SV/IELE_V
Seeds – own ratio (if SE290>0)	Value of seeds produced on farm on total value of used feeds	SE290/SE285

[a] Available only from 2014
[b] Available only before 2014

3.6 Data granularity and potential criticalities

This section presents a brief review of potential weaknesses related to the data granularity.

Parcels aggregation

Generally, farms are composed of many parcels and it happens that only a share of parcels is assigned to treatment. In such a case, data availability at the farm level may potentially lead to bias **due to parcel aggregation**. For instance, when a subsidy puts only selected parcels under contract, then the subsidy's impact should be evaluated in terms of the outcome of the selected treated parcels'. However, when data are available at the farm level, the total farm subsidy corresponds to the total treatment, while the total farm outcome includes results of treated and untreated parcels which differs from the outcome attributable to the treatment. This might lead to an **underestimation of the policy's impact** because the outcome is also implicitly measured over those parcels not under the treatment.

Treatments aggregation

Many policy instruments are targeted at different objectives; thus, it could be inferred that each policy should be evaluated on its targeted outcomes.

This means that, ideally, the necessary information whould allow us to distinguish the policy/target pairs (i.e., which treatment addresses which targets). In realty, this is often not possible. Table 5 displays an example of this type of bias, by presenting results of an evaluation study by (Bertoni et al., 2020). The study aimes to evaluate the impacts of three specific agro-environmental schemes under M10 measure: Crop diversification, Grassland Maintenance, and Organic Farming. These schemes are evaluated on their main target outcomes and on all of the outcomes as cross-effects. Then, the additional aggregate treatment as "At least one of three schemes" was the evaluated.

Table 5 displays signs and significance of estimated effects from the three granular treatments and the aggregated one. It is interesting to observe that findings emerged under the evaluations of single schemes', when compared to impacts estimated conditional on specific schemes do not always confirm the ones attained under the aggregate treatment, either in terms of significance or sign.

In summary, the results highlight that **an aggregation bias might occur using aggregate, rather single, treatments**.

The measurement issue

A further criticality concerns with the measurement of unobservable outcomes. Some pollutant outputs, for instance GHG, as mentioned in 3.2 are estimated from models derived by previous studies (IPCC, 2006, 2019) These types of models estimate pollutant outcomes ac-

Table 5: Estimated Effects defining treatments at granular vs. aggregate level. Source: Bertoni et al. (2020)

	Crop diversification	Grassland maintenance	Organic farming	At least one of the three
Main outcomes of Crop diversification				
Main arable crops (ha)	-	-	-	-
Main arable crops (%)	n*[a]	-	-	-
Number of arable crops	p*	-	-	p*
Arable crops heterogeneity	p*	-	-	p*
Leguminous crops (%)	p°	-	-	n*
Non soil-depleting crops (%)	n*	-	-	p*
Main outcomes of Grassland maintenance				
Grassland (ha)	p*	p*	-	-
Grassland (%)	p*	p*	-	n*
Main outcomes of Organic farming				
Organic farming (ha)	n°	n*	p*	p*
Organic farming in conversion (ha)	-	-	p*	p*

[a]Only significant results are displayed. n:=negative; p:=positive; *significant at 95%; ° significant at 90%.

cording to a transformation function that combines observed pollutant inputs (activity data) with pre-estimated emission factors.

Whenever the environmental policy under investigation impacts on the agricultural practices implemented by the farm (which for instance may adopt a water filtration system for irrigation), this will change the emission factors. If the transformation function is not practice-specific, then anytime the policy is effective by changing the practice, improving the way emissions are produced, **the effect of the policy will be underestimated**. In summary, the knowledge of the transformation function actually being implemented by farms plays a crucial role in the evaluation exercise and must be practice-specific. Unbiased evaluation should concern the use of practice-specific transformation function.

4 Greening: payment for agricultural practices beneficial for the environment

4.1 Description and objectives

The Greening Payments introduced in the 2013 CAP reform as the compulsory component of the "Targeting" of those direct payments specifically designed to improve the CAP's environmental performance linked to agricultural production. These subsidies create obligations to farmers and reward them for adopting land management practices deemed beneficial for the environment, therefore, relating their activity to producing **environmental public goods**. The GP is awarded to farmers for adopting three farming practices:

- Maintenance of Permanent Grassland (MPG),
- Crop Diversification (CD) and
- allocation of land to Ecological Focal Areas (EFA).

Maintenance of permanent grassland

Permanent grassland (EU, 2014) is the land used to grow grasses or other herbaceous forage that has not been included in the crop rotation of the holding for a duration of five years or longer. Permanent grasslands cover 34% of the European Union's agricultural area (Eurostat, 2020) and that are vital for human well-being because they contribute to a wide variety of essential ecosystem services (Bengtsson et al., 2019; Habel et al., 2013; O'Mara, 2012). It is an effective means of locking carbon away and benefits local biodiversity.

The MPG requirement has two components:

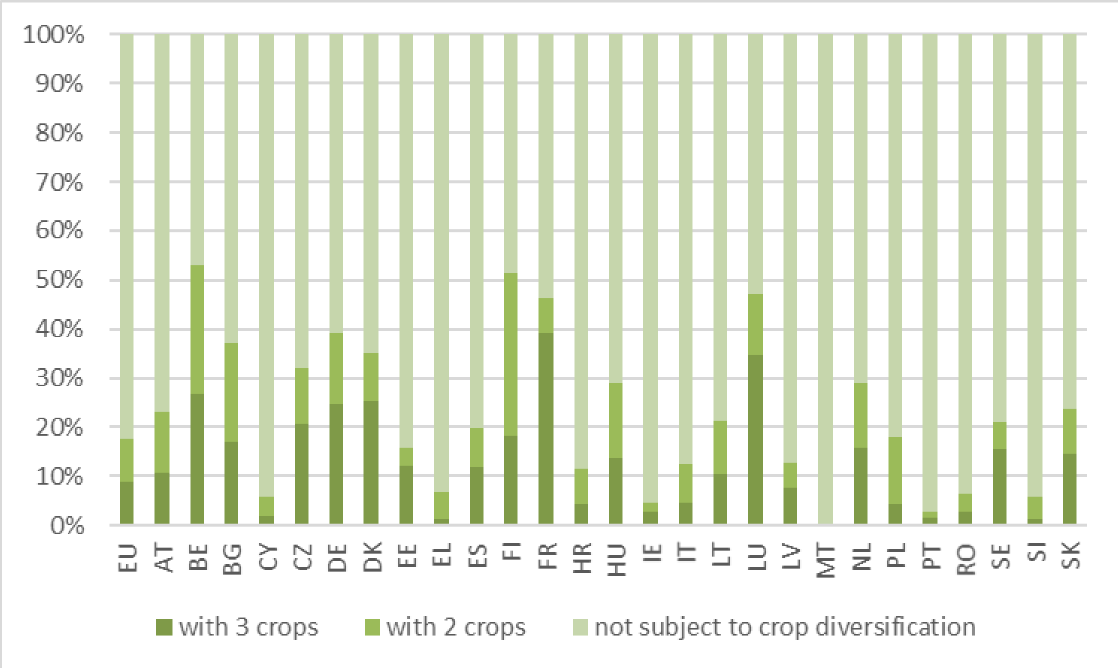
a) Maintaining the ratio of permanent grassland to agricultural area at national or regional level with a 5% margin of flexibility;

b) Protecting the most environmentally sensitive permanent grassland from ploughing-up and converting.

Crop diversification

This obligation imposes restrictions on the minimum number of crops and on the maximum percentage of arable land covered by the main crops in farms. Different rules apply to farms according to their dimension and the type of crops covering the agricultural land. The main rule stipulates that farms with more than 10 ha of arable land must grow at least two crops; this is extended to three crops if it exceeds 30 ha. In addition, the main crop may not cover more than 75% of the arable land and in the latter case the two main crops may not cover

Figure 4: Share of CAP beneficiaries subject to Crop Diversification in 2021.
Source: Agri-food Data Portal



95% of the arable land. This general rule is adapted for farms where the production of grasses or other herbaceous forage of land lying fallow are a significant part of the arable crops.

Growing a greater variety of crops increases soil resilience and protects ecosystems. It helps to improve soil quality by discouraging monocultures; reduces soil erosion, threby helping production capacity; promotes pest and weed control; improves water quality and; reduces the effects of climate change.

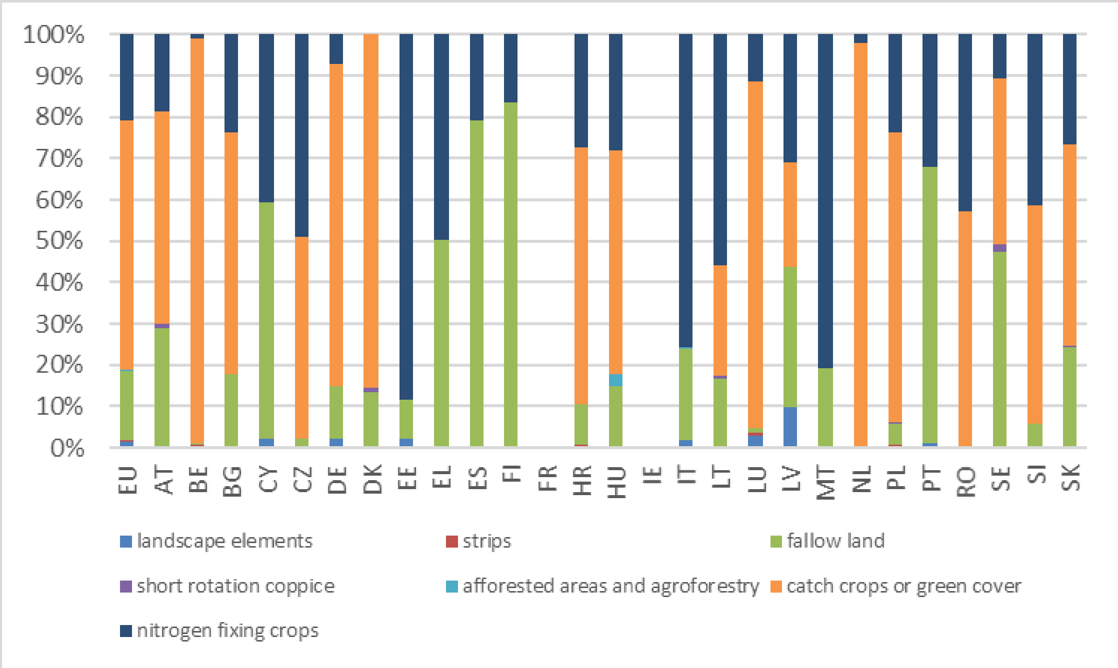
Figure 4 shows the share of CAP beneficiaries subject to the crop diversification requirement by crop number. The large percentage of exempted farms reflects the small size of most EU agricultural holdings since the requirement does not apply to farms with arable land (AL) smaller than 10 ha. More than three-quarters of EU farms are small (i.e., below 10 ha with a large number below five ha).[6]

Ecological Focus Areas

This measure requires farmers to allocate 5% of the arable land to seminatural habitat areas beneficial to biodiversity. Ten types of land-use options qualify as EFA: (i) fallow land, (ii) terraces, (iii) landscape features such as hedges, (iv) uncropped field margins or buffer strips, (v) agro-forestry, (vi) strips along forest edges, (vii) short rotation coppice, (viii) afforested

[6] https://agriculture.ec.europa.eu/common-agricultural-policy/income-support/additional-optional-schemes/small-farmers-scheme_en

Figure 5: Share of EFA in total arable land (%) in 2021.
Source: Agri-food Data Portal



Data of France and Ireland not available at time of download (Autumn 2023).

areas, (ix) catch crops or green cover, and (x) nitrogen-fixing crops.[7] EFA land uses concerning landscape features provide habitats for birds and other species, such as pollinators, and this helps biodiversity.

Figure 5 shows the share of EFA in total arable land in both the EU and MSs. The selection of EFA areas type differs across MS. Some consider all EFA types, while others only have a narrow range. Each MS, thus, has the flexibility to exclude particular measures available in the regulation and make use of a system of conversion or weighting factors when determining whether a farm satisfies the EFA requirement. This implies that the actual proportion of EFA in any particular farm can be above or below the 5% threshold depending on the farmer's choices of EFA type.

Figure 5 shows that while at the EU level, catch crops and green cover dominate the EFA land use type, MSs can be grouped into five groups:

- the first (AT, BG, HR, HU, SK, and also LT, and SE) replicates the EU average and applies a combination of nitrogen-fixing crops, catch crops or green cover and fallow land;
- the second (BE, DE, DK, LU and NL) is dominated by catch crops;

[7] One of the most important adjustments of the original GP requirements has been to include the possibility of planting nitrogen-fixing (N-fixing) crops on the EFAs.

- the third (CY, EL, ES, FI, IT and PT) combine fallow land and nitrogen-fixing crops;
- the fourth (CZ, PL, RO and SI) combine nitrogen-fixing crops and catch crops and;
- the fifth (EE and MT) mostly nitrogen-fixing.

The three farming practices are aimed at improving soil quality (CD, MPG), promoting carbon sequestration (MPG) and safeguarding habitats and improving biodiversity (EFA, MPG). They are designed to influence farmers' land allocation by promoting the diversification of farming systems that have become increasingly intensified by the specialisation of agricultural production. Since the greening measures target land allocation at the farm level, their uptake largely depends on farm-specific characteristics. The measures mainly apply to arable crops, and to monocultures in particular, and less to livestock production. For this reason, farming systems in mountain areas are mostly excluded from the Greening measures.

Compliance with the Greening requirement is not restricted to the three measures above. To accommodate the diversity of farming systems and environmental conditions across the EU, MSs and their farms may comply with the Greening requirements through equivalent alternative practices that are anticipated in the EU regulation. These include measures that produce the same or higher environmental value defined in national/regional certification schemes, Agro-Environmental measures etc.

4.2 Literature review

The impact of the Greening Payments on farms' land allocation choices and consequent environmental impacts has attracted the interest of agri-economists since the implementation of this reform. The existing studies contributing to the policy evaluation differ in several critical dimensions: territorial approach, choice of instrument, scope, outcomes and methodology.

Two main groups can be identified concerning scope and, consequentially, the methods. The first analyses the policy impacts using **ex-ante simulation methods** based on sample-based data. This is the approach of Gocht et al. (2017), Louhichi et al. (2017) and Hristov et al. (2020) that use, respectively, the CAPRI, IFM-CAP and AgriPolis models. While the first two models use FADN and FSS data to provide results for the farm impacts at the EU level, the third analysis is circumscribed to farms in two regions in Sweden. These approaches allow for a simulation of the Greening measures' effects on all aspects of farm choices, such as crop allocation, EFA land type use allocation, input use, crop and animal production, farm income, livestock density, crop diversification measures etc. In some cases, the models estimated the implied impact on biodiversity (AgriPolis model) and other environmental outcomes, such as GHG emissions.

The main findings of these simulation exercises can be summarised as follows. The IFM-CAP model estimates that although the proportion of farms and utilised agricultural area (UAA) subject to CAP greening represents 55% of all farms and 86% of UAA in the EU27, the reallocated area induced by the policy represents only 4.5% of UAA. The CAPRI model finds small economic (land use, production, price and income) and environmental (GHG emissions, N surplus, ammonia emissions, soil erosion and biodiversity-friendly practices) impacts. However, the analysis identifies farms, crop types and MS that may be affected more significantly. The potentially heterogeneous nature of the effects, due to the specific local farming conditions, is also highlighted. The simulated nature of these results relies heavily on the modelling assumptions and may not reflect the actual adjustment behaviour of farms. However, they may provide a rationale for understanding the policy's transition mechanisms and might lead to the relevant outcome variables being chosen.

The second set of contributions is based on **ex-post evaluation exercises from observable data**. This is the approach adopted by Bertoni et al. (2021), which uses parcel-level data from Italian farm, Sauquet (2022) for French farms, and Varacca et al. (2022), also based on Italian arable crops farms. All three studies are territorially limited to those MS, while the last two estimate the effects by using CIE methods. Bertoni et al. (2021) evaluates the impact of Greening on land use changes of farms that were not initially compliant with the crop diversification rules. They find evidence of a shift in farmland use in this group of farms, thereby suggesting that Greening rules induced farmland conversion in farms with a lower degree of crop diversification. This evidence is then used to estimate the greening impact on land allocation measures using machine learning techniques. The analysis provided by Sauquet (2022) quantifies the impact of CD in France and found that farms greater than 30 ha increased both the compliance with the measure and the number of crops grown on their lands. Moreover, farms larger and smaller than 30 ha responded differently to the greening reform, where farms larger than 30 ha increase the farmland used for the third and fourth largest crops. Varacca et al. (2022) assumes that compliance with the CD measures did not pose a challenge to most arable crop farms in Italy. Their study used the FADN Rica dataset and focuses on the EFA measure impact on the farms' crop mixes. It exploited the farm size threshold for the EFA exemption requirement to estimate local effects by using a Regression Discontinuity Design (RDD). They find that farms opted for the least costly adaptation of land use by increasing the share of leguminous crops and by estimating a proxy for the biodiversity impacts.

4.3 Eligibility and exemptions

According to the figures of the Agri-food Data Portal[8] **74% of arable land was subject to the crop diversification obligation in 2020**, and **beyond 9.3 million ha were dedicated to ecological focus area in 2021**. A residual share of arable land is not subject to greening obligation because it reflects a set of exemptions that are applied to specific farming systems

[8] https://agridata.ec.europa.eu/extensions/DataPortal/home.html

and/or farm sizes.
Two groups of farms are exempted from all Greening measures; these are farms under the Small Farmer Scheme (SFS), and organic farms. The first group is excluded for administrative and proportionality reasons; the latter group because it is considered to provide environmental benefits by the intrinsic nature of its activity, thanks to which it receives a Greening payment without conditionality.

Beyond those conditions, additional exemptions from each of the greening practices are set by of the articles 44 (CD), 45 (MPG), and 46 (EFA) of the regulation No 1307/2013.

Obligation and Exemption from Crop Diversification

The conditions of obligation to the Crop Diversification (CD) practice are set out by Article 44 of the Regulation (EU) No 1307/2013, which describes also the related requirements and the exemptions. The article's statement is summarised in Table 6.

The article states which farms are exempted from the CD obligation, following the commas of Article 44. By jointly considering Article 44 to the letter, it becomes possible to identify the farms under the CD obligation. For instance, among non-exempted groups, group 5 of Table 6 is cancelled out by the exemption of comma 3.(a), while the exemption condition expressed by comma 3.(b) has to be added to the definitions of groups 1,2, and 4. Moreover, farms under the conditions posed by commas 3.(c) and 3.(d) are not or not at all observable by using FADN, so they would have to be discarded in an evaluation exercise based on FADN.

Table 6: Crop Diversification obligations and exemptions, and administrative requirements

Article		CD requirements	Group
44.1.			
-	AL < 10 ha	Exempted	1
-	CuW = 100% AL	Exempted	2
-	10 ha < AL < 30 ha and CuW < 100% AL[a]	at least 2 crops % main crop <75% AL	3
-	AL >30 ha and CuW < 100% AL	at least 3 crops % main crop <75% AL % two main crops <95% AL	4
44.2.			
-	GrHfLlf >75% AL and 10 ha < RAL < 30 ha	at least 2 crops % main crop <75% RAL	5
-	GrHfLlf >75% AL and CuW < 100% RAL and RAL >30 ha	at least 3 crops % main crop <75% RAL	6
-	GrHfLlf =100% AL	Exempted	7
44.3.			
(a)	GrHfLlf >75% AL and RAL <30 ha	Exempted	8
(b)	PermGr+GrHfLlf+CuW >75% AA and RAL <30 ha	Exempted	9
(c)	>50% AL not declared the previous year or 100% AL with crop different to previous year	Exempted	10
(d)	62nd parallel or adjacent areas and AL > 10 ha	at least 2 crops % main crop <75% AL	11
-	62nd parallel or adjacent areas and AL > 10 ha and GrHFLlf > 75%	Exempted	12

Notes: AL:= Arable Land; CuW:= Crops under water; GrHfLlf:= Grasses or other herbaceous forage or Land lying fallow; RAL:= AL-GrHfLlf; PermGr=Permanent grasses; AA:=Agricultural area.

[a] i.e. AL is not entirely cultivated with CuW for a significant part of the year or for a significant part of the crop cycle.

In summary, the three groups of farms under the CD obligation, which may be identified using FADN data, are:

- Farms with fewer than 10 ha of arable land (Medium Arable Land) where less than 75% of their arable land is used to produce grasses or other herbaceous forage, or is land lying fallow.
  This group is here named Medium Arable Land (M-AL).

- Farms with between 10 and 30 ha of arable land (Large Arable Land) where less than

Table 7: Farms under Crop Diversification obligation and relative requirements

	Identification criterion	Requirements	Farm label
-	10 ha < AL < 30 ha and CuW < 100% AL and GrHFLlf< 75% AL PermGr+GrHfLlf+CuW <75% AA	at least 2 crops % main crop <75% AL	Medium AL
-	AL >30 ha and CuW < 100% AL and GrHFLlf< 75% AL	at least 3 crops % main crop <75% AL % two main crops <95% AL	Large AL
-	75% AL < GrHfLlf < 100% AL and RAL >30 ha and CuW < 100% RAL	% main crop <75% RAL at least 3 crops	Large RAL

Notes: AL:= Arable Land; CuW:= Crops under water; GrHfLlf:= Grasses or other herbaceous forage or Land lying fallow; RAL:= AL-GrHfLlf; PermGr=Permanent grasses; AA:=Agricultural area.

75% of their arable land is used to produce grasses or other herbaceous forage, or is land lying fallow.
This group is here named Large Arable Land (L-AL).

- Farms with between 10 and 30 ha of arable land (Large Arable Land) where between 75 and 99 % of arable land is used to produce grasses or other herbaceous forage, or is land lying fallow, provided that their residual arable land exceeds 30 ha.
  This group is here named Large Residual Arable Land (L-RAL).

Exemptions from Ecological Focus Areas

Article 46 of the Regulation (EU) No 1307/2013 states the obligations' conditions for the Ecological Focus Area (EFA) practice, the related requirements, and the exemptions. Table 8 summarises the administrative requirements.

Table 8: Ecological Focus Areas administrative requirements

Article		EFA requirements	Group
46.1.			
-	AL < 15 ha	Exempted	1
-	AL >= 15 ha	5% of AL allocated to EFA	2
46.4.			
(a)	GrHfLlf >75% AL and RAL <30 ha	Exempted	3
(b)	PermGr+GrHfLlf+CuW >75% AA and RAL <30 ha	Exempted	4

Notes: AL:= Arable Land; GrHfLlf:= Grasses or other herbaceous forage or Land lying fallow; RAL:= AL-GrHfLlf; PermGr=Permanent grasses; AA:=Agricultural area.

In addition, the policy identifies a “Forest exemption” applied in MS where over 50% of the land surface is covered by forest (EE, FI, LT and SE). In such instances, the EFA measure may not apply in designated areas where more than 50% of the land surface at LAU-2 level (or other contiguous geographical location) is covered by forest, and the ratio of forest land to agricultural land is higher than 3:1.

Article 46 states which farms are exempted from EFA obligations. By comparing those criteria with the information available in the FADN, it turns out that two groups of farms under the EFA obligation may be identified using FADN:

- Medium Large Arable Land (ML-AL): Farms with more than 15 ha of arable land (Medium Large Arable Land) where less tha 75%of their arable land is used to produce grasses or other herbaceous forage, or is land lying fallow.

- Large Residual Arable Land (L-RAL):

  a Farms with more than 15 ha where between 75 and 100 % of arable land is used to produce grasses or other herbaceous forage, or is land lying fallow, provided that their residual arable land exceeds 30 ha.

  b Farms with more than 15 ha where from 75 to 100 % of eligible agriculture area is used to produce grasses or other herbaceous forage, or is land lying fallow, provided that their residual arable land exceeds 30 ha.

Table 9 summarises this information.

Table 9: Farms under the EFA obligation and relative requirements

	Identification criterion	Requirements	Farm label
-	AL > 15 ha and GrHFLlf< 75% AL PermGr+GrHfLlf+CuW < 75% AA	5% of AL allocated to EFA	Medium Large AL
-	RAL > 30 ha 75% AL < GrHfLlf < 100% AL 75% AA < PermGr+GrHfLlf+CuW < 100 % AA	5% of AL allocated to EFA	Large RAL

Notes: AL:= Arable Land; GrHfLlf:= Grasses or other herbaceous forage or Land lying fallow; RAL:= AL-GrHfLlf; PermGr=Permanent grasses; AA:=Agricultural area.

Exemption and exceptions from Maintenance of Permanent Grassland

The Article 45 states that designation of permanent grasslands is set by MSs, and farmers in those areas can neither convert nor plough permanent grassland.

The ratio of permanent grassland is ensured and declared by MSs each year, on the basis of areas declared by the farmers subject to the obligations.

In summary there is not a predetermined group of farms exempted from the MPG obligation, throughout the EU.

4.4 Causal impact identification

Farmers under the obligation to adhere to the CD and EFA measures started that they **adhere to the requirements from 2014**. This provides a **time variation in the treatment**. In addition to time, the actual implementation of the policy is characterised by a set of **size-related and other exemption rules**. These two characteristics allow for the exploitation of two different CIE strategies:

- Size-related exemption rules can be exploited to identify the "local" causal impact of specific Greening measures in a **Regression Discontinuity Design** (RDD) context.
- The clearly defined starting date of the policy implementation provides the basis for a **Differences-in-Differences** (DID) identification strategy in the relevant population of interest provided that a control group can be found.

These two strategies will be exploited in order to discuss casual the effects identification strategies for both the CD and EFA measures. The feasibility of the analysis will be assessed using the FADN dataset.

MPG is set apart from CIE feasibility based on FADN because of several obstacles. Firstly, FADN does not collect information about areas designated by MSs to MPG, thereby, disabling the identification of treated farms in FADN. Secondly, FADN provides little relevant data about the MPG requirement, beyond the variable of permanent grassland (Rega et al., 2021), which is available without reference to specific parcels. Thirdly, the MPG requirement was already set in Article 3 of Commission Regulation 796/2004, and consequently the time variation cannot be exploited to identify causal effects.
FADN data would only allow a researcher to monitor, through descriptive analyses, how many farms maintain permanent grassland and the extent to which this holds true.

The first step in the identification strategy requires selecting the group of farms treated by Greening (i.e., defining the **treatment variable**). The policy treatment effect can be sought **on the farms affected by the policy** (i.e., all those farms under CD/EFA obligations according to the Regulation). This treatment definition allows discussing the issue of policy relevance by investigating how effective the policy was in promoting the desired agricultural practices on targeted farms.

Furthermore, a consideration is requested for **adherence to greening requirements**. Some farms already either (or do not adhere) to standard Greening practices prior to the application of the policy. This certainly applies to the Crop Diversification measure where the empirical literature identifies a significant adherence level of farms with the crop diversification requirements, despite the policy implementation. Note that adherence to regulations' requirements represents the immediate targeted outcome of the policy and are conditional on which beneficial effects are expected on environmental outcomes. Consequently, a proper evaluation exercise requires a distinction to be made between the Greening effect separately on the already adherent and non-adherent farms. If these groups can be identified, then the effect of the Greening policy could be evaluated by comparing the group of non-already adherent farms to the group of already adherent ones. However, a distinction has to be made regarding the two practices. Unfortunately, while farms adherence to CD requirements can be assessed by using FADN, both before and after the policy's implementation, the adherence to EFA can only be observed after the policy's introduction. Indeed, only starting from 2014, FADN provides the information necessary to identify farms that adhere to the EFA obligation.

4.5 Exploiting the size-related exemption/obligation rules

Being treated with CD and EFA measures depends upon criteria that impose restrictions on different farming types. These criteria, are defined by thresholds on farm size-related measures that determine the obligation to adhere to the Regulation's administrative requirements. These thresholds can be exploited in order to estimate local treatment effects in a **Regression Discontinuity Design** identification strategy. The principle behind it is those farms that are sufficiently close to both sides of the threshold are similar enough to provide a valid counterfactual. For this reason, the farms typologies described in Tables 7 and 9 provide subpopulations in which the local treatment effect can be estimated. The CIE strategies to exploit the size thresholds for CD and EFA practices are exposed in the analysis that follows. The treated population is the population under CD/EFA obligations, and except for the farms exempted by the regulation, the thresholds fully determine the treatment assignment. All farms to the right of the threshold (e.g., larger than 10 or 30 ha for CD and larger than 15 ha for EFA) are treated and all farms to the left are not treated, thereby producing a **Regression Discontinuity Design**. Once again in this case interest may lay in assessing how effective the policy was to induce an adherence behaviour on the farms under the Greening obligations. Once this is established, it can be investigated whether or not the policy was also effective on other variables with environmental content, among the ones observable through the lenses of FADN data.

The presented CIE strategies may be firstly implemented in a cross-sectional context, thereby omitting the data's time dimension of the data. If repeated observations are available, before and after the policy's implementation, then the proposed CIE may be repeated over farms grouped by adherence status priori to the policy's implementation. This will provide information about the distinct impact of the policy on **already adherent farms**, focusing on the proportion of farms which either maintain or change their practices.

Exploiting the threshold 10 ha for CD

In this setting, RDD is a CIE method that allows for the estimation of the effect of CD requirements on farms with medium (M-AL, $10-30ha$), compared to small arable land ($\leq 10ha$).

The relevant population of interest is comprised by farms that are neither organic nor under the Small Farmer Scheme. Farms under the CD obligation with arable land larger than 10 ha have to be compared to farms with arable land smaller than 10 ha. In order to improve the comparison, farms below the threshold should satisfy all of the same conditions as the farms above the threshold and have to be equal in all but the arable land size (Crops under water less than 100% AL and Grasses, herbaceous forage, and land lying fallow <75% AL).

Outcomes of interest are the percentage of farms adherent to the practice, the number of crops, the percentage of AL covered by the main crop, as well as the other input usages available in the FADN dataset. The proposed CIE may be repeated over farms grouped by adherence status before the policy and is limited to farms that are observed both before and after the policy's implementation. This will provide information on the distinct impact of the policy on the degree of CD maintenance from already adherent farms and on the non-adherent farms.

Exploiting the threshold 30 ha for CD

In this setting, RDD is a CIE method that allows for the estimation of the effect of changing CD requirements to farms with large (L-AL, $> 30ha$) as compared to medium (MAL, $10-30ha$) arable land.

The relevant population of interest is comprised by farms that are neither organic nor under the Small Farmer Scheme, and are under the CD obligation. The first RDD exercise may be implemented by comparing CD treated farms just above the threshold of 30 ha AL to treated farms just below that threshold. The exercise can be repeated, thereby, accounting for farms which adopted standard CD requirements for or "CD equivalent practices". These comparisons provide evaluations of the impact of changing the requirements according to by size of arable land. Outcomes of interest are the percentage of practice adherence, the number of crops, the percentage of AL covered by the main crop, as well as the other input usages available in the FADN dataset.

Though limited to farms that are observed both before and after the policy implementation, the proposed CIE may be repeated for farms grouped by adherence status prior to the introduction of the policy. This will provide information about the distinct impact of the policy on the degree of CD maintenance from already adherent farms and on the non-adherent farms.

Exploiting the threshold 15 ha for EFA

In this setting, RDD is a CIE method that allows for the estimation of the effect of EFA requirements on farms withthat are medium large (ML-AL, $> 15ha$). The relevant population is comprised of farms that are neither organic nor fall under the Small Farmer Scheme. Farms under the EFA obligation with arable land larger than 15 ha have to be compared to farms with arable land smaller than 15 ha. To improve the comparison, farms below the threshold should satisfy all of the same requirements as the farms above the threshold, except in terms of the arable land size (Grasses, herbaceous forage, and land lying fallow <75% AL).

Outcomes of interest are the percentage of adherence to the practice, the percentage of AL dedicated to EFA as well as the other input usages that are available in the FADN dataset.

4.6 Tips for RDD's applications

In general, RDD results are valid if two main **assumptions** hold. The first assumption, **smoothness of the counterfactual outcome at the cutoff** requires that, if treatment status actually has not changed at the cutoff (if no farm near the cutoff had been treated, or if everyone had), then there would be no jump or discontinuity in the outcome; this corresponds to the assumption that the only plausible cause of the observable jump is the policy intervention. This is an assumption that cannot be formally checked by means of statistical tests. An understanding of the context under investigation is required paired with careful thinking about what else might have changed at the cutoff.

The second assumption, **random assignment around the cutoff**, corresponds to the exclusion of the manipulations of the running variable's values or having precise measures for the running variable (AL ha). This assumption may be verified through formal statistical tests.

As for other counterfactual methods, placebo tests may help to making the result more robust. They are implemented by applying the method (here RDD) to a set of variables that the treatment should not affect; these include control variables, for instance. If a large number of placebo tests are run, then it might happen that non-zero effects are found. In case where non-zero effects are not prevalent, the variables with the failed placebo tests should be added to the model as control variables.

Previous **empirical analysis** of Green Direct Payments based on RDD methods to CD and EFA are respectively presented in Sauquet (2022) and Varacca et al. (2022) respectively.

4.7 Exploiting the starting date of the policy's implementation

The evaluation of the policy may exploit the time variation by means of the Difference-In-Differences (DID) method bacause the obligation to adhere to the Greening policy started in

2014. This requires defining treated and control groups and involves measuring how outcomes changed in the two groups in the period **after** the policy intervention as well as compared to the period **before** the policy's implementation. The Greening measures, while imposing obligations to a group of farms (treated farms), left the agricultural practices of the remaining ones (control farms) unchanged. If treated and control groups can be identified and observed prior to the policy's implementation, the change in outcomes' trends between the two groups can be exploited in a DID context.

The **treated group** may be formed by exploiting the farms under the groups identified by obligation conditions. The DID may, in theory, be implemented both for evaluate CD and EFA as the conditions to define the treated farms (ha of arable land, and ha of grasses, herbaceous forage and land lying fallow) are observable before and after 2014.

The second requirement for implementing a DID strategy is the identification of a **control group**. This is defined as a group of farms that were not constrained by changing their practices regardless of their entitlement to the payment.
From a theoretical perspective, several control groups can be identified for the CD, EFA practices, where the practical usability is subsequently to be further investigated based on the available data.

a) Farms under the Small Farmer Scheme;
b) Organic farms;
c1) Farms with arable land smaller than 10 exempted from the CD requirements not under the small farmer scheme neither organic;
c2) Farms with arable land smaller than 15 ha exempted from the EFA requirements not under the small farmer scheme neither organic;
d) Farms that always adhered with the CD requirements before the policy implementation.

Unfortunately, not one of the previous groups, from a) to c2), represents a valuable control group for CIE purposes. Indeed, farms under the SFS and organic farms observable within FADN are too few, and, moreover, organic farms are not uniformly spread across MSs. The groups formed by farms smaller than 10ha (or 15ha) represent farming systems inherently incomparable to medium and large arable farms.
In the end, the only feasible CIE exploiting the time of the intervention is to compare non-already adherent farms to already adherent farms. In this setting the interest is twofold: how outcomes of non-already adherent farms changed conditional to Greening implementation; and what was the effect of the policy on agricultural practices of already adherent farms?

Note that this analysis is not feasible when considering the EFA requirement, because this requirement is not available/observable in FADN prior to 2014.

To implement a DID the three ingredients – timing of policy implementation, treated and control group(s) – allow for the implementation of a DID strategy to identify the causal effects of the CD policy.

The general equation for a given outcome y_{it} observed for farm i at year t is:

$$y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treat_i + \delta Post_t Treat_i + X'_{it}\gamma + \varepsilon_{it} \tag{2}$$

where $Post_t = 1(t > 2013)$ is a dummy variable selecting observations in the post-Greening period, $Treat_i = 1(\text{if treated})$ is a variable identifying the treated units and X_{it} is a set of control variables chosen to control for other variables that might influence the outcome (typically time and farm specific effects). The relevant parameter of interest that measures the average treatment effect on the treated is δ.
The DID regression can then be implemented in the treatment and control groups previously proposed, and the treatment effect can then be estimated separately for CD. The treatment variable is defined in terms of the obligation conditions set by the regulation. Group of already adherent farmers to CD requirements need longitudinal data in order to be identified.

4.8 Tips for DID's applications

It is required that **common trend** assumption holds in order to infer causality from DID, that is the trend of changes over time is common in the treatment and control groups. The parallel trends **assumption** states that, if no treatment had occurred, then the difference between the treated group and the control group would have remained the same in the post-treatment period as it was in the pre-treatment period. This assumption is inherently unobservable, as is the counterfactual of what would have happened if treatment had not occurred. What is actually feasible is to test whether treated and control groups already have parallel trends in the period prior to the treatment.

Empirical analyses of Green Direct Payments based on DID methods to CD are not available, at the best of our knowledge.

Box 1 Greening Evaluation questions

Evaluation questions	**Analysis Proposal**
EQ.G.1 Local impact (at 10 ha of AL threshold) of CD Treated: Medium Arable Land (M-AL) Control: Arable Land < 10 ha (S-AL$_{<10ha}$) Method: RDD	1
EQ.G.2 Local impact (at 30 ha of AL threshold) of CD Treated: Large Arable Land (L-AL) Control: Medium Arable Land (M-AL) Method: RDD	2
EQ.G.3 Local impact (at 15 ha of AL threshold) of EFA Treated: Medium-large Arable Land (ML-AL) Control: Arable Land < 15 ha (S-AL$_{<15ha}$) Method: RDD	3
EQ.G.4 Average impact of CD on not already adherent farms as compared to farms already adherent to CD requirements Treated: M-AL/L-AL not already adherent to CD Control: M-AL/L-AL already adherent to CD Method: DID	4

5 Rural Development environmental measures

This section investigates another subset of policy interventions under the CAP 2014-2022 that were designed with (mostly) environmental goals in mind, namely the Rural Development Programmes' (RDPs) measures. First, a general overview of RDPs commitment to environmental outcomes is provided, and a literature review of available empirical findings on their effects on environmental outcomes is critically examined. The mostly relevant RDPs' measures -M10, M11, and M13- are discussed regarding different aspects of CIE feasibility. The evaluation questions are isolated for any measure, and the most suitable CIE methodologies to apply are presented. A summary table reporting the conditions for CIE feasibility on FADN data is provided in the last part of the section.
The analysis of the CIE feasibility using FADN is described in Section 6.

5.1 Description and objectives

RDPs, referred to as the second pillar or Pillar 2 of the CAP, were financed by the European agricultural fund for rural development (EAFRD) and were co-financed by national budgets. They consist of measures and projects that contribute to the EU-wide objectives of: - improving the competitiveness of agriculture; - encouraging sustainable management of natural resources and climate action; and - achieving a balanced territorial development of rural economies and communities.

The Member States (MS) are required to spend a minimum of 30% of the total contribution from EAFRD to each Rural Development Programme on climate change mitigation and adaptation, and environmental issues such as protecting natural resources, and enhancing biodiversity.

Much of this environmental contribution is channeled through grants and annual payments to farmers, by supporting investments and farming activities that contribute to climate action and to the sustainable management of natural resources through the promotion of organic farming and the responsible management of inputs like pesticides and fertilisers.
The three highest budgets allocation shares of the EU's expenditure (EAFRD, excluding national co-financing) are: the agri-environment-climate measure (M10), organic farming (M11), and areas facing natural or other constraints (M13).
Table 10 shows the percentage shares of expenditure for RDPs on environment and climate in 2020. At the EU27 level, M13 shows the highest share followed by M10 and M11, respectively 19%, 15% and 9% of the total RDPs funding respectively, while their distribution is rather heterogeneous across MSs. As a matter of fact, Pillar 2 Measures activated on a quasi-voluntary basis are beyond the compulsory threshold of 30%.

In this section, the CIE feasibility of the second pillar's measures, which is mostly targeted at environmental goals (M10, M11, and M13) is analysed from a theoretical perspective. The

Table 10: Percentage Shares of EU expenditure spent on environment and climate for RDP and by measure in 2020.
Source: Agri-Food Data Portal

MS	M10 AEC	M11 Organic	M13 ANC	Other Other	Total
AT	25	12	22	3	62
BE	26	11	4	13	54
BG	4	5	10	13	33
CY	18	7	14	21	60
CZ	24	14	34	3	76
DE	22	15	11	5	53
DK	18	29	0	37	84
EE	23	14	0	5	42
EL	9	13	30	5	57
ES	12	8	7	19	46
FI	24	12	40	1	75
FR	8	7	44	3	62
HR	6	9	13	8	35
HU	28	5	0	14	46
IE	40	1	36	3	79
IT	16	14	10	7	47
LT	6	13	1	4	24
LU	31	8	24	1	62
LV	8	16	0	10	34
MT	13	0	11	40	63
NL	38	0	0	27	65
PL	9	3	15	3	31
PT	20	3	20	24	65
RO	10	5	18	11	44
SE	26	13	26	1	66
SI	20	7	28	5	60
SK	10	8	32	3	52
EU27	**15**	**9**	**19**	**8**	**51**

analysis of the CIE feasibility using FADN is described in Section 6. The proposed analyses may be applied to all of the outcomes with environmental content directly available within FADN (see Tables 3 and 4), or to any other outcome that may be computed by using FADN data (See Section 3.5).

5.2 Literature Review

In the empirical literature, the analyses that use CIE methods to evaluate the impact of Pillar 2 measures on environmental outcomes in the EU are rather limited. Tables 11 to 13 list some of the papers that discuss causal evaluations of CAP policies and outline the main characteristics in terms of data sources, policy instruments, spatial coverage, outcomes, results, and

methods employed.
Evidence on the causal effects of M13 is missing, thereby highlighting the difficulty of implementing a proper CIE in this case. On the contrary, all contributions that concern M10 and M11 measures are based on CIE matching methodologies; in the majority of cases, in terms of the propensity score matching (PSM). Whenever the time dimension is available, it is accounted for by recurring to the class of matching-DID approach. A number of recent papers exploit more advanced propensity score estimation methodologies in order to improve and to make more robust the selection of the relevant control covariates more robust, such as lasso or machine learning methods (Bertoni et al., 2020; Giannarakis et al., 2022; Pufahl and Weiss, 2009; Stetter and Sauer, 2022).
They generally consider only specific MS/regions with the exception of Arata and Sckokai (2016) who investigate the impact of Pillar 2 greening policies separately for five MSs, from 2003 to 2006.
The units of observation are either farms or, less frequently, parcels when IACS or LPIS are used. Tables 11 to 13 describe those contributions distinguishing by data sources.
Table 11 illustrates empirical findings based on FADN or similar datasets, like the German LAND. These papers use as outcomes mainly FADN variables related to environment (see Tables 3 and 4) as outcomes.
Table 12 presents papers using IACS or LPIS that address only single regions/MS. In those cases, the data coverage is limited because datasets are probably delivered for specific case studies by regional/national entities. It might be observed that the access to more granular data allows for the CIE to be enlarged to more detailed schemes, beyond the aggregate M10 or M11 payments. While FADN is a suitable data set for EU agri-environmental policy impact evaluation, it lacks data on farms' participation in specific programmes. Recording the value of overall financing does not allow, for instance, for a distinction to be drawn between interventions targeted at soil and at water and, consequentially, to identify their impact, albeit separately. Finally, Table 13 illustrates analyses based on original or experimental data that are not publicly available. Tsakiridis et al. (2022) use an ad-hoc survey to collect habitat features, Giannarakis et al. (2022) consider leveraging climate data and land use information to estimate the effect of Pillar 2 Greening practices on the field-level Soil Organic Carbon. Latruffe et al. (2017) use FADN data integrated by data collected (from FADN farms) through a face-to-face survey. This last paper does not exploit a CIE method but provides a first important attempt to show that the effect of farm subsidies on technical efficiency changes when environmental (greenhouse gas emissions, nitrogen balance and ecological focus areas) outputs are incorporated in the calculation of technical efficiency.
In sum, this review highlights the huge effort invested by the scientific community in searching for new directions by which to investigate the CAP's environmental impact.
As for the empirical findings, there is evidence of a significant positive effect on outcomes that are directly related to farm activities. Instead, the evidence is mixed when considering limited

areas or experimental outcomes. In both cases, the impact of Pillar 2's Greening policies is stronger, the higher is the financial or planning commitment is.

Table 11: CIE studies on environmental related outcomes in EU: main characteristics

Author (year)	**Data**	**Policy measure**	**Period**	**Spatial coverage**	**Outcomes**	**Estimated impact**	**CIE method**
Arata and Sckokai (2016)	FADN	AES	2003-2006	5 EU MS separately	Number of crops per farm, Fertilizer expenditure, Crop protection expenditure, Share of grassland.	The effects of the AES adoption largely depend on the share of the agri-environmental payment on farm revenue. If this share is larger than 5%, participation in AESs is effective in promoting greener farming practices in all countries but Spain	PSM
Cisilino et al. (2019)	FADN	Organic	2013, 2015	IT-Marche	Pesticides/UAA, Nitrogen/UAA, Phosphorus/UAA, LU/UAA ,Number of crops per farm	Organic farms have decreased environmental pressure on the soil by using less pesticides and fertilizers, and improved biodiversity by diversifying crop rotation. The study gives evidence that environmental performance of Organic Farms is statistically higher than conventional ones, while the income indicators considered are not statistically different between the two groups.	PSM-DID
Uehleke et al. (2022)	FADN	AES	2000-2006	Western Germany	Fertiliser expenditure, Plant protection expenditure, Grassland share	AES generate moderate decreases in plant protection expenditure and moderate increases in grassland shares	M-DID
Pufahl and Weiss (2009)	LAND data	AES	2000-2005	DE	Area under cultivation, Grassland, Cattle livestock units, Cattle livestock density, Fertiliser expenditures (per ha), Pesticide expenditures (per ha)	Positive and significant treatment effect of AES on the area under cultivation, in particular grassland, resulting in a decrease of cattle livestock densities. Furthermore, participation significantly reduced the purchase of farm chemicals (fertiliser, pesticide). We also find differences in the treatment effect among individual farms (heterogeneous treatment effects)	PSM-DID + PSM(L[a])

[a] Lasso

Table 12: CIE studies on environmental related outcomes in EU: main characteristics - continued 2

Author (year)	**Data**	**Policy measure**	**Period**	**Spatial coverage**	**Outcomes**	**Estimated impact**	**CIE method**
Michalek (2022)	FADN + GIS + LPIS + IACS	AES	2014-2020	2 SK regions	Surface water, Ground water, GHG: NH3, CH4, N2O.	Estimates show that the net effects of the AES were rather mixed but only partially favourable from a policy perspective.	PSM-DID
Stetter et al. (2022)	FADN +IACS	AES	2014-2020	DE-Bavaria	Fertilisers per ha, Pesticides per ha, Farm (bio)diversity (Gini-Simpson Index), Farm level Carbon Footprint Index.	Rather small statistically significant effects of AES on land-use diversity. Regarding fertiliser, modest reduction effects for 30 per cent of the sample, while it is barely found any impact on pesticide expenditures. In terms of GHG emissions, mostly insignificant or adverse effects.	PSM(ML[a])
Chabé-Ferret and Subervie (2013)	IACS +SAPM + FSS	AES: single schemes +cross-over effects	2003, 2005	France	Number of crops, Area under crop (%UAA), Area under crop (ha), Cover crops (ha), Organic farming (ha).	Organic farms under conversion (ha) AES exhibit positive additional effects. AES which impose strong requirements, such as the AES aiming to subsidize conversion to organic farming, have large additional effects and almost non-existent windfall effects. AES with modest aims, such as the AES only requiring farmers to add one crop to the rotation, have generated very limited additional effects	Matching - DID
Bertoni et al. (2020)	IACS + LPIS	3 schemes + aggregation	2007-2013	IT-Lombardy	Main arable crops (ha), Main arable crops (%), Number of arable crops, Arable crops heterogeneity, Leguminous crops (%), Non soil-depleting crops (%), Grassland (ha), Grassland (%), Organic farming (ha), Organic farming in conversion (ha).	AES considered were apparently effective in improving the environmental performances of farms participating in these policy schemes. Most of the selected outcome variables proved to be affected by the implementation of the policies in a direction consistent with the policy-makers' expectations. However, the results are more nuanced when cross-over effects are considered.	PSM(CM[b])

[a] Machine Learning
[b] Coarsened Matching

Table 13: CIE studies on environmental related outcomes in EU: main characteristics - continued 3

Author (year)	**Data**	**Policy measure**	**Period**	**Spatial coverage**	**Outcomes**	**Estimated impact**	**CIE method**
Giannarakis et al. (2022)	LPIS + ERA5 + earth observations	AES	2017-2021	Lithuania	Soil Organic Carbon (SOC)	No significant effects	PSM(ML[a])
Tsakiridis et al. (2022)	Ad hoc survey	AES	2012	Ireland	Share of habitat area, Length of linear habitats, FBEGS index	Not enough robust results due to small sample size and limited balancing. Small but positive effect on habitat share and habitat quality	PSM
Latruffe et al. (2017)	FLINT	DP, SFP, AES, LFA.	2018	EU	GHC, Nitrogen.	Results indicate that the effect of the CAP operational subsidies on farm technical efficiency changes when environmental outputs are taken into account in the efficiency calculation: some effects change significance, and more importantly, some effects change sign.	

[a] Machine Learning

Even when if no study on the effect of M13 ANC was found, it is worth mentioning that a limited number of papers analyses the impact of similar measures from a CIE perspective. Takayama et al. (2021) analyse direct payment scheme for hilly and mountainous areas for Japan, where the variation in receipt of payments at the rural community level allows for a distinction to be drawn between treatment and control group. Their results support a positive effect of payment schemes to less-favoured areas in maintaining farmland.
The papers by Noack et al. (2021) and Ali et al. (2014) propose interesting usages of RDD by exploiting geographical boundaries. Noack et al. (2021) leverage the former inner German border as a natural experiment to estimate the causal impact of farm size on biodiversity. The main results show that the increase in farm size, and the consequent land cover simplification, at the former inner German border reduces bird diversity by 15%. Ali et al. (2014) evaluate the impact of a pilot land tenure regularization programme in Rwanda using a geographic discontinuity design and find a very large impact on investment and the maintenance of soil conservation measures.

Some pieces of evidence can be drawn from the literature reviewed. Firstly, the evaluation of CAP environmental measures lacks of rigorous CIE analysis providing estimations of the impact of the policies, and, whenever available, empirical evidences do not cover the entire EU. Secondly, there is need and room to enlarge CIE feasibility to a wide range of environmental outcomes (beyond FADN), and to the joint economic and environmental evaluation. Thirdly, additional effort has to be exerted to make M13 evaluation feasible. The present report is an attempt to address these issues.

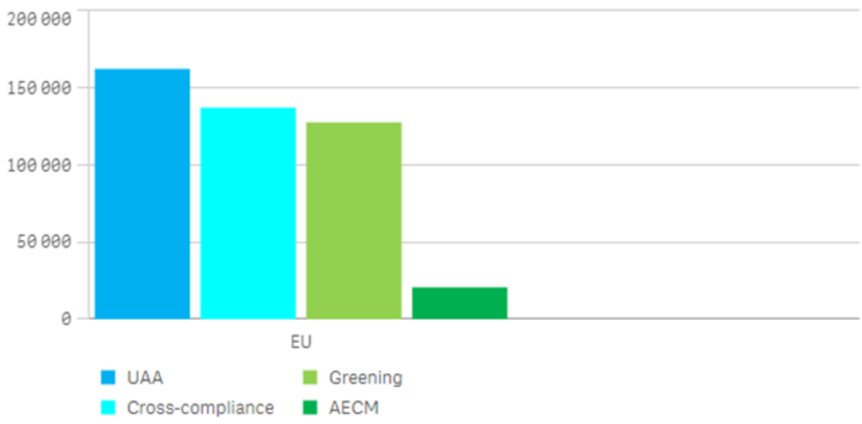
5.3 M10. Agri-environmental-climate measures

Description and Objective

Measure 10 (M10) Agri-environment-climate commitments “aims to preserve and promote the necessary changes to agricultural practices that make a positive contribution to the environment and climate” (Regulation (EU) No 1305/2013 Article 28,). On top of the introduction of the Greening measures under Pillar 1 of the CAP, the Commission recommended the use of agri-environmental commitments to address more targeted, specific, and locally-relevant environmental outcomes. As a rationale, it consists of a compensation, “for all or part of the additional costs and income foregone resulting from the commitments made”, in compliance with the World Trade Organisation (WTO) agreements (Annex 2 of the WTO agreement on agriculture is particularly relevant). The duration of commitments is indicated as a period of five years (with some exemptions).
M10 is articulated in two sub-measures: M10.1 and M10.2.

- M10.1 Agri-environment-climate measure (AECM) - mandatory for RDP - supports commit-

Figure 6: Agricultural area subject to environmental requirements (1000 ha) in 2020.
Source: Agri-Food Data Portal



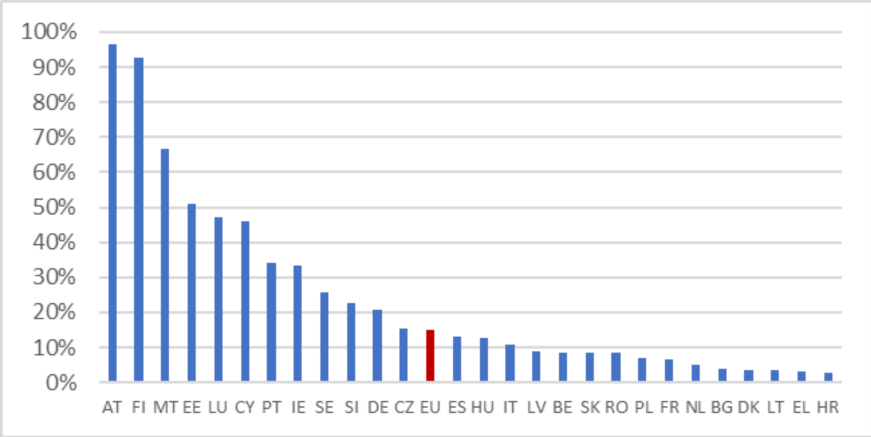
ments that go beyond the relevant mandatory standards in key issues of climate change, water, soil, biodiversity and landscapes.

- M10.2 Genetic Resources in agriculture provides support for conservation and sustainable use, and development of genetic resources in agriculture.

M10 is the second most climate-relevant RDP measures in terms of expenditure share (see Table 10) and the AECM represents a large majority of M10 subsidies; the share of expenditure for the sub-measure M10.2 , during the period 2014-2020, only reached the 1.5%.
In 2020, M10 covered about 20 million hectares of land, 12.7% of the EU's total agricultural area across EU (Figure 6). The spread of the intake is highly heterogeneous across MSs (Figure 7). In the majority of the cases, M10.1 is implemented alongside M02 – Advisory services- where M02 is generally used to increase beneficiaries' knowledge and understanding about the objectives of the AEC operations to which they commit and to know what actions are required for their successful implementation (ENRD European Network for Rural Development, 2016a,b).

M10 expenditures are reported under Priorities 4 and, to a minor extent, under Priority 5. Note that a rule states that each policy intervention must be attributed solely to the most relevant Priority, even if it affects multiple priorities. Consequently, an intervention addressing both biodiversity and climate change, with a greater emphasis on the former, will only be accounted for in the expenditures related to Priority 4. In 2014-2020, M10 represents respectively the 35% (EUR 25 020 million) and 11% (EUR 1 349 million) of planned public expenditures under priorities 4 and 5 (ENRD, RDPs 2014-2020: Key facts & figures – Rural Development Priority 4 and 5). The thematic objectives mentioned most frequently by RDPs include: biodiversity, landscapes, water and soil, included in Focus Areas of Priority 4 (See Table 14).
Table 15 describes how the M10 budget was been spent in the period 2014-2020 in the EU28

Figure 7: Agricultural area subject to environmental requirements divided by agricultural area subject to Cross-compliance (%) in 2020.
Source: Elaboration from Agri-Food Data Portal



territory. The largest expenditures are devoted to Landscapes, habitats, grasslands, and High Natural Value (HNV) farms (31.2%), and to the Management of input (20.7%). Cultivation practices, animal feed regimes and manure management, crop rotation and diversifications, and the upkeeping of ecological focus areas are the relevant expenditures' targets in this instance.

Table 14: M10.1 contribution to Priorities and Focus Areas and Number of RDP counts.
Source: Synthesis of ENRD documents

Objectives	FA	No RDPs
Biodiversity	FA 4A –Biodiversity restoration, preservation and enhancement	70
Landscape	FA 4A –Biodiversity restoration, preservation and enhancement	67
Water	FA 4B –Water management	64
Soil	FA 4C –Soil management	51
Climate change	P5-Resource efficiency and climate	34
GHG emissions	FA 5D –Greenhouse gas and ammonia emissions	11
Resource efficiency	P5-Resource efficiency and climate	9
Carbon sequestration	FA 5A –Carbon conservation and sequestration	8

Table 15: Shares of expenditures for M10 in 2014-2020 by class of farming practice.
Source: Elaboration of Annual Implementation Report (AIR)

Target	Share of Expenditure
Cultivation practices	9.5
Animal feed regimes, manure management	3.3
Crop diversification, crop rotation	6.8
Reduction of drainage, management of wetlands	3.5
Reduction of irrigated areas and/or irrigation rate, irrigation techniques	1.0
Management of inputs incl. integrated production (reduction of mineral fertilizers, reduction of pesticides)	20.7
Creation, upkeep of ecological features (e.g. field margins, buffer areas, flower strips, hedgerows, trees)	7.6
Maintenance of HNV arable and grassland systems (e.g. mowing techniques, hand labour, leaving of winter stubbles in arable areas), introduction of extensive grazing practices, conversion of arable land to grassland	31.2
Others	14.8
Sub-measure M10.2	1.6
No. RDPs	109

Eligibility criteria and exemptions

M10.1 is mandatory for RDP implementation and therefore it must be guaranteed in all RDPs. Conversely, the inclusion of sub-measure 10.2 in RDPs is not compulsory.
Both sub-measures are voluntary for farmers.
Concerning M10.1, a near majority of RDP beneficiaries are farmers and in some RDPs land managers. As for M10.2, beneficiaries of in situ operations are farmers, managers of protected areas or other land or livestock managers; beneficiaries of ex situ operations, rather, are public and/or private conservation entities.
Given the focus on specific and locally-relevant environmental outcomes, M10.1 has many linkages and connections with related EU/national strategies and legislation, such as the existing Natura 2000 network; the EU Biodiversity Strategy; the Water Framework Directive.
No support can be granted under M10 for commitments that are covered under the organic farming measure (M11). Member States must ensure that double funding with Pillar 1's Greening measures is avoided.

Different implementation models across MS and regions

MSs and regions have developed their specific RDPs in response to the heterogeneity of the EU's territory and offer to farmers predetermined packages of operations under the AECM. A wide range of operations have been subsidised under AECM across the EU, either related to agricultural practices (soil management, crop rotation, sustainable irrigation method, etc.), or to type of habitats (arable; boundaries, trees and orchards; coastal operations; grassland; etc.); to objective or to landscape type (preventing landscape abandonment, improving irrigation systems and wetlands, reducing the use of chemical agricultural inputs; etc.). Moreover, as observed by the ENRD review (ENRD European Network for Rural Development, 2016a), RDPs might offer operations singularly, as part of a scheme, or by a mix of the two; they might also differ by number of offered operations and by the degree of involvement and consultations of local operators and farmers.

Causal impact identification using FADN

As farmers apply to M10 on a voluntary basis; the treated group consists of those farmers that ex-post received the subsidy starting in 2015.

The causal impact of the policy on environmental outcomes can be estimated by comparing the performances of farms that receive M10 with those with similar characteristics that do not receive the subsidy. When considering farms, FADN data on `M10 subsidy` might be exploited. This will identify a treated group while the control group is selected among farms that do not receive the subsidy, preferably after the exclusionof organic farms. Once constructed the two comparison groups by observed characteristics and matching methods can be implemented. Indeed, those estimators work by matching treated farms with non-treated farms with similar observed characteristics and interpreting the difference in their outcomes as the effect of the treatment. This would allow for the first evaluation question, EQ1, to be answered concerning what is the effectiveness of M10 subsidy on outcomes of interest.

However, it has to be acknowledged that considering the M10 commitments in a unified framework might be rather questionable. M10 measures are extremely heterogeneous in terms of objectives and it would be desirable to identify treatment and analyse outcomes according to pre-specified target. Currently, information on the composition of the expenditure on M10 is only available at the RDP level.
In order to pursue an analysis with a more accurate policy definition, the information on expenditure at RDP level (aggregated by regions or MSs level) might be exploited, at least for an analysis at EU level. For this purpose, the method proposed by Dumangane et al. (2021) might help to identify the relative effectiveness of M10 policy mix on environmental outcomes by defining a multivalued treatment (Imbens, 2000).

RDPs are clustered by typology of M10-mix implementation in the first stage of this methodology. This allows for the identification of groups of RDPs which implement M10 with similar target composition. Second, the treatment level is assigned to farms with respect to the

(NUTS2 or NUTS1 or MS) region to which they belong, according to the RDP M10 policy mix. It should be borne in mind that, at this stage, a check on the applicability of the M10-mix to the specific farming system is anticipated.

To provide an example a clustering exercise has been run that groups RDPs in three subgroups. The expenditures' compositions by cluster are depicted in Table 16.

Table 16: Expenditures' compositions for different M10 practices of RDPs clusters.
Source: Elaboration of Annual Implementation Report (AIR)

	Shares of Expenditure by Cluster		
M10 practice	C1	C2	C3
Cultivation practices	6.6	22.1	3
Animal feed regimes, manure management	8.4	0.0	3.8
Crop diversification, crop rotation	6.7	1.2	3.7
Reduction of drainage, management of wetlands	2.4	0.0	0.2
Reduction of irrigated areas and/or irrigation rate, irrigation techniques	0.1	3.2	0.9
Management of inputs incl. integrated production (reduction of mineral fertilizers, reduction of pesticides)	45.5	11.7	10.7
Creation, upkeep of ecological features (e.g. field margins, buffer areas, flower strips, hedgerows, trees)	7.0	1.6	7.1
Maintenance of HNV arable and grassland systems, introduction of extensive grazing practices, conversion of arable land to grassland	11.9	8.5	61.7
Others	8.0	48.9	7.5
Sub-measure M10.2	3.5	1.7	1.2
No. RDPs	41	19	48

Clusters 1 and 3 regroup highly specialised RDPs, respectively in the Management of inputs including integrated production, and in the Maintenance of HNV and grassland systems respectively. They could be named respectively "Predominantly management of inputs systems", and "Predominantly maintenance of HNV systems" respectively. Cluster 2 is the least specialised, presenting a high share of expenditure aimed at other practices. It is named "Other and cultivation practices"

The clustering results may be exploited in terms of a multivalued treatment, where each cluster is assumed as one out of three discrete treatment levels plus the Level untreated. The additional treatment level (C0) group untreated farms not receiving M10 funds. Indeed, if farms may be assigned to their RDPs according to the regional code, then the following four groups of treated farms, which differ by M10-policy mix, become identifiable:

C0: Farms with `M10 subsidy`= 0;

C1: Farms under "Management of inputs" RDPs with `M10 subsidy`> 0;

C2: Farms under "Other and cultivation practices" RDPs with `M10 subsidy`> 0;

C3: Farms under "Maintenance of HNV and management of inputs" RDPs with `M10 subsidy`> 0.

The first level, C0, corresponds to the lack of treatment, while each of the following three levels corresponds to a specific policy-mix of M10 measures, thereby making possible the evaluation and comparison of the relative effectiveness of the implemented policy mixes possible by recurring to matching method based on the Generalised Propensity Score . The evaluation questions and the related treatment levels are summarized in Box 1.

It is worth noticing that further issues on the composition of the groups need to be addressed, depending on the availability of data, in the process of adopting a matching approach.

A first issue concerns with timing. The matching method can be applied in a pooled framework by comparing groups observed at the treatment year. Nevertheless, in case more time observations are available, the treatment timing may be exploited to monitor the time evolution of the impact: considering either (i) at least two periods; or (ii) the longest observable time window. If a panel or at least two farm observations are available, then more robust techniques (such as DID) might be implemented in addiction to matching.

Furthermore, depending on the data, comparable groups might be created using a number of different dimensions type, size, location (biographical region) or/and MSs. In the empirical literature, the matched sample is usually selected according to similarity of farming systems and geo-physical properties.

Clearly, the actual feasibility of the study depends upon data availability.

Consequentially, the analysis can either be comprehensive of all the MSs or more specific in order to emphasise the heterogeneity of MSs and/or farming types.

Box 2 M10 Evaluation questions

Evaluation questions	Analysis Proposal
EQ.M10.1 Average impact of receiving M10 in terms of environmental outcomes Treated: `M10 subsidy`> 0 Control: `M10 subsidy`$= 0$	5
EQ.M10.2 Average impact of receiving M10 policy-mixes in terms of environmental outcomes Untreated: C0 Treated under treatment level 1: C1 Treated under treatment level 2: C2 Treated under treatment level 3: C3	6

5.4 M11. Organic Farming

Description and Objective

The CAP both recognises and supports the role of Organic Farming (hereafter OF) in responding to consumer demand for more environmentally friendly farming practices. The OF support measure (M11) is a payment that aims to encourage farmers to convert from conventional methods and to apply organic farming methods as defined in the Council Regulation (EC) No 834/2007 as well as to maintain these methods after the initial period of conversion.

M11's objective is to both establish and maintain a sustainable management system for agriculture. The farming practices contribute to improving soil and water quality, to mitigation and adaptation to climate change and to improved biodiversity. In particular, it promotes avoiding the use of synthetic plant protection and synthetic fertilisers and encourages crop rotation, the use of organic fertilisers, and improvement to soil matter; it also set maximum livestock densities and maximum manure input.

Support for OF was part of the compulsory agri-environment measure during the 2007-2013 programming period. For the programming period 2014-2022, there were several measures to recognise the importance of organic farming in contributing to various rural development objectives and priorities, primarily Priority 4 and Priority 5 - in particular Focus Area 5E (carbon conservation and sequestration). [9]

The organic agriculture measure (M11) and the agri-environment-climate measure (M10) are strictly connected by specific selection criteria that aimi to establish complementarity and to avoid double funding. Furthermore, organic farmers can also apply for other forms of CAP income support and mostly qualify automatically for Greening payments (they typically comply with the three rules: maintain permanent grassland; crop diversification; and maintain an "ecological focus area".)

More specifically, M11 provides support for:

- **M11.1 The conversion of conventional farming to organic farming**. Conversion support is intended to recognise the income foregone and additional costs (combining reduced output, higher prices, lower variable costs and higher fixed costs such as labour) of converting to organic. The conversion period is mostly defined as two or three years followed by two to five years of maintenance support. In this period organic methods are used but the resulting product cannot be sold as organic. Support is needed because organic methods often produce lower yields and there is no price premium in the conversion period.

[9] All MSs allocate the majority of their M11 budgets to Priority 4 that aims to restore, preserve, and enhance ecosystems. Only five RDPs (FR-Bretagne, MT, IT-Liguria, ES-Valencia, GR) allocate a proportion of M11's budget to Priority 3 and 5, see the ENRD RDP analysis (ENRD European Network for Rural Development, 2016c).

- **M11.2 The maintenance of certified organic farming**. Maintenance support have the same regulatory basis as conversion payments, covering the income foregone and additional costs of continuing to manage farms organically once the 2-3-year conversion period has been completed. The payments recognise that these farms are continuing to deliver environmental benefits on an ongoing, voluntary basis, with the option to revert to intensive non-organic methods at any time, and that the costs of doing this might not be fully compensated by the specialist market for organic food. The maintenance supports are generally lower than the conversion supports.

The land area under organic management has grown from 9.8 million hectares (Mha) in 2014 to about 15 million hectares (Mha) in 2020, in the EU27-2020; the proportion of UAA in the EU agricultural area raised from 6.5% in 2015 to 9.1% in 2020, so too has the expenditure on policy support, see Table 17. Organic areas receiving specific CAP support rose from 5 million hectares (Mha) in 2015 to about 9 million hectares (Mha), in 2020. In 2020, the 61.6% of the organic area received specific CAP measures. The EU organic sector is indeed developing rapidly, but its development varies significantly both among and within MSs. The proportion of UAA devoted to organic farming grew in all MSs with the exceptions of CZ and IE; in 2020, it was above the 20% in AT, EE and SE whereas it was less than 3% in BG, IE and MT. In 2020 the share of EU27 expenditure for RDPs spent on organic was above the 15% in DK, LV and DE, 1% in IE and 0% in MT and NL, see Table (10). As mentioned by ENRD European Network for Rural Development (2016c), the proportion of the RDP's total public budget allocated to M11 ranged from 22.2% in IT-Calabria, down to 0.1% in PT-Madeira. 41 RDPs have allocated a proportion of their RDP budget to M11 that is above the EU average of 6.4% and 66 RDPs have allocated a budget below the EU average. RDPs in the Southern Europe are mostly below the EU average whereas most of the RDP are above the EU average in Western Europe; in Eastern Europe, all MSs except the Czech Republic have allocated a budget proportion below the EU average.

The average of specific CAP support per ha also varies significantly across MSs both in terms of EU funds and in terms of national co-financing and does not seem to be correlated with the share of organic farming that is devoted to organic farming. There is no identifiable pattern in the relationship between the importance that MSs attribute to organic farming, and the size of their national organic sector. Actually, MSs might actually follow quite different strategies for organic farming development. The percentages shown in Table 17 concern with for organic farming under the RDPs. However, the MSs may support organic farming by exploiting alternative channels. They may support organic from national funding sources rather than through the EAFRD, such as in the NL, for example; they may opt to provide a support for organic land only in conversion (as in SE, in some regions of RO, BG, ES and in FR after 2017) or support organic farming by using other CAP measures like M10.

Some RDPs link the rationale for organic farming support to specific, identified needs or priorities. For example, the DE-Niedersachsen/Bremen RDP mentions that it responds to the growing consumer demand for organic produce. DE-Bavaria particularly targets the conversion support to horticulture in response to the identified market weakness and consumer demand. In PT-Madeira, organic farming is considered to contribute positively to the tourist image of the region. Many countries and regions have specified environmental priorities for the areas preferential allocation of organic farming support. For example, funding will be allocated preferably to farms within Natura 2000 areas in GR and some regions in IT and ES; in some regions in IT and ES, they will also be allocated preferentially to farms within nitrate vulnerable areas whereas IT-Lazio mentions that priority will be allocated to farms in critical agricultural areas identified in the river basin management plans. In PT mainland, funding will be allocated preferably to areas defined in the National Action Programme to Combat Desertification. Some countries and regions have decided to allocate organic farming support to particular sectors. For example, DE-Bavaria particularly targets the conversion support to horticulture in response to identified market weakness and consumer demand. Organic beekeeping is explicitly supported by a few RDPs (e.g., BG and some regions in ES).

Eligibility criteria and exemptions

Two possible types of beneficiaries are eligible for the support under the OF measure:

- Active farmers;[10]
- Groups of organic farmers.

The eligibility of groups of farmers stems from the potential of such groups to multiply the environmental and climate benefits related to organic farming practices and can play a significant role in providing public goods.

Farmers or groups of farmers would be eligible provided that they met the above aforementioned activity criterion. According to the EU rural development regulation, beneficiaries of support under the organic farming measure are also eligible for the agri-environment-climate payments as long as they commit to carry out commitments going beyond the agri-environment-climate measure's baseline and which differ from the commitments supported under the organic farming measure. Hence, eligible farmers might voluntarily decide to opt for either M10 or M11 depending on their own convenience.

[10]According to Article 9 of Regulation(EU) No 1307/2013of the EU regulation on direct payments an active farmer is a farmer (i.e., a natural or legal person, or a group of natural or legal persons) whose holding is situated within the EU, and who exercises an agricultural activity. The following are excluded from the 'active farmer' definition: i) groups and/or natural or legal persons working in the field of transports, infrastructures, and recreational activities; and ii) farmers whose agricultural areas are naturally kept in a state suitable for grazing or cultivation and who does not carry out a minimum activity on those areas. Where appropriate, MSs may exclude other non-agricultural businesses or activities, and decide not to grant payments to other persons or groups whose agricultural activities form an insignificant part of their overall economic activities, and/or whose principal activity or company objectives do not consist of exercising an agricultural activity.

Table 17: Share of UAA for organic farming and average specific support

MS	Share organic farming in total UUA (%)		Average specific CAP support per ha EUR/ha	
	2015	2020	EU Funds	National co-financing
AT	20	22	118	113
BE	5	7	101	146
BG	2	2	265	88
CY	4	4	306	268
CZ	14	15	99	33
DE	6	10	174	72
DK	6	11	129	43
EE	16	22	78	26
EL	8	10	278	78
ES	8	10	92	41
FI	10	14	168	46
FR	5	9	128	42
HR	5	7	318	56
HU	2	6	157	45
IE	2	2	82	72
IT	12	16	153	136
LT	7	8	148	49
LU	3	5	244	0
LV	12	15	73	34
MT	0	1	426	142
NL	3	4	0	0
PL	4	4	124	71
PT	7	8	51	14
RO	2	3	170	34
SE	17	20	109	56
SI	9	11	162	54
SK	9	12	78	28
EU27	6.5	9.1	137	67

Notes: AEC shows the expenditure on M10 on total EU expenditure under M10; similarly, for M11 -organic -and M13 - ANC. Source Agri-Food Data Portal.

Only a few RDPs specify that M11 is incompatible with some or all of M10 agri-environment-climate schemes, whereas others give priority to farmers who also participate in M10 (see regions in ES). Some RDPs mention that catch crops are excluded from funding in order to avoid double funding under the Greening measure. A minority of RDPs define the crops and farming systems that are eligible for support (regions in CY and ES) whereas some RDPs mention a minimum size threshold (regions in AT, DE, IT, and ES).

Different implementation models across MSs and regions

There is very wide variation in payment rates both between and within countries in terms of both for conversion and maintenance .

- M1.1 Conversion. In most cases, higher rates are applied for the two conversion years defined by the organic regulations (sometimes three years in the case of perennial crops). From the third year, maintenance payments normally apply, even in the context of a five-year agreement. For livestock farms, this may not reflect the actual time needed to get organic status on the livestock and to produce finished organic products. This approach can also have the unintended consequence of high(er) payments coinciding with the sale of livestock to reduce stock numbers, thereby leading to additional tax liabilities. In some countries, higher conversion payments are distributed over the full five years of the agreement, with at least one case –Saarland in DE –offering a choice of both options.
  - The NL, AT, and EE pay no conversion support.
- M11.2 Maintenance. There is very wide variation in payment rates both between and within countries, with implications for the EU's market organic food. A number of reasons for the differences can be identified:
  - Differences in scale (with average areas per agreement ranging from 1 ha in MT to 120 ha in the UK) affecting the per ha values of certain fixed costs like certification;
  - Differences in production systems and intensity due to location specific factors (climate, soils etc.);
  - Differences in cost calculation methods, with some costs included in some countries but not in others;
  - Differences in specificity of land use definitions. Some countries adopted broad categories such as grassland and arable, recognizing the system context of organic farming. Others, for example ES, implemented very detailed payment rates for individual crop and animal species and uses, with the potential for more direct market impacts;
  - Differences in treatment of farms of different sizes within regions, which may be relevant where certain 'fixed' costs such as certification need to be recognized, but maximum payments per farm, and standard percentage reductions for larger farms, may not reflect the actual costs on the additional hectares (which is relevant if variable costs such as fertiliser and spray costs and output factors such as yields and prices predominate).
  - Differences in intervention rates. MSs may choose not to fully compensate the calculated costs for policy reasons (e.g. not to be perceived to over-incentivise farmers

to join a scheme) or for budgetary reasons, so that available resources can stretch further.

- the NL and some regions in RO, BG, and ES pay no maintenance support.
- France withdrew maintenance support in 2017, although some regions continued to provide support without a national contribution.

Causal impact identification using FADN

The eligibility criteria identify the population targeted by the policy. As farmers applied to M11 on a voluntary scheme, the treated group consists of those farmers that ex-post received the subsidy for either maintenance or converting purpose starting from 2014.

Hence, the effectiveness of M11 can be evaluated in terms of environmental outcomes distinguishing those two groups by means of a multiple treatment imputations.

The causal impact of the policy can be estimated by comparing the performances of organic farms that receive M11 with those of farmers with similar characteristics that do not receive the subsidy.

Matching methods can be implemented once comparison groups are constructed according to observed characteristics. Indeed, those estimators work by matching treated farm with non-treated farms with similar observed characteristics and interpreting the difference in their outcomes as the effect of the treatment, see Cisilino et al. (2019).

The first condition to performing a matching exercise is to identify a treated group. In order to have an exhaustive picture, FADN information on `Organic farming Code` and `Organic farming Subsidy` needs to be combined in order to discriminate between the two M11 measures, M11.1 and M11.2. In fact, while `Organic farming Subsidy` does not distinguish between M11.1 and M11.2, the `Organic farming Code` allows for the identification, among organic farms, those that are converting, see the section 6 for a detailed description of the variables.

The second requirement to perform a CIE strategy is to identify a control group that is basically comprised by farmers that do not receive the subsidy. Notice that this set may contain either **conventional farms or organic farms that do not receive subsidies**.

As a consequence, a number of different research questions can be addressed depending on the definition of the groups. The most comprehensive question concerns the impacts of M11.1, of M11.2 and of being organic with no subsidy in terms of environmental outcomes. In this case, comparable groups must be defined as:

A. Organic farmers receiving M11.1 (`Organic farming Code`=4 and `Organic subsidy`>0)

B. Organic farmers receiving M11.2 (`Organic farming Code`=2,3 and `Organic subsidy`>0)

C. Organic farmers not receiving M11 (`Organic farming Code`$\neq$1 and `Organic subsidy`=0)

D. Conventional farmers (`Organic farming Code`= 1)

Clearly, M11.1 and M11.2 can also be evaluated together by creating a unique group that leads to the identification of the impacts of M11, as a whole. The control group might also consist of either conventional farmers or organic farmers that do not receive support solely. In such a case, the research question needs to be refined slightly. It could be noticed, in passing, that organic farmers are usually excluded by the control group in the empirical literature, see Cisilino et al. (2019).

It is worth noticing that, in the process of adopting a matching approach, further issues on the composition of the groups need to be addressed depending on the availability of data.

Furthermore, depending on the data, comparable groups might be created using a number of different dimensions type, size, location (biographical region) or/and MSs. In the empirical literature, the matched sample is usually selected by similarity of farming systems and geo-physical properties. For example, using FADN data for the production of olives in Italy, Raimondo et al. (2021) consider macro-areas and size of the farms in terms of UAA. Cisilino et al. (2019) integrate FADN data with administrative database about beneficiaries or farms funded by the Marche RDP and exploit information type, size, location, UAA, family working units, machine power, age, and gender. Latruffe et al. (2017) use FLINT data and consider as similar farms with an analogous business structure.

Clearly, the actual feasibility of the study depends on data availability. Consequentially, the analysis can be either comprehensive of all the MSs or can be more specific to emphasise the heterogeneity of MSs and/or farming types.

The evaluation questions and the related treatment levels are summarized in Box 2.

Box 3 M11 Evaluation Questions

Evaluation questions	**Analysis Proposal**
EQ.M11.1 Average impact of being organic with respect to conventional farms in terms of environmental outcomes Treated under treatment level (A+B+C)[a] Treated under treatment level D	7

[a] from the organic holdings

5.5 M13. Area with Natural Constraints

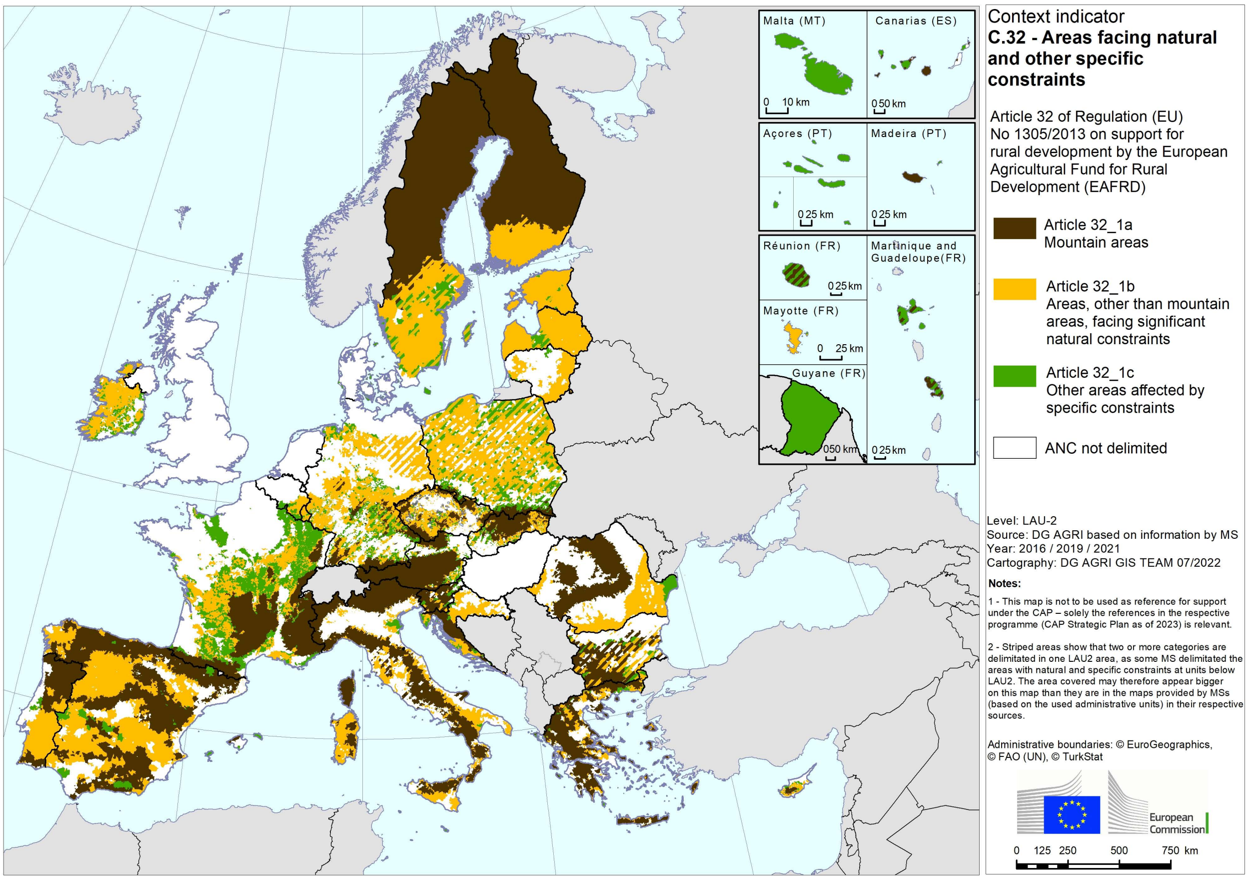
Description and Objective

Measure 13 (M13) - Payments to areas facing natural or other specific constraints (ANC) provides payments to farms located in areas in which farming is more difficult due to natural constraints, production costs increase and agricultural opportunities reduce.
M13 acts as total or partial compensation to farmers for additional costs and income foregone related to natural or specific disadvantages. The main goals are allowing farmers to continue agriculture and land management, thereby addressing rural depopulation, maintaining certain agricultural land use, and protecting the environment. In the European Union, aids for these types of areas, previously named Less Favoured Areas, date back to 1975 with several reforms.

In the 2014-2022 CAP, there are three different types of Areas facing Natural Constraints (ANCs):

- **Mountain areas**, characterised as those areas handicapped by a short growing season because of a high altitude, or by steep slopes, or by a combination of the two at a lower altitude. Areas north of 62nd parallel are also considered to be mountain areas due to the shortened growing period.
- **Areas facing significant natural constraints other than mountain**, whose designation is based on a set of eight common biophysical criteria: low temperature, dryness, excess soil moisture, limited soil drainage, unfavourable texture and stoniness, shallow rooting depth, poor chemical properties and slope. Member States may use a variety of indicators for the designation and the coherence of the methodology is assessed by Commission services.
- **Areas affected by specific constraints**, which can make up no more than 10% of the Member State's territory, identified according two distinct sets of criteria:
  a) Areas in which it is necessary for land management to be continued in order to conserve or improve the environment, to maintain the countryside, to preserve the tourist potential of the area or to protect the coastline.
  b) Areas where:
    - at least 60% of the agricultural area meets at least two of the biophysical criteria each within a margin of not more than 20% of the threshold value indicated, or
    - at least 60% of the agricultural area is composed of areas meeting at least one of the biophysical criteria at the threshold value indicated, and areas meeting at least two of the biophysical criteria each within a margin of not more than 20% of the threshold value indicated.

Figure 8: Areas facing natural constraints and other specific constraints (ANCs).
Source: Agri-Food Data Portal



The overall area falling under ANCs in the EU-27 is around 52 898 984 ha in total. It covers 58.6% of the Total EU's UA. The 28% of ANCs are mountain areas, the 69% are areas with other significant constraints, and the remaining 3% are areas with specific constraints[11] (See Figure 8).

In 2020, payments for ANCs comprised 19% of the EU's expenditures on environment and climate for RDP (see Table 10). Indeed, in the period 2014-2020, M13 represents the 37% of planned public expenditure on Priority 4, and marginal residuals shares on other Priorities.

Eligibility criteria and exemptions

Active farmers are eligible to receive ANCs payments, without specific conditionality conditions concerning agricultural practices beyond the mandatory cross-compliance. Some regions

[11] In February 2017.

(specifically in Spain) require having > 50% of income from agricultural activities, some others not being pluri-active farmers, not receiving any other social allowances, pensions, unemployment benefits. Farms must have the registered place of the holding within the ANC area to be eligible in France, Germany, and in some Spanish regions.

A number of RDPs have introduced additional eligibility conditions regarding the minimum number of hectares in ANC area, or the minimum livestock density, or the minimum number of animals in holding, or others. Eligibility conditions are rather heterogeneous across MSs, but are usually set at low values. This excludes only very small marginal farms (located in ANC areas) from the ANC eligibility.

Different implementation models across MSs and regions

Areas of interest to the ANC are decided at the MS level. For their establishment, MS define a variety of indicators for the designation of ANC. Hence, the biophysical delimitation is assessed by JRC and AGRI whereas the fine-tuning is assessed by AGRI.

Payments are entitled per hectare of eligible farms and are different according to ANC type. The minimum annual payment rate for all types of ANCs is 25 Euro per hectare. The maximum rates vary between the types of ANCs: for mountain areas, the maximum rate is 450 Euro per hectare; for areas facing natural constraints other than mountain areas and in areas with specific constraints, the maximum rate is 250 Euro per hectare. The support rates can be higher in specific cases.

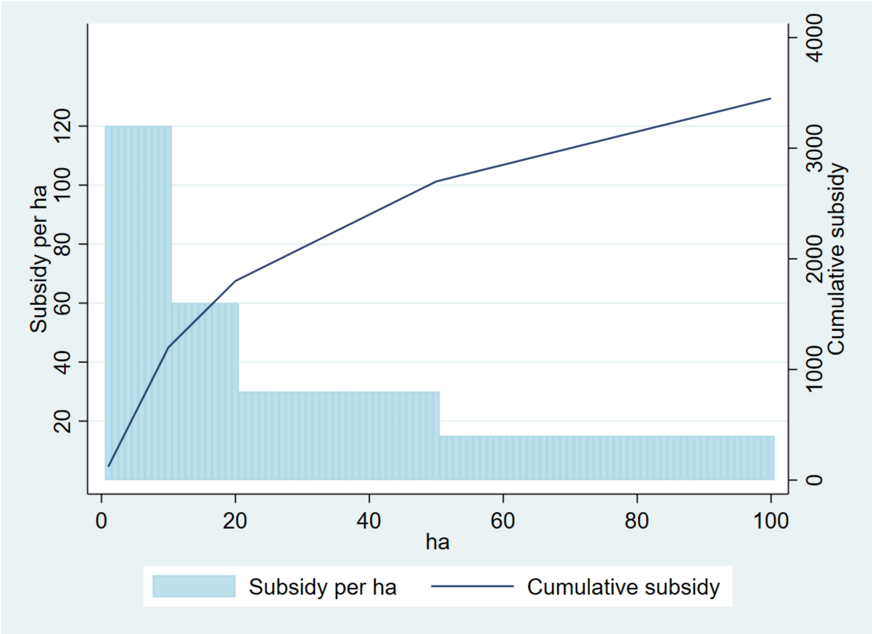
Payment rates are set by the MS and are uniform inside the territory. Additional national financing is not frequently adopted.

A number of MSs and regions adopt degressive payment schemes according to which per ha payment rates decrease for classes of increasing ANC area. For instance, in the Italian region of Abruzzo[12] the subsidy amounts to €120/ha and the payments rates follows a degressive scheme, such as: a) ANC area of up to 10 ha: 100% of payment; b) ANC area of 10.01 to 20 ha: 50% of payment; c) ANC area of 20.01 to 50 ha: 25% of payment and 12,5 % over 50 ha, see Figure 9. The threshold of degressivity is not uniform across either the MS or RDPs.

MSs have also the opportunity to provide payments to farmers in ANCs under Pillar 1 as decoupled area-based payments. The 5% of the annual national ceiling for Pillar 1 can be earmarked for this purpose. Yet, double-funding must be avoided. Currently this payment is only provided by Denmark and Slovenia.

[12] See: Note to Mr Power, Head of Cabinet of Commissioner Phil Hogan Ref. - 17/05/2017

Figure 9: ANC payment scheme. IT-Abruzzo. Source: DG AGRI. Annex 6: Examples of ANCs payment calculations

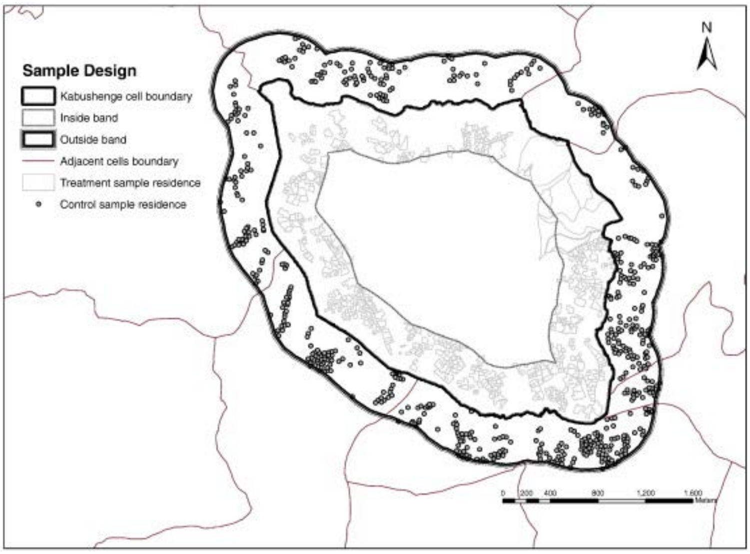


Causal impact identification using FADN

M13 is reported as a green measure under Priority 4. The main objective of M13 is to support farmers' income to prevent land abandonment in ANC. The rationale is that the mere existence of active farms in those areas, will have a positive impact on the environment. Unlike other measures, M13 is not systematically linked to effective measure in favour of greenhouse gas reduction or climate adaptation; indeed, the impact of M13 on livestock production, the most usual type of farming in these areas, is difficult to establish in terms of production and thus GHG emissions. There is potential for reducing GHG emissions if the abandonment of previously farmed land is followed by vegetation (herbaceous, shrub and wood) and forest. However, erosion effects with subsequent loss of soil carbon are also possible ((European Commission, 2021b)).

Evaluating the causal impact of M13 using FADN data might be challenging for at least two reasons: first, the outcomes of interest are not sufficiently detailed; furthermore, the control samples are difficult to define.
Regarding the CIE outcomes, M13 should be evaluated in terms of the potential drawbacks related to land abandonment (Benayas et al., 2007), such as biodiversity loss, increase of fire frequency and intensity, soil erosion and desertification, reduction of landscape diversity and of water provision. Those outputs are largely unavailable within FADN, but might be partially

Figure 10: Example of a sample design for geographical RDD. Source: (Ali et al., 2014)



recovered using geospatial satellite data sourced by Copernicus. Notice in passing that FADN data does provide information on farmers' income but this is beyond the scope of the present Report which focuses on environmental outcomes.

Concerning the control groups, CIE requires a comparison between the outcome of farms receiving specific ANC measures (the treated group) and the outcome of a control group that is similar in all respects to the treated one, save for the fact they did not receive the subsidy. Since all farms located in ANCs receive the financial aid, the policy design does not allow for the definition of a proper control group within ANC. At the same time, as shown by European Commission, Directorate General for Agriculture and Rural Development (2023), farms outside ANC areas are largely different in terms of many socio-economic factors such as economic size, workforce, stocking density, and intermediate consumption. In this circumstance it matching CIE exercise results not feasible because of the lack of a comparable control group.

A potential solution might be to evaluate the impact of M13 measure exploiting the ANC typology. A suitable control group would comprise farms just outside the ANC boundary that share the same characteristics of farms within the treated areas. By using a geographical Regression Discontinuity Design (RDD), it could be possible to identify the effect of the subsidy as the difference between the outcome of farms located within the ANC with the outcome of those just outside the boundary. Similar exercises have been performed by (Ali et al., 2014) to evaluate the impact of a land tenure regularization programme in Rwanda, see Figure 10 where treated and control groups are defined by location (Ali et al., 2014). Currently, FADN data do not disclose this information (See Section 6). However, this CIE exercise would become feasible whenever farms close to the ANC area were identifiable.

It is certainly clear that such an information would lead to comparisons between farms located in the same country or in the same topological area. Biophysical criteria defining the ANCs differ widely across the European territory, and thus, farming systems, even if they are located in ANC, are hardly comparable across MSs. For instance, it would be mostly inconvenient to compare the outcome of a group of farms located in the Italian Alpes with that of similar farms in Sweden. Following this reasoning, it is obvious that the heterogeneity of the policy across MS might not be exploited for a proper evaluation exercise. In summary, the CIE of the ANC subsidies does not result feasible for the lack of proper control groups.
Instead, the payments' heterogeneity across treated units, might be used to possibly evaluate the impacts of changes in the M13 subsidy on ANC farms within specific ANC and MS. In particular, the degressive payment scheme introduces a heterogeneity of payments among comparable farms. Hence, by means of the Regression Kink Design (RKD) (Card et al., 2016), it is possible to perform a CIE analysis in the case that the treatment variable is assumed to have one/more kinks at specified values of the underlying assignment variable. In somewhat greater detail, in M13, when limiting the analysis to farms located in specific ANC, payment rates exhibit discrete jumps at pre-specified values (thresholds) of Utilised Agricultural Area ha. This allows for an investigation of changes intervening in slopes of the relationship between the outcome of interest and the assignment variable at the exact location of the kinks in the policy treatment to take place. Provided that observations on either side of the kink thresholds are "similar", any kink in the outcome can be attributed to the treatment effect of the policy variable. RKD involves the estimation of quantities "close" to the thresholds using (local) polynomial approximations, thereby focusing on estimating slope changes.

5.6 Tips for PSM's applications

Matching methods are designed to ensure that impact estimates are based on outcome differences between comparable units.

Generally speaking, two **conditions** must be satisfied in order to implement this method: the conditional independence or unconfoundedness assumption and the common support or overlap condition.

First, the conditional independence or unconfoundedness assumption asserts that selection into the intervention is based only on observable characteristics of the eligible units, and that the expected outcome in the absence of treatment does not depend on treatment status after conditioning on these variables influencing participation. Unfortunately, this assumption is not directly testable in formal, statistical terms but might require justification and discussion, see Caliendo and Kopeinig (2008)

Second, the common support or overlap condition states that there must be a positive probability of finding both a treated and an untreated unit in order to ensure that each treated unit can be matched with an untreated unit, in order to calculate the difference in mean outcomes for each value of the covariates, for each possible value of the vector of covariates. Indeed, if some units in the treatment group have combinations of characteristics that cannot be matched by those of units in the comparison group, it is not possible to construct a counterfactual. In this case, assessing the quality of matching might be performed by statistical tests that importantly check whether the propensity score adequately (i) balances characteristics between the treatment and comparison group units and (ii) relies on overlap or on a region of common support between treatment and comparison groups.

Empirical analyses using PSM on FADN data that evaluate the impact of the AES or the Organic measure are presented in Arata and Sckokai (2016), Cisilino et al. (2019), Michalek (2022), Pufahl and Weiss (2009) and Stetter et al. (2022).

6 Fiches

The following Fiches summarise the feasibility of the seven analyses discussed in previous Sections using FADN as **Data sources**. This section describes the content of the fiches in detail.

Data set

Table 18 shows the number of observations within FADN by country and year, from 2010 to 2020.
In light of the feasibility study, three datasets have been built that respond to different answers in terms of the time perspective: **All**, **Pooled**, and **Panel**.

a. The **All** dataset includes all observations available from the original source of data from 2010 to 2020. The All dataset allows for an investigation to take place into the impact of the policies, for the payment year, on average one year after the treatment started. The representativeness of its aggregated statistics is guaranteed according to regions (NUTS2), economic size, and farming type.
   The research question in this case will generally be: What are the impacts of receiving the subsidy at time t in terms of environmental outcomes at time t?

b. The **Pooled** dataset collects one observation for each farm observed from 2015-2020. Duplicates have been discarded in order to preserve the same representativeness for each observation independently of the number of times each farm participates into the survey. Note that the Pooled dataset contains more observations than each yearly dataset (see Table 19). The Pooled dataset allows for an investigation of the immediate impact of the policies to take place, at the payment year, on average one year after the treatment starts. The research question in this case will generally be: What are the impacts of receiving the subsidy at time t in terms of environmental outcomes at time t ?

c. The **Panel** dataset, collects repeated observations from t to $t + s$. The Panel dataset provides a detailed description of the policy's impact over time. The size of this sample reduces depending on which years are retained (see Table 19). The Panel dataset does not necessarily replicate the All dataset in terms of representativeness as, for instance, it is more likely to observe larger farms. Then, the final representativeness of each analysis must then be discussed.
   The research question in this case will generally be: What are the impacts of subsidy at time t in terms of environmental outcomes at times $t, \ldots, t+s$?

Table 19 briefly describes the three data sets.

Table 18: Number of FADN farm-observations by country and year

COUNTRY	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
BEL	1201	1252	1251	1229	1208	1297	1078	1070	1044	981	988
BGR	2291	2245	2180	2228	2228	2267	2251	2244	2236	2250	2232
CYP	432	470	484	472	445	458	483	506	509	518	514
CZE	1429	1417	1369	1401	1363	1366	1351	1343	1373	1292	1146
DAN	1855	1818	1785	1796	1869	1812	1849	1845	1828	1724	1579
DEU	8999	8922	8957	8928	8823	8881	8821	8941	8960	8858	8328
ELL	3457	3712	4427	4775	4235	4212	3939	3878	3636	3784	3560
ESP	8195	8135	8698	8726	8716	8695	8677	8738	8730	9181	9202
EST	659	657	655	660	658	659	659	663	659	654	658
FRA	7438	7401	7531	7510	7557	7552	7471	7487	7458	7457	7314
HRV	-	-	-	1177	1220	1253	1221	1237	1338	1371	1324
HUN	1918	1918	1978	1974	1982	1961	2142	2171	2146	2164	2168
IRE	1049	1052	952	937	915	907	899	903	908	900	866
ITA	10720	10903	10591	10778	9948	8830	9329	10098	10124	10543	10488
LTU	1056	1098	1109	1064	1153	1121	1150	1126	1166	1118	1134
LUX	445	443	447	446	446	446	445	445	448	450	449
LVA	993	996	999	998	998	998	998	998	998	998	998
MLT	494	506	497	499	498	490	489	494	490	477	486
NED	1479	1472	1519	1513	1503	1507	1502	1497	1498	1498	1480
OST	2088	2034	2126	2117	2142	2126	2009	1860	1872	1862	1867
POL	11194	11076	11114	12321	12315	12311	12329	12297	12272	11878	12289
POR	2270	2298	2246	2215	2084	2163	2065	2046	2056	1964	1904
ROU	5616	5729	5687	5885	4031	4670	5968	5987	5085	5076	5044
SUO	926	888	854	846	830	817	792	763	722	726	715
SVE	1047	1010	1056	1075	1040	1035	1044	1025	1010	1054	1035
SVK	520	531	529	558	562	559	559	559	559	560	566
SVN	959	929	1142	944	904	882	912	883	890	862	825
UKI	2739	2723	2763	2813	2756	2793	2832	2851	2848	2686	2675
Total	81469	81635	82946	85885	82429	82068	83264	83955	82863	82886	81834

Table 19: All, Pooled and Panel datasets: Number of farms by country

	All (2015-2020)		Pooled (2015-2020)		Panel 1 (2013, 2017-2019)			Panel 2 (2014-2020)		
Country	average n	% of Total All	unique n	% of Total Pooled	yearly n	% of Total Panel 1	% of Country All	yearly n	% of Total Panel 2	% of Country All
BEL	1076	1.3	1,643	1.3	777	1.8	72.2	544	1.4	50.5
BGR	2247	2.7	3,641	2.9	1,035	2.5	46.1	952	2.4	42.4
CYP	498	0.6	714	0.6	198	0.5	39.8	201	0.5	40.4
CZE	1312	1.6	1,883	1.5	844	2.0	64.3	655	1.7	49.9
DAN	1773	2.1	3,799	3.0	218	0.5	12.3	129	0.3	7.3
DEU	8798	10.6	13,856	10.8	4,157	9.9	47.2	3,133	8.0	35.6
ELL	3835	4.6	5,214	4.1	2,685	6.4	70.0	2,374	6.1	61.9
ESP	8871	10.7	11,926	9.3	5,910	14.0	66.6	5,865	15.0	66.1
EST	659	0.8	930	0.7	410	1.0	62.2	399	1.0	60.6
FRA	7457	9.0	10,951	8.6	4,200	10.0	56.3	4,059	10.4	54.4
HRV	1291	1.6	1,801	1.4	738	1.8	57.2	732	1.9	56.7
HUN	2125	2.6	2,806	2.2	1,418	3.4	66.7	1,355	3.5	63.8
IRE	897	1.1	1,162	0.9	686	1.6	76.5	631	1.6	70.3
ITA	9902	12.0	16,872	13.2	3,418	8.1	34.5	3,572	9.1	36.1
LTU	1136	1.4	2,239	1.8	287	0.7	25.3	198	0.5	17.4
LUX	447	0.5	688	0.5	221	0.5	49.4	184	0.5	41.1
LVA	998	1.2	1,269	1.0	619	1.5	62.0	720	1.8	72.1
MLT	488	0.6	705	0.6	299	0.7	61.3	282	0.7	57.8
NED	1497	1.8	1,971	1.5	992	2.4	66.3	981	2.5	65.5
OST	1933	2.3	2,693	2.1	1,340	3.2	69.3	1,296	3.3	67.1
POL	12229	14.8	19,415	15.2	6,071	14.4	49.6	5,958	15.3	48.7
POR	2033	2.5	3,119	2.4	1,205	2.9	59.3	981	2.5	48.3
ROU	5305	6.4	9,566	7.5	1,033	2.5	19.5	751	1.9	14.2
SUO	756	0.9	1,038	0.8	504	1.2	66.7	476	1.2	63.0
SVE	1034	1.2	1,472	1.2	698	1.7	67.5	650	1.7	62.9
SVK	560	0.7	907	0.7	295	0.7	52.6	281	0.7	50.1
SVN	876	1.1	1,398	1.1	359	0.9	41.0	381	1.0	43.5
UKI	2781	3.4	4,072	3.2	1,505	3.6	54.1	1,303	3.3	46.9
Total	82,812	100.0	127,750	100.0	42,122	100.0	50.9	39,043	100.0	47.1

Outcomes

The environmental outcomes are common to all of the analyses and are described in Section 3, Tables 3 and 4.

Treatment

Either multiple or single treatments are considered, depending on the analysis. This subsection describes how groups are defined.

Identification strategy

This section specifies the suggested methodology to perform a CIE.

Feasibility

The feasibility of each analysis proposal is associated with the availability of a minimum number of treated and non-treated observations, assuming that treated and non-treated observations are *randomly selected* from the respective populations of treated and non-treated units.[13]

This minimum number is set to 200 treated and 200 non-treated units for MS and NUTS2. This number was chosen to obtain a Type I error (the probability of rejecting a true null hypothesis) as low as 0.05 and a power (the probability of rejecting a false null hypothesis), as high as 0.8 or 0.9 (See Appendix A.2). Because these units are assumed to be selected at random from the respective populations, this situation is assumed to be sufficient to guarantee enough power to detect significant difference between treated and control groups.

At the level of EU28, the minimum number of treated units is set equal to at least 5% for each MS and such that a larger number of non-treated units at MS level become available. The number of MSs that satisfy these conditions is then reported as a percentage, called **MS coverage**, as compared to the number of MS which have units treated.

For instance: if 20 MSs satisfy the criteria out of 28 MSs (with treated units), then the MSs coverage is 71% = 20/28.

Each analysis proposal has a causal identification strategy or CIE methodology. This identification strategy may require to further discard data that are for instance away from the threshold

[13] Schemes for how observations are selected into treatment (or missing) may be more elaborate than the **missing at random**; they are not entertained here, in order to keep the analysis as simple as possible. See Little and Rubin (2002).

(RDD), or outlying data (DID), or statistical units that lack information on controls (PSM). This may entail further loss of observations when doing the analysis.

This additional loss of observations is not discussed further here.

A similar remark applies to representativeness at the EU28 level, where one needs to discuss if the MS in the available sample is representative of the whole EU28, and if the distribution of farms across MSs is representative of the whole farm population. The final representativeness of any of these analyses must hence be discussed in a case by case fashion after carrying out the analysis.

Table 20 contains summary information on the feasibility on three level of representativeness: NUTS2, MS, and EU28. Each row refers to a treatment while the columns distinguish three farms types: Crop, Livestock, and Mixed defined by TF8. [14]

Each row contains the following summary information and the color provides a visual representation of the feasibility. At NUTS2 and MS levels, numbers indicate the number of regions or MS for which at least 200 treated units are available. The color of the cell indicates how far they are from 0 (minimum, red) to the maximum (28 for MS, 286 for NUTS2, green).

At the EU level, the numbers indicate the MS coverage in %, from 0 to 100. The color of the cell indicates how far this number is from 0 (minimum, red) to the maximum (100, green).
In Annex A.3 the lists of MS and NUTS2 regions for which CIE analyses are feasible are presented.

[14] From TF8 Type of Farming (see RICC 1750) Crop includes Field crop, Horticulture, Wine, Other Permanent Crop; Livestock includes Milk, Other Grazing Livestock, Granivores, the remaining are Mixed

Table 20: Legenda of feasibility tables

NUTS2				MS				EU			
Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All
r_c	r_l	r_m	r_a	s_c	s_l	s_m	s_a	w_c	w_l	w_m	w_a

r_t := n. of NUTS2 regions with at least 200 treated and 200 untreated farms of type t

$:= \sum_{i=1}^{I_{NUTS2}} I[n_{NUTS2,t,i}^{treated} > 200 \& n_{NUTS2,t,i}^{untreated} > 200]$

where:

$n_{NUTS2,t,i}$:= n. of farms (treated/untreated) of type t in NUTS2 i

I_{NUTS2} := n. of NUTS2 regions in EU28 (305)

s_t := n. of MS with at least 200 treated and 200 untreated farms of type t

$:= \sum_{i=1}^{I_{MS}} I[n_{MS,t,i}^{treated} > 200 \text{ and } n_{MS,t,i}^{untreated} > 200)]$

where:

$n_{MS,t,i}$:= n. of farms (treated/untreated) of type t in MS i

I_{MS} := n. of MS in EU28 (28)

w_t := % of MS, among the ones implementing the specific policy, with at least 5% of farms of type t in the treated group and the untreated group larger than the treated group

$:= \frac{h_t}{k_t}\%$

where:

$$h_t := \sum_{i=1}^{I_{MS}} I(\frac{n_{MS,t,i}^{treated}}{n_{MS,t,i}} > 5\%) \text{ and and } n_{MS,t,i}^{treated} \leq n_{MS,t,i}^{untreated}$$

$$k_t := \sum_{i=1}^{I_{MS}} I(n_{MS,t,i}^{treated} > 0)$$

Data requirements using FADN

The FADN variables needed for treatment identifications of RDPs environmental measures are listed in the following Box.

FADN variables

	FADN Code
M10 subsidy represents the value of subsidy to farms under M10, without distinction between M10.1 and M10.2.	SAEAWSUB_V
Organic farming Code classifies farmers as 1. holding that does not apply organic production methods 2. holding that applies only organic production methods for all its products 3. holding that applies both organic and other production methods 4. holding that is converting to organic production methods [a].	ORGANIC
Organic farming subsidy reports the subsidy value for the farm.	
Small farmers Subsidy represents the value of subsidy to farms under the Small farmers scheme	SSFS_V
Arable land (AL) AL	SE026
Crops under water (CuW)	CRICE_A
Grasses or other herbaceous forage (GrHf)	CGRSTMP_A
Land lying fallow (Llf_a)	CFLNDNOSUB_A + CFLNDSUB_A
Grasses or other herbaceous forage or land lying fallow (GrHfLlf)	GrHf+Llf_a
Agricultural area (AA)	SE025
Residual arable land (RAL)	AL- GrHfLlf
Permanent grasses (PGrass)	SE028

[a] If the holding is converting only a part of its production to organic production methods, it should be reported under code 4

Crops included in `Number of crops` (from 2014 on)

`Number of crops`$= \sum 1_{(FADNCode>0)}$

	FADN Code
Common wheat and spelt	CWHTC_A
Durum wheat	CWHTD_A
Rye and winter cereal mixtures (maslin)	CRYE_A
Barley	CBRL_A
Oats and spring cereal mixtures (mixed grain other than maslin)	COAT_A
Grain maize and corn-cob mix (included Other plants harvested green - Green maize)	CMZ_A + CFODMZ_A
Rice	CRICE_A
Triticale, sorghum and other cereals n.e.c. (buckwheat, millet, canary seed, etc.)	CCEROTH_A
Field peas, beans and sweet lupins	CPEA_A
Lentils, chickpeas and vetches	CLNTL_A
Other protein crops	CCRPPROTOTH_A
Potatoes (including early potatoes and seed potatoes) or Other potatoes	CPOT_A + CPOTOTH_A
Sugar beet (excluding seed)	CSUGBT_A
Other root crops n.e.c.	CFODRTBR_A
Tobacco	CTOBAC_A
Hops	CHOP_A
Cotton	CCOTN_A
Rape and turnip rape seeds	CRAPE_A
Sunflower seed	CSNFL_A
Soya	CSOYA_A
Other oil seed crops n.e.c.	CCRPOILOTH_A
Other fibre crops n.e.c.	CFIBOTH_A
Aromatic, medicinal and culinary plants	CMEDIC_A
Sugar cane	CSUGCN_A
Energy and other industrial crops n.e.c.	CCRPINDOTH_A
Cauliflower and broccoli	CCFL_A
Lettuce	CLTUCE_A
Sweet corn	CCRNSWT_A
Onions	CONION_A
Garlic	CGRLC_A
Carrots	CCRT_A

Crops included in `Number of crops` (from 2014 on)- continue

	FADN Code
Strawberries	CSTRBER_A
Melons	CMELON_A
Other vegetables	CVEGOTH_A
Flowers and ornamental plants (excluding nurseries)	CFLWOUT_A
Flowers and ornamental plants (excluding nurseries) under glass or high accessible cover	CFLWUG_A
Temporary grasses and grazings	CGRSTMP_A
Leguminous plants harvested green (if dried pulses and protein cops=0)	CLEG_A if (CPEA_A+CLNTL_A+ CCRPPROTOTH_A)=0
Other plants and cereals (excluding green maize) harvested green n.e.c.	CFODOTH_A if (CWHTC_A+ CWHTD_A+ CRYE_A+ CBRL_A+ COAT_A+ CRICE_A+ CCEROTH_A)=0
Fallow land without any subsidies and Fallow land subject to the payment of subsidies, with no economic use	CFLNDSUB_A + CFLNDNOSUB_A
Kitchen gardens	CKGAR_A
Cultivated mushrooms	CMUSH_A
Other root crops n.e.c.	CFODRTBR_A if (CPOT_A + CPOTOTH_A+ CSUGBT_A + CFODRTBR_A)=0

List of Analysis Proposals

1. Local impact (at 10 ha of AL threshold) of CD
2. Local impact (at 30 ha of AL threshold) of CD
3. Local impact (at 15 ha of AL threshold) of EFA
4. Average impact of CD on not already adherent farms as compared to farms already adherent to CD requirements
5. Average impact of receiving M10
6. Average impact of receiving M10 policy-mixes
7. Average impact of being organic with respect to conventional farms

Analysis proposal 1

What is the local impact (close to the 10 ha threshold) of the Crop Diversification obligation on promoting agricultural practices beneficial for the environment in the eligible population at time *t*?

Data sources

FADN

all variables are expressed at the farm level

Data set

Pooled

Outcomes

Number of crops, Percentage of arable land allocated to the main crop; Nutrients, Pesticides, Energy, Animal welfare, Biodiversity, Water management

see Tables 3, 4

Control variables

to be defined later

Treatment

Medium AL farms under CD obligation

Identification strategy

RDD

Feasibility

Interval (5, 15)ha	NUTS2	MS	EU*
data year 2014	2	5	64
data year 2016	3	5	68
data Pooled	5	6	71

Notes

*:=% of MS, among the ones implementing the policy, with at least 20 farms of the specified type below and above the threshold.

Analysis proposal 2
What is the local impact (close to the 30 ha threshold) of the Crop Diversification obligation on promoting agricultural practices beneficial for the environment in the eligible population at time *t*?

Data sources

FADN
all variables are expressed at the farm level

Data set

Pooled

Outcomes

Number of crops, Percentage of arable land allocated to the main crop; Nutrients, Pesticides, Energy, Animal welfare, Biodiversity, Water management
see Tables 3, 4

Control variables

to be defined later

Treatment

Large AL farms under CD obligation

Identification strategy

RDD

Feasibility

Interval (25, 35) ha	NUTS2	MS	EU*
data year 2014	0	4	63
data year 2016	0	3	44
data Pooled	0	4	74

Notes

*:=% of MS, among the ones implementing the policy, with at least 20 farms of the specified type below and above the threshold.

Analysis proposal 3
What is the local impact (close to 15 ha) of the Ecological Focus Areas obligation on promoting agricultural practices beneficial for the environment in the eligible population at time *t*?

Data sources
FADN
all variables are expressed at the farm level

Data set
Pooled

Outcomes
Percentage of land allocated to EFA; measures of EFA type land allocation; Nutrients, Pesticides, Energy, Animal welfare, Biodiversity, Water management
see Tables 3, 4

Control variables
to be defined later

Treatment
Medium-large farms under EFA obligation

Identification strategy
RDD

Feasibility

Interval $(10, 20)$ha	NUTS2	MS	EU*
data year 2014	1	6	79
data year 2016	1	6	75
data Pooled	5	7	89

Notes
*:=% of MS, among the ones implementing the policy, with at least 20 farms of the specified type below and above the threshold.

Analysis proposal 4

What is the average impact of Greening Crop Diversification
on promoting agricultural practices beneficial for the environment
of not already adherent farms as compared to already adherent farms?

Data sources

FADN
all variables are expressed at the farm level

Data set

Panel

Six panels of Medium and Large AL farms (under CD obligation) are considered before and after introduction of the Greening policy (2014). Panels differ by starting/ending year respectively: (2011,2014);(2012,2015);(2013,2016); (2010,2014); (2011,2015);(2012,2016)].

Outcomes

Number of crops, Percentage of arable land allocated to the main crop; Nutrients, Pesticides, Energy, Animal welfare, Biodiversity, Water management
see Tables 3, 4

Control variables

to be defined later

Treatment

$$t_a = \begin{cases} 1, & \text{if never/occasionally adherent before 2014} \\ 0, & \text{if always adherent before 2014} \end{cases}$$

$$t_s = \begin{cases} 1, & \text{if never adherent before 2014} \\ 0, & \text{if always/occasionally adherent before 2014} \end{cases}$$

Identification strategy

DID

Feasibility

	Medium AL		Large AL	
Treatment	MS	EU*	MS	EU*
t_a	2	89	4	96
t_s	3	89	6	100

Notes

Number in cells are maximum values over the 6 panels.
*:=% of MS, among the ones implementing the policy, for which panel contain at least the 25% farms of average number of farms unedr the CD obligation during the period 2012 to 2016.

Analysis proposal 5

What is the average impact of receiving M10 at time $t + 1$
in terms of environmental outcomes (b) at times $t + 1, \ldots, t + s$? or (c) at time $t + 1$

Data sources

FADN

all variables are expressed at the farm level

Data set

(b) Panel $t = 2018$ $s = 3$

(c) Pooled

Outcomes

Nutrients, Pesticides, Energy, Animal welfare, Biodiversity, Water management

see Tables 3, 4

Control variables

to be defined later

Treatment

Receiving `M10 Subsidy` (`M10 Subsidy` > 0)

Identification strategy

Matching

Feasibility

	NUTS2				MS				EU			
Dataset	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All
(b)	0	0	0	1	5	7	2	11	64	75	78	79
(c)	6	3	0	21	13	13	2	22	78	82	78	82

Notes

Analysis proposal 6
What are the impact of receiving M10 policy-mixes at time *t* in terms of environmental outcomes at time *t* ?

Data sources

FADN
all variables are expressed at the farm level

Data set

Pooled

Outcomes

Nutrients, Pesticides, Energy use, Animal welfare, Biodiversity, Water management
see Tables 3, 4

Control variables

to be defined later

Treatment

1. Receiving `M10 Subsidy` and Being under the M10-mix "Management of inputs"
2. Receiving `M10 Subsidy` and Being under the M10-mix "Other and cultivation practices"
3. Receiving `M10 Subsidy` and Being under the M10-mix "Maintenance of HNV systems and Management of inputs"

Identification strategy

Matching

Feasibility

	NUTS2				MS				EU			
M10-mix	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All
1	6	2	0	11	7	7	2	11	64	64	64	64
2	0	1	0	8	6	8	1	12	56	88	75	75
3	0	0	0	2	3	4	0	7	60	89	50	60

Notes

- The M10-mixes are derived by a clustering exercise over 108 EU RDPs' M10 expenditures compositions. See Tables 16. The clustering exercise is an example and it could be adapted to specific objectives.
- Values in cells describe the CIE feasibility of each M10-mix as a binary treatment.

Analysis proposal 7

What is the impacts of being organic with respect to conventional farms at time $t+1$ in terms of environmental outcomes (b) at times $t+1, \ldots, t+s$? or (c) at time $t+1$

Data sources

FADN

all variables are expressed at the farm level

Data set

(b) Panel $t = 2018$ $s = 3$

(c) Pooled

Outcomes

Nutrients, Pesticides, Energy, Animal welfare, Biodiversity, Water management

see Tables 3, 4

Control variables

to be defined later

Treatment

Organic farms (`Organic`* $\neq 1$)

Identification strategy

Matching

Feasibility

	NUTS2				MS				EU			
Dataset	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All	Crop	Livestock	Mixed	All
(b)	0	0	0	1	3	1	0	6	68	74	65	78
(c)	10	1	0	15	8	11	1	19	81	75	89	82

Notes

*`Organic`: A_CL_140_C Organic farming Code classifies farmers as

1. holding that does not apply organic production methods
2. holding that applies only organic production methods for all its products
3. holding that applies both organic and other production methods
4. holding that is converting to organic production methods

7 Conclusions

This report discusses and provides evidence on the following main issues.

- It promotes a greater awareness of the **significance of assessing the impact of past Common Agricultural Policy (CAP) cycles through a Counterfactual Impact Evaluation (CIE) framework**, with a specific focus on **environmental outcomes**
  - The underlying, more far-sighted goal of this objective is to set up a framework that is able to quantify the **causal chain** between **policy intervention**, **behaviour** of any targeted units and **outcomes of interest**.
  - Particular emphasis is placed on to sustainable "Greening" practices as policy interventions and environmental variables as outcomes of interest. In-depth analyses are conducted for CAP measures such as Greening practices, Agri-environmental-climate (M10), Organic (M11), and ANC (M13).
  - The following CIE methods were discussed: Regression Discontinuity Design and Difference in Difference for the evaluation of Crop Diversification and Ecological Focus Area; Propensity Score Matching for the evaluation of M10 and M11.
  - Ex-post evaluations allow for a thorough assessment of interventions and enhancement of policy outcomes for subsequent implementations. Counterfactual Impact Evaluation (CIE) is recognised as the most suitable tool for evaluating (public) policies as it can isolate the causal contribution of legislative acts to achieving policy goals by relying on carefully implemented quasi-experimental settings.
- It offers a **comprehensive overview of European-level data sources** that are useful for conducting counterfactual impact evaluations on the CAP's environmental dimension. Notably, it demonstrates the utility of the Farm Accountancy Data Network (FADN) as a detailed farm-level dataset from which one can draw micro-level information, along with various datasets addressing critical outcomes such as soil quality, water management, and biodiversity preservation.
  - It provides a discussion on current challenges faced by empirical researchers when it comes to linking the aforementioned data sources. Focus is drawn on the geographical accuracy of measurements and farm locations, geographical complexity of environmental relationships, nad timing of micro-data release, timing of environmental impacts.

    This discussion is instrumental for future research endeavours and towards fostering consciousness about the need to maintain and improve European-wide data infrastructures, thereby enabling evidence-based policy planning in both an accurate and timely manner.

- It delves into the **present-day feasibility of conducting CIE analyses on the environmental effects of CAP**, accompanied by concise and informative summaries, while considering multiple levels of geographical aggregation within the European Union.

As a natural follow-up to this report, work is currently being undertaken to actually implement a number of the environmentally-focused CIE evaluations, the feasibility of which has been explored in this work.

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Main Directives, Regulations and other Documents of the European Commission

- **Agenda 2000** https://eursc-my.sharepoint.com/:w:/g/personal/pirramfr_teacher_eursc_eu/EccDmM6y4gpCqBy3F3vK1xkBibwhL3D5giAd40Lu4vfA2g
- **Better Regulation Agenda** https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52015DC0215
- **Biodiversity** European Environmental Agency https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal/actions-being-taken-eu/EU-biodiversity-strategy-2030_en
- **Birds Directive** Directive 2009/147/EC of the European Parliament and of the Council of 30 November 2009 on the conservation of wild birds https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32009L0147
- **European Grean Deal** European Environmental Agency https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en
- **Farm to Fork** European Environmental Agency https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal/actions-being-taken-eu/farm-fork_en
- **Habitats Directive** Council Directive 92/43/EEC of 21 May 1992 on the conservation of natural habitats and of wild fauna and flora https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A31992L0043
- **Nitrates Directive** Council Directive 91/676/EEC of 12 December 1991 concerning the protection of waters against pollution caused by nitrates from agricultural sources https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex%3A31991L0676
- **Water Framework Directive** Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32000L0060&qid=1697101693595
- **Regulation EAFRD** REGULATION (EU) No 1305/2013 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 17 december 2013 on support for rural development by the European Agricultural Fund for Rural Development (EAFRD) and repealing Council Regulation (EC) No 1698/2005 https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:347:0487:0548:en:PDF

- **Regulation DIRECT PAYMENTS** Consolidated text: Regulation (EU) No 1307/2013 of the European Parliament and of the Council of 17 December 2013 establishing rules for direct payments to farmers under support schemes within the framework of the common agricultural policy and repealing Council Regulation (EC) No 637/2008 and Council Regulation (EC) No 73/2009 `https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:02013R1307-20220101`
- **Regulation ORGANIC** Council Regulation (EC) No 834/2007 of 28 June 2007 on organic production and labelling of organic products and repealing Regulation (EEC) No 2092/91 `https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32007R0834`

List of Abbreviations

AD Activity Data

AES Agri-environment schemes

AECM Agri-environment-climate measure

AFOLU Agriculture, Forestry and Other Land Use

AIR Annual Implementation Report

AL Arable Land

ANC Area with Natural Constraints

BD Biodiversity

BDS Biodiversity Strategies

CAP Common Agricultural Policy

CATS Clearance Audit Trial System

CC-ME Competence Centre on Microeconomic Evaluation

CD Crop Diversification

CIE Counterfactual Impact Evaluation

CLC Corine Land Cover

CS Carbon Sequestration

DID Difference-In-Difference

DP Direct Payments

EAFRD European Agricultural Fund for Rural Development

EAGF European Agricultural Guarantee Fund

EEA Enruopean Environmental Agency

EF Emission Factors

EFA Ecological Focus Areas

ENRD European Network of Rural Development

ESDAC European Soil Data Centre

ESI European Structural and Investment Fund

EU EU European Union

EU15 European Union - 15 countries (1995-2004)

EU27-2007 European Union - 27 countries (2007-2013)

EU27-2020 European Union - 27 countries (from 2020)

EU28 European Union - 28 countries (2013-2020)

F2F Farm to Fork

FADN Farm Accountancy Data Network

FSDN Farm Sustainability Data Network

FSS Farm Structure Survey

GAEC Good Agri-environmental Conditions

GHG Greenhouse Gas Emissions

HB Habitats Directive

HNV High Natural Values

HRL High Resolution Layers

IACS Integrated Administration and Control System

IFS Integrated farm statistics

IPCC Intergovernmental Panel on Climate Change

JRC JRC Joint Research Center

L-AL Large Arable Land

L-RAL Large Residual Arable Land

LF Landscape Features

LPIS Land Parcel Identification System

LUCAS Land Use/Cover Area frame Survey

LUISA Land Use based Integrated Sustainability Assessment

M08 M08 - Investments in forest areas

M10 M10 - Agri-environment-climate

M11 M11 - Organic farming

M12 M12 – Natura 2000 and WFD

M13 M13 - Areas with natural constraints

M-AL Medium Arable Land

ML-AL Medium-Large Arable Land

MFF Multiannual Financial Framework

MPG Maintenance of Permanent Grassland

MS Member States

NUTS0 Nomenclature of Territorial Units for Statistics, Level 0

NUTS2 Nomenclature of Territorial Units for Statistics, Level 2

NUTS3 Nomenclature of Territorial Units for Statistics, Level 3

OF Organic Farm

PSM Propensity Score Matching

RDD Regression Discontinuity Design

RDP Rural Development Plan

RKD Regression Kink Design

S Soil

SAC Special Area of Conservation

SEBI Streamlining European Biodiversity

SFM Sustainable Forest Management

SFS Small Farmer Scheme

SOC Soil Organic Carbon

SPA Special Protection Area

SUF Scientific Use Files

SWF Small Woody Features

TE Technical Efficiency

UAA Utilised Agricultural Area

WFD Water Framework Directive

WQ Water Quality

WTO World Trade Organisation

List of Figures

List of Tables

Annexes

A.1 CIE resources

Hyperlinks Resources made available by European Commission, DG JRC S.3 Competence Centre on Microeconomic Evaluation (CC-ME)

- **Videos describing some CIE methods**
  `https://knowledge4policy.ec.europa.eu/microeconomic-evaluation/policy-impact-evalua`
  `en`

- **Other tools for CIE**
  `https://knowledge4policy.ec.europa.eu/microeconomic-evaluation/cc-me-tools_`
  `en`

Books

- **Data-driven Policy Impact Evaluation** (Crato and Paruolo (2019)).
  `publications.jrc.ec.europa.eu/repository/handle/JRC107550`

- **Advanced counterfactual evaluation methods - Guidance document**
  `https://youtu.be/IpWQlHapifU`

Handbook Resources made available by European Commission, DG Employment, Social Affairs & Inclusion

- **Counterfactual impact evaluation of European Social Fund interventions in practice**
  `https://ec.europa.eu/social/main.jsp?catId=738&langId=en&pubId=8313&furtherPubs=`
  `yes`

- **How to use administrative data for European Social Funds counterfactual impact evaluations**
  `https://ec.europa.eu/social/main.jsp?catId=738&langId=en&pubId=8303&furtherPubs=`
  `yes`

A.2 Sample size determination

Statistical hypotheses state the propositions the researcher plans to examine in a sample to be able to find out if they are correct in the relevant population. There are two commonly used types of hypotheses in statistics: the null hypothesis ($H0$) and the alternative ($H1$) hypothesis. The null hypothesis $H0$ expresses the proposition that there will be no effect from the treatment. The $H1$ represents the researcher's expectation of what will be the situation after the treatment is applied.

Tests of hypothesis are used by the researcher to discriminate between the two hypotheses. Any decision based on a test of hypothesis commits two types of errors with certain probabilities: the error of rejecting $H0$ when it actually is true; this is called a Type I error; and is a false positive. The α defines the probability of a Type I error. The most common α level chosen is 0.05, meaning the researcher is willing to take a 5% chance that a result supporting the hypothesis will be untrue in the full population.
It is also possible to make an erroneous decision in the opposite direction; by incorrectly rejecting $H1$ and thus wrongly accepting $H0$. This is called a Type II error (or a false negative). The probability of a Type II error is defined the β. The probability of rejecting a false null hypothesis, the power, is calculated as $1-\beta$. For a Type II error of 0.15, the power is 0.85. The ideal power of a study is considered to be 0.8 (which can also be specified as 80%).

When the sample size is fixed, a trade-off exists between the minimum allowed levels for Type I and Type II errors, as the reduction in the probability of committing a Type II error increases the risk of committing a Type I error (and vice versa). On the other side, studies may be designed to include a sufficient number of observations to adequately address the research question, that is to ensure that a test of hypothesis has a high probability of detecting a meaningful difference in the parameter of interest. Determining the sample size should guarantee to obtain a Type I error as low as 0.05 or 0.01 and a power as high as 0.8 or 0.9.
In a CIE setting, the hypotheses state propositions concerning the difference between the average potential outcomes under and in absence of the treatment

$$H0 := \mu_1 = \mu_0,$$
$$H1 := \mu_1 \neq \mu_0,$$

where μ_1 and μ_0 are the means of potential outcomes in the two comparison groups. The formula for determining the sample sizes to ensure that the test has a specified power is:

$$n_i = 2\left(\frac{Z_{1-\alpha/2}+Z_{1-\beta}}{ES}\right)^2$$

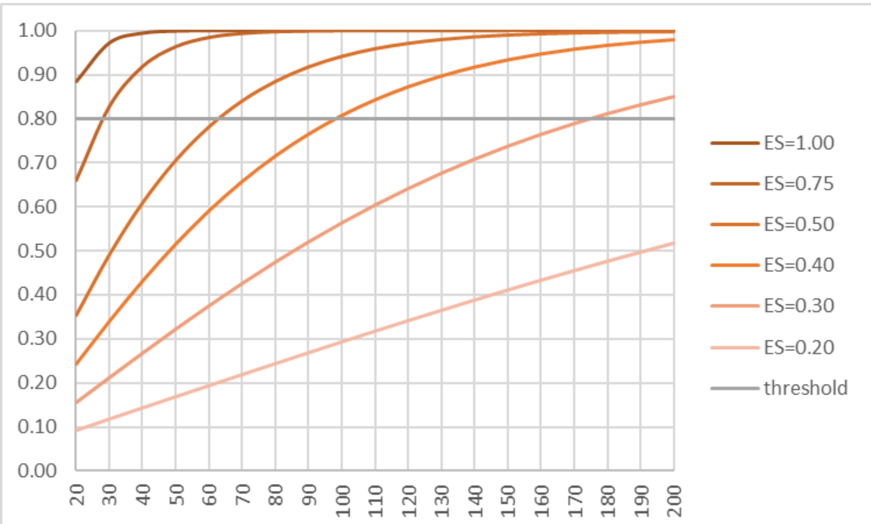
where n_i is the sample size required in each group ($i = 1, 0$), α is the selected level of significance and $Z_{1-\alpha/2}$ is the value from the standard normal distribution holding $1-\alpha/2$ below it, and $1-\beta$ is the selected power and $Z_{1-\beta}$ is the value from the standard normal distribution holding $1-\beta$ below it, ES is the effect size, defined as:

$ES = \frac{|\mu_1 - \mu_2|}{\sigma}$.

The ES is measured dividing the absolute difference between the means by the standard deviation (common to the two populations), thus providing a measure of the difference between two means in terms of units of standard deviations. ESs around 0.2 may be considered small, around 0.5 medium, and above 0.8 large effect size (Cohen).

Figure 11 summarises the needed group sample size for comparing two groups (of equal size), when $\alpha = 0.05$, Gaussian distributions are assumed, and effect sizes are set at different values. The higher the effect size, the lower the sample size needed to guarantee power at 80-90%. For moderate effect sizes, the sample size has to increase to guarantee enough power.
When effect sizes are larger than 0.4 and observations per group at least 100, the power is always above 90%. When effect size is equal to 0.3, about 170 observations are needed in order the power reaches 80%. For effect size below 0.3, 200 observations per group do not guarantee a sufficient power to the test.

Figure 11: Power as a function of sample size for different level of Effect Size (ES)



Setting the minimum size per group at n = 200 allows to target a power of at lest 80% for effect size larger than 0.3. As it is expected that a certain percentage of observations in any groups will drop because of missing and/or outlying data, the power is expected still above

80% until less than 10% of observations per group will drop out of the study. As far as the loss of observation will get more severe, the power will start to decrease.

A.3 List of feasible CIE analyses at NUTS2 and MS level

Analysis proposal 1

Interval (5,15)ha	NUTS2	MS
data year 2014	PL41, PL92	DE, ES, GR, IT, PL
data year 2016	PL41, PL84, PL92	DE, ES, GR, IT, PL
data Pooled	PL41, PL71, PL81, PL84, PL92	DE, GR, ES, IT, PL, RO

Analysis proposal 2

Interval (25,35)ha	NUTS2	MS
data year 2014	-	DE, ES, IT, PL
data year 2016	-	DE, IT, PL
data Pooled	-	DE, ES, IT, PL

Analysis proposal 3

Interval (10,20)ha	NUTS2	MS
data year 2014	PL41	DE, EL, ES, FR, IT, PL
data year 2016	PL41	DE, EL, ES, FR, IT, PL
data Pooled	PL41,PL61,PL81,PL84,PL92	DE, EL, ES, FR, IT, PL, RO

Analysis proposal 4

	Medium AL	**Large AL**
Treatment t_α		
2011-2014	-	ES, IT
2012-2015	ES	DE, ES, IT, PL
2013-2016	ES, PL	DE, ES, IT, PL
2010-2014	-	ES
2011-2015	-	ES
2012-2016	-	ES, IT
Treatment t_s		
2011-2014	ES, IT, PL	DE, ES, FR, HU, IT, PL
2012-2015	ES, IT, PL	DE, ES, FR, HU, IT, PL
2013-2016	ES, PL	DE, ES, IT, PL
2010-2014	ES, IT, PL	DE, ES, FR, HU, PL
2011-2015	ES, PL	DE, ES, FR, HU, PL
2012-2016	ES, PL	DE, ES, HU, IT, PL

Analysis proposal 5

All	**NUTS2**	**MS**
(b)	PT11	BE,BG,DE,ES,FR,HU,IE,IT,PL,PT,UK
(c)	CY00, DE11, DE14, DE94, DEF2, DK03, DK04, EE00, ES24, ES51, ES61, HU33, ITC1, ITG2, ITI2, LT02, LV00, PL61, PT11, PT16, SI03	BE, BG, CY, CZ, DE, DK, EE, EL, ES, FR, HR, HU, IE, IT, LT, LV, PL, PT, SE, SI, SK, UK

Analysis proposal 6

All	**NUTS2**	**MS**
1	CY00, EE00, ES51, ES61, HU33, ITC1, ITI2, PL61, PT11, PT16, SI03	BE, CY, DE, EE, ES, FR, HU, IT, PO, PT, SI
2	DE11, DE14, DE94, DEF0, DK00, DK04, ES24, LT02	BE, BG, CZ, DE, DK, ES, FR, IT, LT, SE, SI, UK
3	ITG2, LV00	EL, ES, HR, IE, IT, LV, UK

Analysis proposal 7

All	NUTS2	MS
(b)	ES62	AT,DE,EL,ES,FR,IT
(c)	EE00, ES61, ITF4, ITF6, ITG1, ITI1, ITI4, LV00, RO11, RO12, RO21, RO22, RO31, RO41, RO42	AT, BG,CZ,DE,DK, EE, EL, ES, FR, HR, IT, LT, LV, PL, PT, RO, SE, SI, UK

Science for policy

The Joint Research Centre (JRC) provides independent, evidence-based knowledge and science, supporting EU policies to positively impact society

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