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Research article

# Non-monetary motivations of the EU agri-environmental policy adoption. A causal forest approach

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ABSTRACT

This paper investigates the non-monetary motivations of farmers' adoption of agri-environmental policies. Unlike the monetary (income) motivations, non-monetary drivers can not be directly observed but can be identified from observational data within appropriate quasi-experimental designs. A theoretical justification of farmers' choices is first formulated and a consequent natural experiment setting is derived. The latter admits heterogeneous, i.e. Individual, Treatment Effects (ITE) that, in turn, can be interpreted in terms of more targeted and tailored policy expenditure. A Causal Forest (CF) approach is adopted to estimate these ITEs for both the treated and not treated units. The approach is applied to two balanced panel samples of Italian Farm Accountancy Data Network (FADN) farms observed over the 2008–2018 period and concerns agri-environmental policies delivered through the Common Agricultural Policy (CAP). Results show how heterogeneous the farmers' response and the associated non-monetary motivations can be, thus indicating room for a more efficient policy design.

## 1. Introduction: Objective of the work

This paper investigates the behavioural foundation of the farmers' voluntary adoption of environmental policies. The existence and extent of non-monetary motivations, in particular, is of major policy relevance as it would either point to space for public expenditure savings, still obtaining the same environmental performance, or to the amount of additional expenditure needed to improve this performance (Esposti, 2022).

So far, the assessment of these behavioural motivations has been almost exclusively performed through experiments (Andrews et al., 2013; Thomas et al., 2019; Chabé-Ferret et al., 2023). The main reason is that only well designed experiments may bring to the surface those usually unobservable individual motivations that have a role in agents' decisions about policy adoption. This paper relies on the idea that this kind of assessment can be carried out also using observational data by adopting appropriate modelling and estimation solutions. Though empirically challenging, this approach seems to be advantageous not only because observational data reflect real-world behaviour and not choices within "artificial" circumstances (i.e., laboratory experiments), but also because sound lab-based or field experiments may be difficult to design and organize (Angrist and Pischke, 2010). This may be the case of environmental measures targeted to farming activities on which the present paper focuses on.

The present study can be included within that broad and recent research body investigating the farmers' response to agri-environmental policies (henceforth, AEPs). This literature strongly emphasizes the multidimensional nature of this response and, therefore, insists on the need of a multidisciplinary approach to the topic and of the adoption of integrated assessment tools (Vergamini et al., 2020). This valuable literature is of interest here as it points to the main open issues in this field. However, the approach here adopted is quite the reverse. Although the farmers' response to these policy measures may have a multidimensional nature (the environmental impacts are themselves multidimensional), what is under investigation here is the multidimensional nature of the farmers' motivation of adoption and consequent response. Farmer's motivation is essentially economic but not necessarily monetary and may have multiple facets. While the investigation inside these multiple economic motivations has itself received attention in recent literature (Lakner et al., 2020; Huber et al., 2023), the novelty here is twofold as it concerns both the definition of its conceptual underpinnings and the consequent methodological strategy.

Firstly, farmers' behaviour is modelled in order to make the role of non-monetary motivations explicit. This theoretical framework derives the income implication of the farmers' voluntary policy choice according to a treatment-effect logic. This then allows to interpret farmer's

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behaviour also from a different decision making perspective, that of the policy maker. Secondly, and consequently, this theoretical derivation shows how the presence and sign of the unobserved non-monetary motivations can be extracted from these treatment effects within an appropriate quasi-experimental setting. As farms are heterogenous for a whole set of observable conditioning features, as well as for the unobserved utility function and non-monetary motivations, treatment effects are themselves heterogeneous and an appropriate identification and estimation approach is thus required.

In recent years, different methodological solutions have been put forward to identify and estimate Individual Treatment Effects (ITE). Among these, Causal Forest (CF) estimation has attracted increasing attention for its flexibility and robustness but also for its desirable econometric properties (Athey et al., 2019; Athey and Wager, 2019). This estimation approach is here adopted. The derivation of the farmers' non-monetary motivations within a theoretically founded quasi-experimental setting, and the adoption of Machine Learning (ML) techniques to investigate the heterogenous farmer's response to AEPs represents the main novel contributions of this study and it adds to the existing econometric toolkit in the field (Lakner et al., 2022). Stetter et al. (2022) and Coderoni et al. (2023) have recently applied an identification and estimation strategy based on CFs similar to the one here adopted. However, their application concerns the impact of AEPs and not the identification of the underlying non-monetary motivations.

The rest of the paper is structured as follows. Section 2 overviews the multidisciplinary literature in the field and, then, the policy context and relevance underlying the empirical investigations. Section 3 illustrates the theoretical framework and motivates its treatment-effect interpretation. Section 4 presents the adopted CF estimation approach. Section 5 describes the empirical application. It concerns the sample of Italian Farm Accountancy Data Network (FADN) farms over the 2008–2018 period (Coderoni and Esposti, 2018) and, within this context, it concerns the AEPs delivered through Common Agricultural Policy (CAP) before and after its 2013 reform. The main estimation results are detailed and discussed. Section 6 draws the main policy remarks and conclusions.

## 2. Farmers' response to environmental policies

### 2.1. Overview of the multidisciplinary literature and an economist's perspective

With AEPs here we mean all those measures that are specifically and exclusively targeted to farms and that imply payments (or sanctions) conditional on the respect/achievement (or not) of some environmental standard/performance. The environmental motivation for the policy support granted to farmers has gained increasing relevance in both developed and developing countries (Guerrero, 2021). One main reason for this scholars' interest in this topic consists in assessing whether these policies and, consequently, the underlying public expenditure, are really able to achieve the declared objective and do it efficiently. Assessing the impact of the policy thus inevitably implies assessing how farms respond to it. In this respect, we have recently observed a huge growth of studies trying to assess the impact of environmental policies a farmers' choices and, then, on their economic and environmental performance.

Within this empirical literature an increasing emphasis on multidisciplinary approaches has recently emerged, encompassing both the economic motivations and consequences of farmers' choices and their environmental implications that are, in fact, the target of the policies themselves. The multidimensionality of this recent literature on the integrated assessment of AEPs is twofold. On the one hand, the economic, environmental, energetic and, sometimes, social aspects of the farmers' response to AEPs are concurrently considered. On the other hand, they also use a mixture of approaches deriving from the different disciplines. Prime examples of this are the combination of typical engineering and ecological assessment methods (like Life-Cycle Assessment or LCA, exergoeconomic analysis, ecological footprint) with techniques of economic performance assessment (like Data Envelopment Analysis, or DEA; and Life-Cycle Costing) (Nabavi-Pelesaraei et al., 2021; Koley, 2022; Nabavi-Pelesaraei and Damgaard, 2023; Maklavany et al., 2023).

This combination of economic performance, energy efficiency and environmental impacts within these multidisciplinary assessment tools is particularly valuable also because they can be flexibly adapted to different specific contexts. Limiting the attention to the agricultural sector, the applications proposed in recent studies either concern very distinctive farming and geographical contexts (Saeidi et al., 2022; Hatim et al., 2023) or extend to the whole supply-chains or agri-food sector (Hosseinzadeh-Bandbafha et al., 2017; Hamidinasab et al., 2023).

The present study aims to contribute to the recent multidisciplinary literature from a different perspective. The multidimensionality of the farmers' response to AEPs does not consist here either in some multicriterial assessment or in the application of multidisciplinary tools. It rather insists on the multidimensionality of farmers' motivation of their response. The main difference with respect to the abovementioned studies consists in the fact that they focus on the multidimensional nature of the farmers' response given their economic motivation. The present paper focuses on the economic outcome to recover the underlying multiple non-economic motivations. The conceptual and methodological background here adopted is, therefore, purely economic but the motivations it investigates can be non-economic or, more accurately, non-monetary. Understanding these complex motivations may thus be of help for the assessment of the response also within other disciplines and tools.

Also regarding this strictly economic assessment of the farmers' response to AEPs, the empirical literature is abundant with very recent and innovative contributions (Stetter et al., 2022; Coderoni et al., 2023). This body of works, however, has to be contextualised to the specific policy environment to which the assessment applies since the policy design is what eventually drives the response. In particular, here, we focus on the AEPs within the CAP (OECD, 2012).[1]

### 2.2. Assessing the environmental measures within the CAP: evolution and open issues

The AEPs made their first appearance within the CAP in 1988 with the introduction of the so-called set-aside incentive scheme: a payment was granted to farmers that left part of their land out of production. This voluntary approach was reinforced with the 1992 Reform (known as MacSharry reform) with the introduction of the Agri-environmental Measures (AEMs), i.e., further voluntary measures implying payments upon the adoption of environmentally friendly agricultural practices. At the same time, however, set-aside became a mandatory requirement in order to be eligible to receive the novel compensatory direct payments. Since then, the AEPs within the CAP have been a combination of these two lines of action: conditional measures entitling farmers to receive the ordinary direct payments (in this sense, mandatory); voluntary measures implying additional compensatory payments targeted to some environmental standard or performance.

These two lines can be intended as realizations, within the farming activity, of two well-known different philosophies in environmental policy making (Harrington and Morgenstern, 2007). On the one hand, environmental standards are imposed on agents (farmers) under the risk of a monetary sanction (the loss of direct payments). This approach is also called Command & Control environmental policy. On the other hand, agents are offered a monetary incentive (additional payment) to achieve a better environmental performance.

The combination of conditional measures and additional payments has been maintained and reinforced with the following reform (the Agenda, 2000 CAP reform). By designing the CAP architecture into two

[1] For other recent studies performing economic assessment of AEPs see also Lakner et al. (2020) and Barreiro-Hurle et al. (2021).

pillars, this reform also formally separated the two lines of AEPs. The first pillar had to deliver the direct payments in respect of the mandatory set-aside requirements. The second pillar (or Rural Development Policy, RDP) included a long list of measures implying the voluntary participation of farmers in order to be entitled to receive an additional payment (the incentive): the AEMs were included among these.

The full decoupling of the first-pillar direct payments, first established with the 2003 CAP Reform (or Fischler's Reform), and then completed by the 2008 (or Health Check) Reform, finalized this twofold strategy of the environmental part of the CAP. The environmental conditionality of the direct payments was mainstreamed through a set of additional and compulsory environmental standards (the so-called *Cross-Compliance*, *CC*, requirements): non-complying farmers were sanctioned with the loss of part or all of their direct payments proportionally to the degree of non-compliance.[2] At the same time, the second pillar *AEM*s were mostly confirmed and their overall financial support expanded.

The 2013 Reform took the final step in this direction. Not only first pillar direct payments remained conditioned on a set of mandatory (*CC*) requirements. In addition, part of the direct payments themselves was reserved in respect of additional environmental standards, the so-called Greening payment: 30% of the total direct payments become conditional on three environmental management practices (Coderoni et al., 2023).[3] The greening measure can be considered as a sort of additional or super conditionality (Matthews, 2011). Unlike the CC requirements, however, it brings about a payment that is additional to the basic direct payments. Therefore, complying farmers who respect both CC and greening requirements, receive a total payment corresponding to the sum of basic and greening direct payments.

The CAP regime established by the 2013 Reform is the regime currently into force as its application was extended to 2022. Nonetheless, European institutions already agreed that the new CAP applies from 2023 to 2027. A deeper and more technical discussion about the different AEPs within the CAP is beyond the scope of the present study (Guerrero, 2021). What is worthwhile noticing here is that, beside the often overemphasized technicalities, two invariances emerge across this thirty-years sequence of reforms.

The first invariance concerns the consolidation, after the initial reform steps, of a long-term strategy based on the two abovementioned lines of action. All changes that occurred after 2003 only reinforced and refined this strategy without substantially affecting it. This seems true, in particular, for the 2013 reform. It changed the extent and modality of the environmental conditionality associated to direct payments. But from the farmers' perspective this regime modification did not change the kind of choices they had to make and the consequent monetary implications. The only major change this reform might have generated could actually refer to the non-monetary motivations associated with this revised environmental conditionality (see next section). As a consequence, even though the years before and after 2015 (the first year of implementation of the 2013 reform) can not be compared, these two sub-periods can still be considered as two replications of an analogous policy regime. The same methodological approach may also be replicated and the evidence emerging in these two subperiods can be compared in order to identify the main commonalities and differences regarding these non-monetary motivations.

The second invariance concerns the substantial equivalence of the distinct CAP AEPs from the farmers' perspective. Mandatory environmental standards and voluntary environmental incentives considerably differ regarding the modalities that are designed and provided to farmers. As clarified in the next section, however, from the farmer's perspective they both resolve into a monetary net incentive (the additional payment associated to the *AEM*s combined with the consequent loss of revenue and/or additional costs) or net disincentive (the loss of direct payments upon non-compliance of the *CC* and greening standards combined with the consequent gain of revenue and/or lower costs) (see next section). Moreover, they both eventually behave as voluntary AEPs since in both cases farmers are expected to evaluate this set of incentives/disincentives and then decide whether or not to adopt the respective policy regime. Farmers' response could thus be the same, and somehow indistinguishable, in the two cases unless different non-monetary motivations are activated. Beside these invariances, therefore, the open question about the farmers' response to different AEPs remains whether the analogous incentives/disincentives they deliver induce a different response due to different motivations they activate (Fattorini et al., 2020; Chabé-Ferret et al., 2023).

Eventually, both before and after 2015, farmers were confronted with three possible regimes and, therefore, had to choose among them. On the one hand, they could ignore any environmental standard implied by the CAP, thus losing all the CAP payments but also taking advantage of the possible cost reduction and/or revenue gain. On the other hand, they could decide to take on all environmental standards (both mandatory, or conditional, and voluntary) the CAP puts forward, thus seizing direct payments and *AEM* but also possibly incurring revenue losses and/or higher costs. As a rational compromise between these two "extreme" choices, farmers could decide to "save" the direct payments by respecting the corresponding mandatory standards while dropping the additional (voluntary) *AEM*s standards and payments.

According to these arguments, if the farmers' decisions were exclusively driven by monetary considerations, it would be possible, by observing the individual net incentives and disincentives, to predict the impact of a policy regime in terms of adoption. Consequently, it would also be possible to progressively improve policy design and implementation in order to maximize the environmental outcome and minimize the policy expenditure. However, not only this information on individual net incentives/disincentives might be unavailable. More importantly, how farmers eventually behave may critically depend on those unobservable non-monetary motivations that are, in turn, the result of their idiosyncratic features.

## 3. The theoretical framework

### 3.1. The non-monetary motivations of farmers behaviour

The research question underlying the present study is the following: what is the behavioural response of farmers to these AEPs and how heterogeneous is it? In order to answer this question, a theoretical representation of farmers' behaviour is needed. The basic idea is that farmers pursue utility maximization. Utility is the combination of a monetary component (profit or, as most agricultural production units are family farms, *net income*) ($\pi$) and a non-monetary component (*NM*). The behaviour factors underlying this *NM* term can be many and largely vary across farm typologies. An extensive review of these aspects is well beyond the scope of the present study[4] where the key focus is rather on putting forward a theoretical framework and a methodological approach to identify and eventually estimate the overall size of this *NM* term.

Given this main objective, here we want to summarize these behavioural factors in a few general categories. Following Thomas et al.

[2] These requirements are the so-called Good Agricultural and Environmental Conditions (GAECs). In fact, other environmental standards apply to the farming activity (the Statutory Management Requirements, SMRs), but they concern all farmers regardless of their *DP*s entitlements.

[3] On a Member-State basis, the total amount of greening payment must correspond to 30% of the total direct payments. In several EU countries (and this is the case of Italy) this condition is satisfied by automatically assigning to eligible farms 30% of total direct payments as greening payment.

[4] The reader can see Zimmermann and Britz (2016), Dessart et al. (2019), Brown et al. (2021) for recent and extensive reviews of both structural and behavioural factors underlying farmers' decisions.

(2019), we consider that *NM* is the combination of four farm-specific terms (Thomas et al., 2019). So, there are five fundamental behavioural drivers[5]

1. *Net-income* (±): is due to the farmers' pursuit of net income maximization (where net income also includes policy incentives and disincentives).
2. *Warm-glow effect* or *Green-guilt aversion* (+): is due to the sense of reward (or guilt) the farmers feel whenever they act in favour (or against) the environment. Thus, they derive a positive utility from pro-environment actions regardless of the net income implications (Beedell and Rehman, 2000).
3. *Control aversity* (−): is due to the nuisance the farmers feel for the control they have to overgo on their environmental performance especially when they perceive the policy instrument as an attempt to control their individual decisions. This effect is amplified if farmers do not agree with the policy objectives or think the choice of instrument was inappropriate (Vollan, 2008). Therefore, whether or not environmental measures are mandatory, farmers may decide to drop their adoption even though this would in fact imply a net monetary loss.
4. *Loss aversity* (+): is due to the fear the farmers feel of the possible future loss of support (i.e., income) due to their current unsatisfactory environmental performance. Cumulative prospect theory predicts that losses motivate behaviour more than equal gains and this is particularly true when people feel a sense of an initial endowment (Babcock, 2015). Given that most current farmers have always received CAP payments, these payments are very likely perceived as an initial endowment and, therefore, the possibility of losing them activates this effect. A tightened conditionality may induce loss averse farmers to adopt measures even with a consequent net income loss.
5. *Attrition effect* (±): this generic term expresses all those factors that prevent voluntary adoption of a policy, whether it is pro-environment or not. These factors make policy adoption unfeasible even though farmers would like to adhere, in principle, to the measures. All CAP measures, in particular, require some formal application by farmers. For bureaucratic reasons or other individual-specific circumstances, farmers may be unable to apply effectively.[6]

The sign in parenthesis after any item indicates the direction of response to AEPs ( ± means more/less intense). In any case, except for net income, none of these drivers of the farmer's response can be directly observed. Even though there are arguments and experiments suggesting that these non-monetary drivers are relevant especially for specific groups of farms (Greiner, 2015), they remain somehow residual, that is, they can only be deduced from observed behaviour net of the net-income effect. In addition, the observable response, as well as the observable net-income is the overall effect of the combination and of the relative strength of these four non-monetary drivers. As will be discussed later, magnitude and direction of these drivers can be identified with an appropriate empirical strategy.

### 3.2. The model

In order to formally investigate how all these effects combine to eventually induce the farmer's response to policy, consider a panel of *N* production units (farms) observed over *T* periods and represent the i-th unit specific utility as follows (Janssen et al., 2010; Mack et al., 2019)[7]

$$U_{it} = \pi_{it} + NM_{it} = (R_{it} - C_{it}) + S_{it} + NM_{it},\ i = 1, \dots, N;\ t = 1, \dots, T \quad (1)$$

where: $R_{it}$ and $C_{it}$ indicate the i-th farm revenues and costs, respectively, at time t, and $S_{it}$ indicates the policy support (net of possible sanctions) received by i-th farm at time t. Thus, $[(R_{it} - C_{it}) + S_{it}]$ indicates the farm-level net income ($\pi_{it}$). $NM_{it}$ stands for the net non-monetary utility components of the i-th farm at time t coming from the combination of the four abovementioned sources.

Designate the generic k-th policy regime (treatment) at which the i-th farm is assigned at time t, and consider the three kinds of payments directly or indirectly associated to some environmental standards as expression of three different AEPs.[8] The first AEP consists in conditioning a direct payment (*DP*) in respect of a set of mandatory environmental standards. These become prerequisites to receive *DP* and, as anticipated, are usually identified as cross-compliance (*CC*) (OECD, 2012). Farmers can still voluntarily decide to not respect the *CC* conditions thus losing the *DP*.

The second AEP consists in an additional direct payment that is only granted if further environmental standards are met (*G*). *Strictu sensu*, this AEP is voluntary since the farmer can still decide to not meet these additional standards yet saving the *DP*. Nonetheless, also this AEP takes the form of a conditionality as the payment it is neither designed nor quantified to cover the additional costs and/or revenue losses associated to the standards.

The third AEP consists in a typical voluntary measure where the farmer participates in a (sometimes competitive) call in which she/he stipulates a sort of contract with the funding institution (usually a national or regional government) (Henke et al., 2018). In respect of a specific set of environmental standards, the farmer receives a compensatory payment (*AEM*) whose aim is to cover the additional costs and/or revenue losses the farmer incurs to meet these standards. As this compensation is calculated as an average at some aggregation level, at the farm level it is usually weakly correlated to the actual revenue losses and/or higher costs (Thomas et al., 2019). As this AEP is strictly voluntary, its environmental standards are more demanding for the farmers than those associated to *DP* and *G*.

Given the nature of these three different AEPs and the way farmers usually perceive them, the first can be interpreted as an *environmental disincentive* (or pecuniary sanction) (*-DP*), the second as an *environmental incentive* (+*G*) and the third as an *environmental compensatory payment* (+*AEM*). Due to this different nature, they also activate different, or to a

[5] In fact, this list does not necessarily exhaust the set of possible drivers of the farmers' response. In more specific production and environmental conditions other aspects might also be taken into account (Lakner et al., 2020). Here, only the more general and arguably relevant drivers are considered. In this respect, it could also be possible to include risk-aversion (i.e., the tendency of the farmers to minimize the response to any external change, policy included). Since production decisions must be taken ex-ante, their consequences are evidently subject to some degree of uncertainty. Consequently, under risk neutrality, farmers actually maximize $\mathbb{E}[U_{it,k}]$ while under risk-aversion also the variance of $U_{it,k}$ would matter. For simplicity, it is here assumed that farmers are risk neutral. Therefore, this further effect is excluded but it can represent a future improvement of the proposed approach.

[6] Non-voluntary unadoption may be caused by circumstances independent of farmers' choices. In some cases, the application can be prevented by the fact that, at some programming level, funds have run out or the maximum number of potential beneficiaries has been reached. This may be particularly the case of *AEMs*. Moreover, farmers may encounter specific exclusion or ineligibility conditions. In any case, these circumstances are not the consequences of farmers' motivations thus are not considered in the present study. Their existence, however, suggest specific caution in the interpretation of results here obtained.

[7] The additive nature of (1) is evidently a simplifying assumption, this form being the easiest specification of a generic function $U_{it} = f(\pi_{it}, NM_{it})$. Under the assumptions that $\partial U_{it}/\partial \pi_{it} > 0$ and $\partial U_{it}/\partial NM_{it} > 0$, we can argue that the analysis here proposed qualitatively maintains its validity even for this generic case, but it becomes quantitively more complex.

[8] As illustrated in section 2, these three AEPs evidently summarize the current CAP toolkit but can be more generally intended as three, possibly complementary, policy strategies (Guerrero, 2021).

different extent, the abovementioned non-monetary motivations of the farmers' response and this adds to the net income expressed as the sum of the net revenue losses and additional costs implied by the k-th policy regime, with the policy payment included. In this sense, these motivations are policy dependent. Though with some significant difference often concerning the specific farming context and policy under investigation, this conceptualization of farmers' decision making is shared with several recent studies in the field (Jaime et al., 2016; Vergamini et al., 2020; Bonfiglio et al., 2022, to mention a few).

On this basis, (1) can be expanded as follows[9]

$$U_{it,k} = \left[\left(R_{it} - L^R_{it,k}\right) - \left(C_{it} + L^C_{it,k}\right)\right] + DP_{it,k} + G_{it,k} + AEM_{it,k} + NM_{it,k}, \quad \forall i = 1, \ldots, N;\ \forall t = 1, \ldots, T;\ \forall k = 1, \ldots, K \tag{2}$$

where $L^R_{it,k}$ and $L^C_{it,k}$ represent the i-th farm revenue losses and additional costs, respectively, at time t implied by the k-th policy regime (i.e., by the environmental standards it imposes)[10] $DP_{it,k}$, $G_{it,k}$ and $AEM_{it,k}$ indicate the three abovementioned AEP payments at time t implied by the k-th policy regime. In (2), $L^R_{it,k}$ and $L^C_{it}$ are not observable. As $NI_{it,k} = [DP_{it,k} + G_{it,k} + AEM_{it,k} - (L^R_{it,k} + L^C_{it,k})]$ represents the net monetary incentive/disincentive implied by the k-th policy regime for the i-th unit at time t, also this net incentive remains actually unobserved. Nonetheless, $(R_{it} - L^R_{it,k})$ and $(C_{it} + L^C_{it,k})$ can be observed, as well as $DP_{it,k}$, $G_{it,k}$ and $AEM_{it,k}$. More importantly, in (2) the net income $\pi_{it,k} = [(R_{it} - L^R_{it,k}) - (C_{it} + L^C_{it,k})] + (DP_{it,k} + G_{it,k}) + AEM_{it,k}$ can be observed. Therefore, (2) can be written in a more compact form as:

$$U_{it,k} = \pi_{it,k} + NM_{it,k}, \forall i = 1, \ldots, N; \forall t = 1, \ldots, T; \forall k = 1, \ldots, K \tag{3}$$

As anticipated, $NM_{it,k}$ represents a treatment-dependent term. When treated with the k-th treatment, the i-th unit activates the $NM_{it,k}$ utility component. However, unlike the other utility term $\pi_{it,k}$, $NM_{it,k}$ is unobservable. Therefore, within the present modelling approach, not only $NM_{it,k}$ is policy-dependent but it is, in fact, the consequence of the policy itself: it is the unobservable part of the policy treatment effect (TE) whereas $\pi_{it,k}$ is the observable part. The summation of these two parts constitute what we can call the *full unobserved TE*. Through $\pi_{it,k}$ and an appropriate empirical identification strategy, some information about $NM_{it,k}$ can be recovered (see below). Two assumptions on this term are worth making here.

Firstly, $NM_{it,k}$ can be either a positive or negative term, depending on the dominant underlying non-monetary motivations and, in principle, it could vary across time. However, these motivations are individual-specific and are expression of farmers' heterogeneity (also from a cultural, political and ideological perspective). Therefore, they remain arguably constant over a relatively short period of time. Consequently, it can be reasonably intended as a time-invariant term, i.e. $NM_{it,k} = NM_{i,k}$, $\forall t \in T$.

Secondly, $NM_{i,k}$ could also be either stochastic or deterministic or, to follow the conventional panel data terminology, either a treatment-dependent Fixed-Effect (FE) or Random-Effect (RE). In the former case, it is $NM_{i,k} = a_{i,k}, \forall i \in N, \forall k \in K$. In the latter case, it is $NM_{i,k} \sim N(a_{i,k}, \sigma^2), \forall i \in N, \forall k \in K$. As will be clarified below, the assumption implicitly made here is that this key term is deterministic thus behaving as an individual-specific constant term.

### 3.3. The treatment-effect logic

Can we identify the farm-specific non-monetary motivations on the basis of (2)-(3)? To answer this question we notice that, since farms are not randomly or exogenously assigned to a policy but, in fact, they voluntary choose it, we can assume that for any i-th farm at time t it is $U_{it,k}|T_k \geq U_{it,h}|T_h, \forall k, h \in K, k \neq h$: the utility of the i-th farm that has chosen the k-th policy regime at time t is higher than (or equal to) the utility it would have achieved had it chosen any other h-th regime. Therefore, for income maximizing farms the observed policy can be infomative about the relative magnitude of the underlying utility components in the i-th farm at time t, i.e. $\pi_{it,k}$ and $NM_{i,k}$.

More specifically, for any given i-th unit, three alternative explanations of the k-th treatment choice can be given.

1. $U_{it,k}|T_k > U_{it,k}|T_h$ because $\pi_{it,k}|T_k > \pi_{it,h}|T_h$ ($\Delta\pi_{it} > 0$) and $NM_{i,k} > NM_{i,h}$ ($\Delta NM_i > 0$), so it necessarily is $\pi_{it,k} + NM_{i,k} > \pi_{it,h} + NM_{i,h}$.
2. $U_{it,k}|T_k > U_{it,k}|T_h$ because $\pi_{it,k}|T_k > \pi_{it,h}|T_h$ ($\Delta\pi_{it} > 0$) and $NM_{i,k} < NM_{i,h}$ ($\Delta NM_i < 0$), but it is still $\pi_{it,k} + NM_{i,k} > \pi_{it,h} + NM_{i,h}$.
3. $U_{it,k}|T_k > U_{it,k}|T_h$ because $\pi_{it,k}|T_k < \pi_{it,h}|T_h$ ($\Delta\pi_{it} < 0$) and $NM_{i,k} > NM_{i,h}$ ($\Delta NM_i > 0$), but it is still $\pi_{it,k} + NM_{i,k} > \pi_{it,h} + NM_{i,h}$.

As the i-th farm chooses the k-th instead of the h-th policy in order to achieve a utility gain, $\Delta\pi_{it} = (\pi_{it,k} - \pi_{it,h})$ reveals the income consequence of this choice and, indirectly, reveals the sign and magnitude of the underlying non-monetary motivations, $\Delta NM_i$ relative to this $\Delta\pi_{it}$: whenever $\Delta\pi_{it} < 0$ we can conclude that $\Delta NM_i > 0$ and it is large enough to overcompensate the income loss. Assumed that both $\Delta\pi_{it}$ and $T_i$ can be observed, this information can be interpreted in treatment-effect logic: $\Delta\pi_{it}$ is the observed TE (i.e., on the outcome variable $\pi_{it}$) of moving from h-th policy (or treatment) to k-th policy (or treatment). Since it is farm-specific, $\Delta\pi_{it}$ can be intended as an ITE. Moreover, as will be clarified below, the potential outcome framework allows to separately identify the ITE on the treated and the expected ITE on the untreated units, thus distinguishing between the *Individual Treatment effect on the Treated* (ITT) and the *Individual Treatment effect on the Untreated* (ITU) (Wang et al., 2017).

To make this TE interpretation clearer, two simplifications are useful and are also consistent with the empirical application that will be presented later. First of all, as in the present study the adopted dataset eventually collapses to a cross-sectional sample, henceforth we omit the time index *t*. Secondly, the analysis is restricted to the simplified binary treatment case ($T_{it} = 0, 1$).[11]

Given these simplifications, the *Individualised Average Treatment Effect* (IATE), $\tau(X_i)$, can be identified as (Knaus et al., 2021):

$$\tau(X_i) = \mathbb{E}[\pi_i|X_i, T_i = 1] - \mathbb{E}[\pi_i|X_i, T_i = 0] \tag{4}$$

where $X_i$ is the ($P$x1) vector of $P$ exogenous variables observed for the i-th unit and affecting both the potential outcomes and the assignment to the treatment (also called *confounding variables*).

$\tau(X_i)$ can be given two opposite interpretations depending on how the binary treatment is defined and on the treatment regime of the i-th unit. In one case, the treatment ($T_i = 1$) is pro-environment, so it requires higher environmental standards with a consequent higher support. Alternatively, the treatment ($T_i = 1$) is anti-environment, so it requires lower environmental standards with a consequent loss of sup-

[9] It is worth noticing that (2) implicitly assumes that farmers' behaviour is only driven by individual utility so it disregards all the possible social benefits and costs (positive and negative externalities) of their production decisions. Although these externalities are the real justification underlying any AEP, the assumption is that they are in no case direct drivers of farmers' choices unless they are indirectly incorporated in the $EI_{it,k}$ term or properly compensated through policy incentives (the combination of $L^R_{it,k}$; $L^C_{it,}$; $DP_{it,k}, G_{it,k}, AEM_{it,k}$).

[10] It is implicitly assumed that both for $DP_{it,k}$ and for $G_{it,k}$, $L^R_{it,k}$ and $L^C_{it}$ are independent of the respective payments as, after all, they are mostly intended to support farmers' income. As anticipated, the same may hold true also for $AEM_{it,k}$.

[11] Notice that, under these two assumptions, in the binary treatment case $NM_{i,k}$ can be simply written as $NM_i$ that indicates the extra-income motivations associated to $T_{it} = 1$ (i.e., it is $NM_i = NM_{i,1}$).

port.

In the first case, farms showing $IATT = \tau(X_i|T_i = 1) < 0$ (i.e., $(NM_i|T_i = 1) > 0$) can be associated to greater pro-environment non-monetary motivations, while farms showing $IATU = \tau(X_i|T_i = 0) < 0$ (i.e., $(NM_i|T_i = 0) > 0$) to greater anti-environment non-monetary motivations. According to the discussion above, the pro-environment farms are driven by the prevalence of warm-glow effect/green-guilt aversion, loss aversity and attrition, while anti-environment are driven by the prevalence of control aversity and attrition. In the second case, $IATT = \tau(X_i|T_i = 1) < 0$ indicates greater anti-environment non-monetary motivations, while $IATU = (X_i|T_i = 0) < 0$ greater pro-environment non-monetary motivations. The same interpretation about the prevalence of the non-monetary drivers applies.

Assessing how many and what kind of farms show a negative IATE (IATT or IATU) in these two cases provides empirical evidence on the non-monetary motivations of farms that eventually overcompensate the monetary motivations.

### 3.4. Policy assessment

As discussed above, the logic underlying this theoretical derivation consists in a series of key steps leading from farmers' specific preferences to their eventual AEPs adoption and production decisions. The reliability of this logic is corroborated by several recent studies in the field (Jaime et al., 2016; Lakner et al., 2020; Vergamini et al., 2020; Bonfiglio et al., 2022). What is novel here, however, is that the interpretation of the farmers' behaviour as an ITE also opens a different decision making perspective, that of the policy maker. In fact, the main interest in identifying and estimating the IATE resides precisely in performing a policy assessment.

Within the recent Optimal Policy Learning (OPL) literature (Athey et al., 2020), estimated IATE allows computing the welfare loss (also known as "the regret") associated to the actual individual treatment assignment and, then, the difference with the respect to an ideal (possibly constrained) welfare maximizing assignment net of policy expenditure (Cerulli, 2020). An extensive OPL analysis is beyond the scope of the present study. Here, we want only to show how the IATE estimation can lead to a constructive policy assessment and sketch some initial evidence in this respect.

Assume that the policy maker cares about the net externalities (the balance between positive and negative externalities) of farming and the policy expenditure needed to induce them. A full optimization approach can be challenging as getting a reliable monetary evaluation of these externalities is difficult if not impossible. However, we can still think about a policy maker pursuing a sort of a constrained maximization that can be interpreted in two possible directions: minimize the policy expenditure for a given amount of net externalities; maximize the net externalities with a fixed policy expenditure.

Now, consider a pro-environment treatment. Two policy assessments can be performed. The first consists in computing how much policy expenditure on treated units ($T_i = 1$) could be saved (*Total Policy Saving, TPS*) maintaining the same environmental performance. *TPS* can be computed by considering all those treated farmers whose monetary motivations would lead them to adopt the k-th regime even with a lower policy support. On the basis of the modelling approach illustrated above, it is:

$$TPS = \sum_{i=1}^{M} PS_i \quad \text{with} \begin{cases} PS_i = P_i \text{ if } P_i < IATT_i > 0 \\ PS_i = IATT_i \text{ if } P_i \geq IATT_i > 0 \\ PS_i = 0 \text{ if } IATT_i < 0\ (\Delta NM_i > 0) \end{cases} \tag{5a}$$

where $PS_i$ is the i-th unit policy saving, $P_i$ is the i-th unit CAP support associated to the environmental performance and delivered to the treated units (therefore, dropped by the untreated ones); $M$ is the number of the traded units (i.e., farms moving from the h-th to the k-th treatment), with $M \in N$; $IATT_i$ is the estimated $\Delta\pi_i$ in treated units.

The second policy assessment concerns the untreated units ($T_i = 0$) and follows an analogous logic. In such case, it is possible to compute by how much the policy expenditure should be increased (*Total Policy Extra-Expenditure, TPE*) to improve the environmental net externality, namely, to convince any farm to adopt the pro-environment treatment thus providing a higher environmental performance. Even though this calculation can not be conclusive in terms of policy maker optimization, since the monetary value of this externality gain is unknown, *TPE* can still be a useful information as it can be intended as the shadow social value of this additional net externality. Following the arguments above, it is:

$$TPE = \sum_{i=1}^{N-M} |IATU_i| \quad \text{if } IATU_i < 0(\Delta NM_i > 0) \tag{6a}$$

where $IATU_i$ is the estimated $\Delta\pi_i$ in untreated units.

This policy assessment can be replicated, symmetrically, in the case of an anti-environment treatment. For the treated units ($T_i = 1$), it will be possible to compute:

$$TPE = \sum_{i=1}^{M} IATT_i = \Delta\pi_i \quad \text{if } IATT_i > 0 \tag{6b}$$

For the untreated units ($T_i = 0$), it will be:

$$TPS = \sum_{i=1}^{N-M} PS_i \quad \text{with} \begin{cases} PS_i = P_i \text{ if } IATU_i < 0, P_i < |IATU_i| < 0 \\ PS_i = |IATU_i| \quad \text{if } IATU_i < 0, P_i \geq |IATU_i| > 0 \\ PS_i = 0 \text{ if } IATU_i > 0(\Delta NM_i < 0) \end{cases} \tag{5b}$$

where $P_i$ now is the i-th unit CAP support associated to the environmental performance and delivered to the untreated units (therefore, dropped by the treated ones).

## 4. The estimation approach

### 4.1. The identification strategy

The major empirical issue for the identification of the IATE (IATT and IATU) with observational data consists in finding appropriate counterfactuals for any i-th treated unit. The typical approach to this issue relies on the *potential outcome framework* (Imbens and Rubin, 2015) and its underlying assumption, the *Conditional Independence Assumption* (CIA, or Unconfoundedness) (Imbens, 2020)[12]

$$T_i(\pi_i(0), \pi_i(1))|\boldsymbol{X}_i \tag{7}$$

where $\pi_i(1)$ and $\pi_i(0)$ indicate the potential outcome of the i-th farm with ($T_i = 1$) and without ($T_i = 0$) treatment, respectively.[13]

Under the CIA we can conclude that the observational data can be properly investigated within a quasi-experiment or natural experiment setting (Angrist and Pischke, 2010). Here, this natural experiment assumption is that the reasons why farmers choose a treatment (the unobserved non-monetary drivers included) are independent from the observed treatment effect (i) once we control for **X** or, more explicitly, that these drivers evidently affect the treatment choice but not the potential outcomes (Athey et al., 2020). If CIA holds true, the selection bias is excluded, that it, $\mathbb{E}[\pi_{i0}|X_i, T_i = 1] - \mathbb{E}[\pi_{i0}|X_i, T_i = 0] = 0$ (Angrist and

[12] A second assumption that is assumed as valid here and is needed for the identification of the IATE, is the Stable Unit Treatment Value Assumption (SUTVA). It rules out any influence of an individual's treatment status on another individual's potential outcome.

[13] Condition (7) postulates the independence between the potential outcomes and the treatment conditional on a set of pre-treatment (exogenous) variables, $X_i$ (Athey and Imbens, 2017): given $X_i$, knowledge of $T_i$ provides no information about both $\pi_i(1)$ and $\pi_i(0)$, and viceversa.

Pischke, 2009, p. 54).

It remains true that within a non-experimental context we only observe the potential outcome that corresponds to the realized $T_i$, either $\pi_i|X_i, T_i = 1$ or $\pi_i|X_i, T_i = 0$. Namely, we only observe $\pi_i = T_i\pi_i(1) + (1 - T_i)\pi_i(0)$ while $\tau(X_i)$ remains unobservable. The only possible way to identify $\tau(X_i)$ is to compare $\pi_i|X_i, T_i = 1$ with untreated units (the counterfactuals or controls) that are statistically equivalent to the i-th unit over $X$. As variables in $X$ are expected to deconfound the (self) allocation of farms into the treatment, this identification strategy requires an additional assumption: together with the CIA, the balance (also known as overlap, or positivity, or common support) condition must be respected. It establishes that $0 < Pr(T_i = 1|X_i) < 1$, i.e. a positive probability of both treated and untreated units within different strata of $X$. Empirically, this condition implies that there must be at least one treated unit and one control unit at each possible value of all exogenous variables in $X$ (Sauppe and Jacobson, 2017).[14]

In order to estimate the IATE following this strategy,[15] now assume that the data generation of the outcome variable $\pi_i$ follows a stochastic process defined as:

$$\pi_i = f(X_i, T_i) + \varepsilon_i \tag{8}$$

where $f$ indicates an arbitrarily complex function, and $\varepsilon_i$ represents an additive idiosyncratic disturbance term assumed i. i.d.~N (0,σ$^2$). Therefore, it is $\mathbb{E}[\pi_i|T_i, X_i] = f(X_i, T_i)$ and, according to (4), $\tau(X_i)$ can be estimated as $\tau(\mathbf{X}_i) = \widehat{f}(\mathbf{X}_i, 1) - \widehat{f}(\mathbf{X}_i, 0)$. Consequently, an appropriate specification of function $f(X_i, T_i)$ is needed. It could be explicitly specified as a parametric function but this inevitably constrains the cross-farm technological and behavioural heterogeneity. An alternative solution consists in admitting an individual-specific function and in developing a nonparametric approach to estimate it.

### 4.2. Causal forest estimation and inference

An appropriate approach to estimate (8) and, consequently, the IATE (IATT and IATU) must admit large heterogeneity across farms, thus operating without either information or assumptions about the true parametric form of the response surface. At the same time, this nonparametric estimation approach must also allow inference, that is, IATE estimates grounded on distributional properties and asymptotic theory, with a consequent standard errors estimation.

The widely growing and quickly spreading ML toolbox offers very interesting solutions in this direction: they can deal with large heterogeneous samples, many and interacting confounding variables and possibly nonlinear relationships (Mullainathan and Spiess, 2017; Lu et al., 2018).[16]

These techniques allow flexible (i.e., non-parametric) response surface estimation thus optimizing, within the potential outcome framework here adopted, the search of overlapping observations. Among these ML approaches, in particular, a Causal Forests (CF) estimation is here performed (Athey and Imbens, 2017, 2019; Athey et al., 2019, 2020).[17] The origin of the CF estimation approach traces back to the contribution of Athey and Imbens (2016). These authors developed a method (called *causal trees*) based on the ML method of regression trees but using a different criterion for building the trees: rather than focusing on improvements in mean-squared error of the prediction of outcomes, it focuses on mean-squared error of treatment effects. The method relies on sample splitting, in which a randomly selected half sample is used to determine the optimal partition of the covariates space (the tree structure), while the other half is used to estimate treatment effects within the leaves.

The output of the method proposed by Athey and Imbens (2016) is a TE and a respective confidence interval for each subgroup. However, when the focus of the analysis is on treatment effect heterogeneity, a disadvantage of the causal tree approach is that the estimates are not personalized for each individual as all individuals assigned to a given group have the same estimate. To overcome this limitation, Wager and Athey (2015) proposed a method (i.e., CF estimation) for estimating heterogeneous treatment effects based on random causal trees. Compared to a causal tree, which identifies a partition and estimates treatment effects within each element of the partition, CF estimation leads to estimates of causal effects that change more smoothly with covariates, and in principle every individual has a distinct estimate. Random forests are known to perform very well in practice for prediction problems, but their statistical properties were less well understood until recently. Wager and Athey (2015) show that the predictions from CF are asymptotically normal and centred on the true conditional average treatment effect for each individual. They propose an estimator for the standard error, so that confidence intervals can be also obtained.

This CF approach is here adopted. First, a flexible model for treatment impacts, like (8), is fitted in order to compute the IATE for both Treated (IATT) and Untreated (IATU) units.[18] On the basis of these IATE estimates, the policy assessment is then performed by computing the respective *TPS* and *TPE* (equation 5a,b and 6a,b). Finally, Average Treatment Effects (ATE) and Group Average Treatment Effects (GATE) are obtained by averaging the IATE over the full distribution of $X$, or over subgroups aggregated on some exogenous covariate, respectively. These CF estimation steps are performed with the R *grf* package (Tibshirani et al., 2018)[19] then integrated with STATA functionalities using the *MLRtime* package.

## 5. The empirical application

Section 3 puts forward an implicit working model with causality going from the treatment to the outcome variable as a consequence of the underlying theory (utility maximizing farmers). The theoretical background also serves to better design the quasi-experimental setting, namely, properly defining the treated and the control groups, the outcome, the treatment and the confounding variables. For the sake of space limitations, a comprehensive description of the adopted datasets and of outcome and confounding variables' construction can be found in

[14] Even though we deal here with voluntary participation in the treatments, it is still possible to conclude that both conditions remain valid under farms' heterogeneity if this heterogeneity concerns the utility function but not its determinants. Namely, there can be some relevant unobservable heterogeneity across farms that make farms' utility differ thus justifying their voluntary selection of different treatments. But this does not affect the eventual outcome conditional on **X** (Imbens, 2020).

[15] Alternative identification strategies have been recently proposed to assess the impact of the AEPs. See, for instance, the differences-in-discontinuities design presented in Wang et al. (2023). However, these strategies do not allow the proper identification of the IATE, that is, of the heterogeneity of response to the treatment.

[16] The adoption of ML techniques in this field goes well beyond the economic assessment of farmers' response to AEPs. Their flexibility and adaptability extend the usage also to other forms of environmental assessment. See Nabavi-Pelesaraei et al. (2023) for an example.

[17] An alternative but closely related ML approach to IATE estimation and inference is based on Bayesian Additive Regression Trees (BART). See Coderoni et al. (2023) for an application to the agri-environmental context.

[18] One drawback of this approach is the possible presence of covariate imbalance, that is the violation of the overlap (or common support) assumption. In such case, the CF algorithm may force the model to make out-of-sample extrapolations. In the present application, the lack of overlap may represent a severe problem as the *T1* treatment group is likely to include some peculiar farms, at least for some of the covariates included in $X$ (Esposti, 2017a, 2017b). The first step of the estimation approach thus excludes those units not respecting the overlapping condition.

[19] Updated versions and more details can be found at https://cran.r-project.org/web/packages/grf/index.html.

Annex 1 while Annex 2 reports the respective descriptive evidence.

### 5.1. The treatment sets

As anticipated, the main reason to separately work with the two subperiods is that in both we can find analogous policy regimes therefore allowing a comparable assessment. Within the CAP, the AEP that eventually combine are (*DP* + *CC*), *G* (only applying to years 2015–2018) and *AEM*. Therefore, three possible regimes, or treatments, can be identified: *T0* is the control group or baseline regime/treatment where farms adopt the environmental standards required to receive the *DP* (*G* included); *T1* is the anti-environment regime, where farms do not adopt any environmental standards (but those imposed on all producers) thus dropping all *DP*; *T2* is the pro-environment regime, where farms also adopt the additional requirements implied by the *AEM* payment.

Table 1 summarizes the different AEP regimes that can be observed across the 2008–2018 period, while Fig. 1 displays the respective dynamics over the years. It clearly emerges how, by changing the implementation of first pillar direct payments', the 2013 CAP reform (starting in 2015) made the before-2015 and after-2015 comparison unfeasible. Nonetheless, in both sub-periods three analogous regimes emerge. A peculiar case is represented by those few farms (260 and 81 units in 2008 and 2018, respectively) that receive the *AEM* payment but do not receive first pillar *DP*. Therefore, it is difficult to compare this regime with the others in terms of compliance to environmental standards. For this reason, these farms are excluded from the present analysis.

The empirical analysis is here repeated for the three binary treatment comparisons: *T0* (contol) vs *T1*; *T0* (contol) vs *T2*; *T1* (contol) vs *T2*. Table A1 in Annex 2 reports the aggregation of the abovementioned policy regimes into these three treatments. Comparing the treatment group *T1* with the control group *T0* corresponds to the following quasi-experimental logic: what would happen (in terms of $\pi$ and, consequently, what would it reveal about *NM*) to the control group farms if they were not treated with the first pillar *DP*? Comparing the treatment group *T2* with the control group corresponds to this quasi-experiment: what would happen to the control group farms if they were also treated with the second pillar payments *AEM*? The comparison between treatment groups *T1* and *T2* may finally help in confirming the results of first two "experiments" and, therefore, in assessing whether these results respect what can be referred to as the *monotonic response condition* (Esposti, 2017a, 2017b): passing from *T1* to *T2* is expected to generate a response that is at least as large as that obtained when passing from *T0* to *T2*. Table 2 recaps the logic and the interpretation of these treatment group comparisons.

In fact, the response monotonicity could be observed on average, therefore comparing the respective ATE, but, due to TE heterogeneity, this does not necessarily respect the condition. The theoretical model here adopted actually implies that the response monotonicity applies to any unit, and thus should be observed in the IATE estimates. In the present case, however, the treatment group varies and, therefore, the only possible assessment of the monotonic response condition concerns the treatment group T2. It implies that for any unit of this group the treatment response (i.e., the IATT) regarding control *T1* is of the same sign (either positive or negative) but of a larger magnitude than the IATT observed with respect to control *T0*.

**Table 1**
Policy regimes in the two balanced panel samples.

| Policy regime | Active AEPs | Reference period |
|---|---|---|
| P0 | *AEM* | Both |
| P1 | *None* | Both |
| P2 | *(DP + CC)* | 2008–2014 |
| P3 | *(DP + CC) + AEM* | 2008–2014 |
| P4 | *(DP + CC) + G* | 2015–2018 |
| P5 | *(DP + CC) + G + AEM* | 2015–2018 |

### 5.2. IATE estimates across periods and treatment comparisons

Annex 3 assembles the figures (from A1.1 to A6.3) displaying the heterogenous individual TE estimates ordered from the lowest to the highest value. The sequence of these figures follows this logic. First, the results for the 2008–2014 period are presented (Figures A1-A3); then, those concerning the 2015–2018 period (Figures A4-A6). Within each period, the three comparisons are presented in this sequence: the anti-environment treatment, *T0* (control) vs *T1*; the first pro-environment treatment, *T0* (control) vs *T2*; the second pro-environment treatment, *T1* (control) vs *T2*. In order to better appreciate the critical results, all figures report a sequence of three charts: the first (panel a) shows the estimates over the whole range of variation (so, all units); the second and the third (panels b and c) only the units with a negative and positive individual TE, respectively. Finally, for any treatment comparison the IATE are reported first and then followed by the respective IATT and IATU. This allows to visualize whether, as expected, a TE difference emerges between the treated and the non-treated units.

Without entering into details of the specific case, it is interesting to highlight some robust evidence that seems to regularly emerge across all cases. First of all, for many units the policy responses (i.e., the IATE) is quite close to 0 and, above all, not statistically significant. At the same time, a remarkable heterogeneity emerges in all circumstances with IATE spread over a wide range of values both positive and negative and with few vary large (in absolute terms) IATE. The combination of many close-to-0 values with a large dispersion can evidently generate an average TE (ATE) within the whole sample that is itself not statically significant and also of poor policy relevance.

What is worth noticing here is that in all cases many units show an unexpected result, that is IATT<0 or IATU>0. Again, for many of these cases the estimated TE is not statistically different from 0, so it is inconclusive from a policy perspective. Nonetheless, the number of units showing a statistically significant unexpected response is remarkable (see below) because, as discussed, it can only be justified by the prevalence of specific non-monetary motivations. According to (3), it thus emerges that for many units the $NM_i$ term of the utility can counterbalance the monetary term ($\pi_i$), thus inducing the unexpected response.

Comparing the 2008–2014 and the 2015–2018 subperiods, most of the main evidence discussed above seems to be confirmed. Nonetheless, the second period of observation reveals an overall lower statistical significance of estimated IATE. Despite the larger balanced sample, this may be attributed to the shorter time over which variable averages are computed, thus making their variability larger. As a consequence, the TE heterogeneity is even wider. Although many IATE are not statistically different from 0 on both tails of the IATE distribution, we also observe very high values (in absolute terms). Another difference between the two periods of investigation emerges from comparing the IATT with the respective IATU. It turns out that a higher/lower incidence of statistically negative/positive values is found among the IATU than the IATT. Following the arguments above, this would indicate a relatively greater relevance of the monetary motivations compared to non-monetary ones in both pro- and anti-environment treatments. The comparison of the IATT for the two treatments involving the *T2* group confirms what was observed in the previous period about the monotonic response condition. The larger is the pro-environment nature of the treatment, the more intense are the negative values as should be expected since negative IATT imply relevant pro-environment non-monetary motivations.

It is worth noticing here that, besides the specific interpretation and policy implications of these IATE estimates, they also reveal the potentials of the proposed approach in investigating the complexity and the multidimensionality of the farmers' response to AEPs. In particular, it is our contention that the approach maintains its conceptual and methodological validity even if the attention would be moved from the pure economic dimension to a wider socio-environmental dimension and policy-making objective, like fostering novel social values (Koley, 2022). Nonetheless, this extension would not only require a redefinition

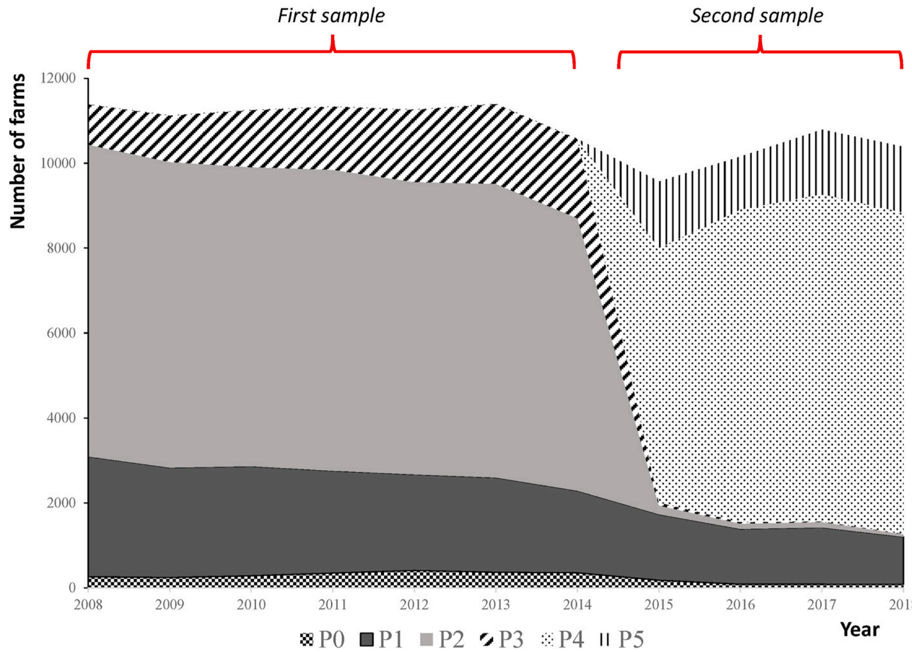


**Fig. 1.** Distribution of farms across policy regimes within the 2008–2018 unbalanced Italian FADN sample (see Table 1 for the policy regime legend).

**Table 2**
Policy treatment sets across the two period and interpretation of the treatment effect ($\Delta\pi_i$) across the treatment comparisons.

| | | AEPs | Interpretation of $\Delta\pi_{it}$ in treatment comparisons | | |
|---|---|---|---|---|---|
| | | | T0 vs T2 | T0 vs T1 | T1 vs T2 |
| Treatment groups | T0 (control) | Only those implied by first pillar DP, G included. (P2 or P4) | Anti-environment (Control aversity and Attrition) | Pro-environment (Warm-glow effect/Green-guilt aversion and Loss aversity) | – |
| | T1 | None (P1) | – | Anti-environment (Control aversity and Attrition) | Anti-environment (Control aversity and Attrition) |
| | T2 | Those implied by both first pillar DP and second pillar AEM. (P3 or P5) | Pro-environment (Warm-glow effect/Green-guilt aversion and Loss aversity) | – | Pro-environment (Warm-glow effect/Green-guilt aversion and Loss aversity) |

of the outcome variable but also the validation of the approach applicability across different geographic spectrums, field-scale included.

### 5.3. ATE and GATE estimates

As discussed in section 4, from these IATE estimates respective ATE and GATE estimates can be obtained. They are interesting results also in the present case but, under such large heterogeneity, they must be taken with caution. It is also worth remembering that heterogeneous effects ranging from negative to positive values may eventually generate small and not statistically significant average values. Following the argument above, here only the significant ATE and GATE estimates will be commented.

Table 3 reports the ATE, ATT and ATU estimates across the three different treatments and the two samples. In the first period (2008–2014), statistically significant ATE, ATT and ATU estimates are obtained only for the *T0* vs *T2* comparison. A positive value emerges, thus indicating a prevalent monetary determinant in the farmers' treatment choice. In fact, this interpretation strictly holds true only for the treated units: the ATT is itself positive and larger, in magnitude, than the ATU. This would suggest that, even if present, possibly anti-environment non-monetary motivations do not compensate the

**Table 3**
ATE, ATT and ATU estimates for the two balanced panel samples.

| | 2008–2014 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | ATE | st. error | Obs | ATT | st. error | Obs | ATU | st. error | Obs |
| T0 vs T1 | 5751.32 | 4604.17 | 2654 | 6317.82 | 4529.69 | 843 | 4505.93* | 4767.91 | 1811 |
| T0 vs T2 | 5013.30* | 2354.02 | 2659 | 5432.85* | 2684.05 | 848 | 4770.59* | 1900.87 | 1811 |
| T1 vs T2 | −1103.72 | 3815.70 | 1691 | −1488.32 | 3726.29 | 848 | −716.84 | 3905.64 | 843 |
| | 2015–2018 | | | | | | | | |
| | ATE | st. error | Obs | ATT | st. error | Obs | ATU | st. error | Obs |
| T0 vs T1 | 1412.99 | 2726.86 | 4893 | 1705.54 | 2888.84 | 1217 | 1316.15 | 2673.23 | 3676 |
| T0 vs T2 | −1726.61 | 2845.85 | 4633 | −264.06 | 2944.61 | 956 | −2051.91 | 2821.19 | 3676 |
| T1 vs T2 | 7750.01* | 2919.08 | 2174 | 7779.13* | 2748.07 | 956 | 7757.11* | 3053.55 | 1217 |

*Statistically significant at 5% level.

stronger monetary incentive to participate in the treatment. Alternatively, it could be argued that pro-environment non-monetary motivations are so strong as to eventually compensate the negative monetary incentive. At the same time, however, also the ATU is positive. The interpretation in this case is the opposite: despite the significant monetary incentive, on average the non-treated units show stronger anti-environment non-monetary motivations that lead them to remain in the control regime *T0*.

For the 2015–2018 period, the only statistically significant ATE concerns the T1 vs T2 case. As discussed, it could be intended as an extremization of the T0 vs T2 comparison with an even stronger pro-environment treatment. Results can thus be interpreted in a similar way. In the 2008–2014 period, this ATE is positive and larger in magnitude than the T0 vs T2 case. Respective ATT and ATU are very similar. This result can be interpreted as the relative importance of the two terms of a farm's utility in generating the regime choice. The ATT signals that the monetary incentive passing from T1 to T2 is so strong that it overcompensates any possibly anti-environment motivations. After all, in this specific case such monetary incentive consists in the combination of DP, G and AEM payments. At the same time, however, the estimated ATU support the idea that for the non-treated units these non-monetary motivations are actually much stronger and convince these farms to remain in the T1 regime despite the loss of a large policy support.

A final remark on these average TE estimates concerns the ATT referring to the T2 group. Comparing the ATT in the two treatment cases T0 vs T2 and T1 vs T2 may be interpreted as an indirect assessment of the monotonic response condition. The ATT estimate is negative, of small magnitude and not statistically significant in the T0 vs T2 case, it remains interesting to notice that a lower ATT observed in the less extreme pro-environment treatment is consistent with the monotonic response condition only if we assume significant pro-environment motivations of these farms and, therefore, what is observed in the T1 vs T2 case is the combination of concordant monetary incentives and non-monetary motivations. The same conclusion should actually apply to the 2008–2014 period.

With the same cautions outlined in the comments about the ATE estimates, also the average TE estimated over subgroups or intermediate aggregation levels of the exogenous covariates (GATE) can be informative. Table 4 reports selected GATE estimates on those covariates that reveal extreme or peculiar IATE values or that assume specific policy interest. First of all, it emerges that gender may matter as female holders tend to show larger TE in absolute terms. However, only in one case is the respective GATE statistically significant and it concerns the *T1* vs *T2* case during the 2015–2018 period. The value obtained is positive as the respective ATE but also much higher suggesting, for these farms, a higher monetary incentive associated to the pro-environment treatment and, consequently, larger non-monetary motivations eventually compensating it.

The other selected GATEs reported in Table 4 concern the sub-group of young farmers and two production specializations (Livestock and Perennial Crops farms) which, especially in the Italian case, are often associated with quite distinctive farm structures and external conditions. In all cases, the statistically significant GATE overlaps with the ATE estimates of Table 3: the *T0* vs *T2* treatment for the 2008–2014 period, the *T1* vs *T2* treatment for years 2015–2018. In both cases, estimated values are positive, but the magnitude is significantly larger than the respective ATE, about two times and three times, respectively. This would suggest that for young holders and Livestock and Perennial Crops farms, the monetary incentive associated with the pro-environment treatment is higher than for all other farms. Consequently, the anti-environment non-monetary motivations of farms remaining in the control regime have to be also stronger.

### 5.4. Policy implications

What is mostly interesting, and novel, in the approach presented here consists in the exploitation of the estimated IATE in order to assess whether and how a rationalization of the policy under investigation can be achieved. Section 3 presented the indicators that can be computed in this respect starting from either IATT or IATU values. Table 5 firstly reports those IATT and IATU estimates in the two balanced panel samples and across the different treatments that, according to the theoretical framework, imply relevant non-monetary motivations ($NM_i > 0$).

Some remarkable differences between the two periods emerge. Starting with the T0 vs T1 case, in the first period (2008–2014) a limited number of IATT is negative (16%), thus revealing anti-environment non-monetary motivations and, on average, this TE amounts to about 9% of the farm net income. On the contrary, most of IATUs are positive (84%) but its average incidence on net income remains the same (9%). Therefore, the presence of positive, that is pro-environment, non-monetary motivations is quite generalized among those units but its magnitude seems quite marginal with respect to the farm's net income.

The T0 vs T2 case presents a similar behaviour though with the opposite interpretation. Only one-quarter of treated units presents a negative IATU, thus revealing pro-environment non-monetary motivations. For all the other T2 farms, the monetary incentive seems to remain sufficiently strong to choose the treatment. On the contrary, three-quarters of control units show a positive IATU thus indicating anti-environment non-monetary motivations leading them to remain in the

**Table 4**
GATE estimates for selected covariates in the two balanced panel samples.

| | 2008–2014 | | | 2015–2018 | | |
|---|---|---|---|---|---|---|
| | GATE | st. error | Obs | GATE | st. error | Obs |
| Gender = Female | | | | | | |
| T0 vs T1 | 10,980.49 | 9562.95 | 202 | 8911.09 | 10,141.64 | 1106 |
| T0 vs T2 | 7241.80 | 7697.94 | 213 | −7322.11 | 8046.56 | 1204 |
| T1 vs T2 | −2895.32 | 14,799.5 | 35 | 21,184.48* | 8762.43 | 471 |
| Age <40 years | | | | | | |
| T0 vs T1 | 11,483.72 | 13,827.25 | 351 | 1666.59 | 7570.58 | 630 |
| T0 vs T2 | 9788.02* | 4699.86 | 380 | −8635.03 | 7041.64 | 358 |
| T1 vs T2 | −2563.38 | 12,583.19 | 125 | 19,801.54* | 8275.87 | 303 |
| Type = Livestock and Livestock&crop | | | | | | |
| T0 vs T1 | 10,495.48 | 12,241.03 | 1033 | 9105.09 | 10,800.98 | 1731 |
| T0 vs T2 | 10,035.91* | 4708.06 | 1217 | −7962.91 | 7909.67 | 598 |
| T1 vs T2 | −1047.76 | 11,657.45 | 344 | 23,200.62* | 9127.13 | 833 |
| Type = Perennial crops | | | | | | |
| T0 vs T1 | 10,422.00 | 15,051.79 | 80 | −2096.61 | 6206.81 | 1492 |
| T0 vs T2 | 10,575.20* | 4879.95 | 765 | −7899.16 | 7271.99 | 586 |
| T1 vs T2 | −4359.69 | 12,984.77 | 308 | 19,553.04* | 8426.36 | 570 |

*Statistically significant at 5% level.

**Table 5**
IATT and IATU estimates implying NM > 0 in the two balanced panel samples.

| | T0 vs T1 | | | | T0 vs T2 | | | | T1 vs T2 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | % | avg. TE | % on π | N | % | avg. TE | % on π | N | % | avg. TE | % on π |
| 2008–2014 | | | | | | | | | | | | |
| IATT<0 | 138 | 16 | −5413 | 8.7 | 211 | 25 | −6431 | 8.1 | 405 | 48 | −5253 | 9.2 |
| IATU>0 | 1540 | 85 | 4340 | 9.0 | 1340 | 74 | 7308 | 7.6 | 448 | 53 | 3808 | 6.1 |
| 2015–2018 | | | | | | | | | | | | |
| IATT<0 | 446 | 37 | −4055 | 9.0 | 496 | 52 | −4846 | 9.8 | 50 | 5 | −2036 | 4.1 |
| IATU>0 | 1324 | 36 | 4437 | 8.8 | 1397 | 38 | 3783 | 7.6 | 1077 | 88 | 9003 | 20 |

control group. Also in these case, the average incidence of these individual TE is lower than 10% of the respective farm' net income.

Finally, the T1 vs T2 case is essentially consistent with that observed in the other two treatments. For both IATT and IATU we observe about 50% of farms revealing decisive non-monetary motivations. As in the T0 vs T2 case, the interpretation is that about half of treated units show pro-environment motivations leading them to adopt the T2 regime despite an income loss. Consistently with the monotonic response condition both the number of units and the magnitude of negative IATT is larger, although just slightly, compared to the analogous T0 vs T2 case. At the same time, about half of the units remaining in regime T1 makes this choice despite income loss (still lower than 10% of the farm's net income, on average) due to the presence of relevant non-monetary motivations.

Moving to the second period of analysis, the main differences are that the incidence of units showing a negative IATT tends to be higher in both T0 vs T1 and T0 vs T2 cases, even though the average incidence of these negative values on the farm's net income remains below 10%. As the two treatments move in opposite directions (anti and pro-environment, respectively), this could be interpreted as an evidence of stronger non-monetary motivations to choose treatments that actually imply an income loss. When the monetary implication of the regime choice becomes too large, as in the T1 vs T2 case, the number of treated units accepting a negative IATT becomes very small (5%), and also the loss declines, on average, to less than 5% on net income.

Also in the case of the observed IATU some differences compared to the first period can be observed. In the T0 vs T1 and T0 vs T2 cases, the number of untreated units showing a positive IATU is a little more than one-third, with a less than 10% average incidence on net income. Therefore, a remarkable reduction in the incidence of these units is observed compared to 2008–2014 suggesting a sort of relative downsizing of the non-monetary motivations (either anti or pro-environment) for units deciding to remain in the control regime. However, the T1 vs T2 case behaves differently as the incidence of these IATU in terms of both units and share on net income is much greater. This indicates that only anti-environment (arguably with a major role of attrition effect) motivations may explain why most firms in group T1 decide to remain in this regime.

The most interesting use of the results presented in Table 5 concerns the calculation of the two policy indicators (*TPS* and *TPE*) expressing the space for rationalizing the policy intervention by either reducing the expenditure or improving the environmental performance. Table 6 reports the consequent calculation of these two indicators across periods and treatments. These calculations were performed considering only those estimated for IATT and IATU that are statistically lower and greater than 0 at the 10% confidence level, respectively. These units range between 40% and 50%, according to the treatment and the period, of the total IATT<0 and IATU>0 units.

In the first period under study, it emerges that the space of policy savings (*TPS*) is lower than the expenditure expansion (*TPE*) required to induce more pro-environment regimes. Considering both T0 vs T1 and T0 vs T2 cases, the space for savings amounts to less than 8% of total expenditure. On the contrary, the needed extra expenditure is about 30%. A strategy compensating this TPE with the respective TPS thus seems unfeasible. As could be expected from the results discussed above, this gap is significantly reduced in the T0 vs T2 case. But the extra expenditure still remains almost double than the potential expenditure savings.

Following the already noticed differences, period 2015–2018 shows a significantly different picture. The T0 vs T1 case presents extra expenditure and expenditure savings of similar size, both amounting to a little more than 10% of total expenditure. In this case, funding the extra expenditure with the correspondent savings seems to be a viable solution. Also in the T0 vs T2 case the gap between TPS and TPE is remarkably lower than in the previous period but it remains quite large, while the T1 vs T2 case is the only one for which not only TPS exceeds the TPE, but the respective gap is the largest observed across the different comparisons. Eventually this suggests that in the more recent period of investigation, there is much more space for a policy rationalization through a better targeting and tailoring of the AEP measures on the specific characteristics of farms.

## 6. Policy remarks

It is largely agreed that better targeting and tailoring is the key to making policy design and implementation more efficient and effective with respect to the declared objectives (Erjavec and Erjavec, 2015; Ehlers et al., 2021). This is particularly true for EU policy making and,

**Table 6**
Policy assessment indicators (TPS and TPE) in the two periods across treatment comparisons (M €)[a].

| | T0 vs T1 | | T0 vs T2 | | T1 vs T2 | |
|---|---|---|---|---|---|---|
| | Level | % total expenditure[b] | Level | % total expenditure[c] | Level | % total expenditure[d] |
| 2008–2014 | | | | | | |
| TPS | 0.47 | 2.14 | 0.83 | 7.74 | 1.76 | 16.1 |
| TPE | 7.86 | 31.7 | 6.48 | 28.3 | 3.12 | 28.7 |
| 2015–2018 | | | | | | |
| TPS | 4.90 | 11.3 | 1.92 | 12.6 | 5.05 | 33.2 |
| TPE | 6.96 | 11.9 | 8.28 | 21.1 | 0.53 | 3.46 |

[a] TPE and TPS are calculated by multiplying the estimated IATT or IATU by the respective family labour units.
[b] The % on total expenditure refers to the control group expenditure.
[c] The % on total expenditure refers to the control (treatment) group expenditure in the case of TPE (TPS) calculation.
[d] The % on total expenditure refers to the treatment group expenditure.

even more, for the CAP. Recent studies, for instance, show that a combination of management plans and AEPs can increase farmers' disposition to adopt nature conservation measures and the consequent environmental outcome (Lakner et al., 2020). But better policy targeting and tailoring must acknowledge that potential beneficiaries are strongly heterogenous also regarding their response to different policy regimes. This seems particularly true in the case of CAP measures that directly or indirectly target some environmental standard or performance, and for which farm's response may significantly depend on unobservable non-monetary motivations.

Grounding this kind of policy on the empirical evidence thus requires the identification and estimation of the individual response to policies. TE or policy evaluation econometrics can be regarded as a mature and well established field of study, but the proper estimation and inference of ITE is a quite novel topic as only very recently have ML approaches proved to be very helpful in this respect. This paper presents a CF approach for the identification and estimation of ITE of the different CAP AEP regimes across the 2008–2018 period.

Results here obtained suggest that the adopted approach seems particularly suitable to estimate ITE and to distinguish between ITT and ITU estimates. These latter are particularly informative as they can reveal the direction and magnitude of those non-monetary motivations eventually leading farmers to the adopted policy regime. In addition, this individual information can be aggregate in order to compute policy indicators expressing the potential rationalization of the policy support, both in terms of possible expenditure saving and in terms of additional needed expenditure to improve the overall environmental outcome. It also emerges that these non-monetary motivations usually do show a limited incidence with respect to farm's net income. At the same time, however, some major change apparently occurred in the relative importance of these non-monetary motivations across the 2013 CAP reform, and could leave more space for the abovementioned forms of policy rationalization.

All these conclusions must evidently be taken with caution and deserve confirmation and validation. In particular, even though the main objective of the present paper is to illustrate the potentials of CF estimation, it should also be clear that these quasi-experimental approaches are always dependent on assumptions about the data generating processes that can hardly be tested and require further investigation and justification on both the theoretical and empirical grounds (Sims, 2010). The ML toolkit is powerful and informative, but it can also be dangerous in generating unjustified and weak extrapolations. Thus, it requires a careful robustness assessment and validation (Coderoni et al., 2023). Refinements in data availability, quasi-experimental design and ML approaches, as well as analogous applications in non-farming contexts, are therefore expected in future research in this field.

Beside result reliability, there is a final aspect on which the validity of the proposed approach should be carefully considered. Assessing the response to AEPs and looking for improvements in their effectiveness and efficiency necessarily involves the multidimensionality of their objectives often concerning multiple environmental aspects but also social and economic values (Koley, 2022). This poses two questions on the applicability of the proposed approach. The first concerns its extension to a wider (i.e., multidimensional) integrated assessment. In this respect, an interesting direction of future research is represented by the combination of the proposed approach within the large recent multidisciplinary literature bringing together diverse outcomes and indicators, perspectives and methodologies (Vergamini et al., 2020). The other question has to do with the applicability of the adopted logic to different geographic spectrums and different scales of analysis, the field-scale included, that may seem more appropriate from a strictly environmental perspective (Baldoni et al., 2023). Also in this respect, future research may provide interesting contributions.

## CRediT authorship contribution statement

**Roberto Esposti:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing - original draft, Writing - review & editing.

## Declaration of competing interest

With reference to the present paper the author declares: no conflict of interest; no specific funding to be acknowledged; no research activity involving human participants and/or animals; no research activity or material requiring informed consent; no use of generative artificial intelligence (AI) and AI-assisted technologies. Moreover, the author declares that the data used in the present study are proprietary and can not be made publicly available.

## Data availability

The data that has been used is confidential.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.119992.

## References

Andrews, A.C., Clawson, R.A., Gramig, B.M., Raymond, L., 2013. Why do farmers adopt conservation tillage? An experimental investigation of framing effects. J. Soil Water Conserv. 68, 501–511.
Angrist, J.D., Pischke, J.-P., 2009. Mostly Harmless Econometrics. An Empiricists' Companion. Princeton University Press, Princeton.
Angrist, J.D., Pischke, J.-P., 2010. The credibility revolution in empirical economics: how better research design is taking the con out of econometrics. J. Econ. Perspect. 24, 3–30.
Athey, S., Imbens, G.W., 2016. Recursive partitioning for heterogeneous causal effects. PNAS- P. Natl. Acad. Sci. USA. 113, 7353–7360.
Athey, S., Imbens, G.W., 2017. The state of applied econometrics: causality and policy evaluation. J. Econ. Perspect. 31, 3–32.
Athey, S., Imbens, G.W., 2019. Machine learning methods that economists should know about. Annu. Rev. Econ. 11, 685–725.
Athey, S., Tibshirani, J., Wager, S., 2019. Generalized random forests. Ann. Stat. 47, 1148–1178.
Athey, S., Wager, S., 2019. Estimating treatment effects with causal forests: an application. Observational Studies 5.
Athey, S., Wager, S., Hadad, V., Klosin, S., Muhelbach, N., Nie, X., Schaelling, M., 2020. Estimation of heterogenous treatment effect. In: Notes Prepared for "Machine Learning and Causal Inference" Class. https://gsbdbi.github.io/ml_tutorial/hte_tutorial/hte_tutorial.html. (Accessed 1 April 2021).
Babcock, B.A., 2015. Using cumulative prospect theory to explain anomalous crop insurance coverage choice. Am. J. Agric. Econ. 97, 1371–1384.
Baldoni, E., Coderoni, S., Esposti, R., 2023. The productivity-environment nexus in space. Granularity bias, aggregation issues and spatial dependence within farm-level data. J. Clean. Prod. 415, 137847.
Barreiro-Hurle, J., Bogonos, M., Himics, M., Hristov, J., Pérez-Domiguez, I., Sahoo, A., Salputra, G., Weiss, F., Baldoni, E., Elleby, C., 2021. Modelling environmental and climate ambition in the agricultural sector with the CAPRI model. Exploring the potential effects of selected Farm to Fork and Biodiversity strategies targets in the framework of the 2030 Climate targets and the post 2020 Common Agricultural Policy. EUR 30317 EN. Publications Office of the European Union, Luxembourg.
Beedell, J., Rehman, T., 2000. Using social-psychology models to understand farmers' conservation behavior. J. Rural Stud. 16, 117–127.
Bonfiglio, A., Abitabile, C., Henke, R., 2022. A choice model-based analysis of diversification in organic and conventional farms. Bio base Appl. Econ. 11, 131–146.
Brown, C., Kovács, E., Herzon, I., Villamayor-Tomas, S., Albizua, A., Galanaki, A., Grammatikopoulou, I., McCracken, D., Alkan Olsson, J., Zinngrebe, Y., 2021. Simplistic understandings of farmer motivations could undermine the environmental potential of the common agricultural policy. Land Use Pol. 101, 105136.
Cerulli, G., 2020. Optimal Policy Learning: from Theory to Practice. Papers 2011.04993, arXiv.org. (Accessed 1 April 2021).
Chabé-Ferret, S., Le Coent, P., David-Legleye, V., Delannoy, V., 2023. Non-monetary incentives to increase enrolment in payments for environmental services. Eur. Rev. Agric. Econ. 50, 1401–1427.
Coderoni, S., Esposti, R., 2018. CAP payments and agricultural GHG emissions in Italy. A farm-level assessment. Sci. Total Environ. 627, 427–437.
Coderoni, S., Esposti, R., Varacca, A., 2023. How Differently Do Farms Respond to Agri-Environmental Policies? A Probabilistic Machine-Learning Approach. Land Econ (forthcoming).

Dessart, F.J., Barreiro-Hurlé, J., van Bavel, R., 2019. Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. Eur. Rev. Agric. Econ. 46, 417–471.

Ehlers, M.-H., Huber, R., Finger, R., 2021. Agricultural policy in the era of digitalization. Food Pol. 100, 102019.

Erjavec, K., Erjavec, E., 2015. Greening the CAP' – just a fashionable justification? A discourse analysis of the 2014–2020 CAP reform documents. Food Pol. 51, 53–62.

Esposti, R., 2017a. The empirics of decoupling: alternative estimation approaches of the farm-level production response. Eur. Rev. Agric. Econ. 44, 499–537.

Esposti, R., 2017b. The heterogeneous farm-level impact of the 2005 CAP-first pillar reform: a multivalued treatment effect estimation. Agric. Econ. 48, 373–386.

Esposti, R., 2022. The coevolution of policy support and farmers behaviour and performance. An investigation on Italian agriculture over the 2008-2019 period. Bio base Appl. Econ. 11 (3), 231–264.

Fattorini, L., Ghodsi, M., Rung, A., 2020. Cohesion policy meets heterogeneous firms. J. Common. Mark. Stud. 58, 803–817.

Greiner, R., 2015. Motivations and attitudes influence farmers' willingness to participate in biodiversity conservation contracts. Agric. Syst. 137, 1–12.

Guerrero, S., 2021. Characterising agri-environmental policies: towards measuring their progress. In: OECD Food, Agriculture and Fisheries Papers. OECD Publishing, Paris. No. 155.

Hamidinasab, B., Javadikia, H., Hosseini-Fashami, F., Kouchaki-Penchah, H., Nabavi-Pelesaraei, A., 2023. Illuminating sustainability: a comprehensive review of the environmental life cycle and exergetic impacts of solar systems on the agri-food sector. Sol. Energy 262, 111830.

Harrington, W., Morgenstern, R.D., 2007. Economic incentives versus Command and control: what's the best approach for solving environmental problems? In: Visgilio, G.R., Whitelaw, D.M. (Eds.), Acid in the Environment. Springer, Boston, pp. 233–240.

Hatim, M., Majidian, M., Tahmasebi, M., Nabavi-Pelesaraei, A., 2023. Life cycle assessment, life cycle cost, and exergoeconomic analysis of different tillage systems in safflower production by micronutrients. Soil Till. Res. 233, 105795.

Henke, R., Benos, T., De Filippis, F., Giua, M., Pierangeli, F., Pupo D'Andrea, M.R., 2018. The new common agricultural policy: ηow do member states respond to flexibility? Common. Mark. S. 56, 403–419.

Hosseinzadeh-Bandbafha, H., Safarzadeh, D., Ahmadi, E., Nabavi-Pelesaraei, A., Hosseinzadeh-Bandbafha, E., 2017. Applying data envelopment analysis to evaluation of energy efficiency and decreasing of greenhouse gas emissions of fattening farms. Energy 120, 652–662.

Huber, R., Späti, K., Finger, R., 2023. A behavioural agent-based modelling approach for the ex-ante assessment of policies supporting precision agriculture. Ecol. Econ. 212, 107936.

Imbens, G.W., 2020. Potential outcome and directed acyclic graph approaches to causality: relevance for empirical practice in economics. J. Econ. Lit. 55, 1129–1179.

Imbens, G.W., Rubin, D.B., 2015. Causal Inference in Statistics, Social, and Biomedical Sciences. Cambridge University Press, Cambridge.

Jaime, M.M., Coria, J., Liu, X., 2016. Interactions between CAP agricultural and agri-environmental subsidies and their effects on the uptake of organic farming. Am. J. Agric. Econ. 98, 1114–1145.

Koley, S., 2022. Exploring social value prospects of Australia's construction industry towards the aboriginal communities, under COVID-19 recovery efforts. Int. J. Eng. Trends Technol. 70, 227–251.

Knaus, M.C., Lechner, M., Strittmatter, A., 2021. Machine learning estimation of heterogeneous causal effects: empirical Monte Carlo evidence. Econom. J. 24, 134–161.

Lakner, S., Zinngrebe, Y., Koemle, D., 2020. Combining management plans and payment schemes for targeted grassland conservation within the Habitats Directive in Saxony, Eastern Germany. Land Use Pol. 97, 104642.

Lu, M., Sadiq, S., Feaster, D.J., Ishwaran, H., 2018. Estimating individual treatment effect in observational data using random forest methods. J. Comput. Graph Stat. 27, 209–219.

Maklavany, D.M., Rouzitalab, Z., Bazmi, M., Askarieh, M., Nabavi-Pelesaraei, A., 2023. Eco-environmental analysis of different routes for the synthesis of MIL-53(Fe): an integrated life cycle assessment and life cycle cost approaches. Acs Sustain. Chem. Eng. 11, 9816–9832.

Matthews, A., 2011. Leaked Legislative Proposals Anticipate Commission CAP Reform Proposals Due. October 12th. 14 September. http://capreform.eu/leaked-legislative-proposals-anticipate-commission-cap-reform-proposals-due-october-12th/. (Accessed 1 April 2021).

Mullainathan, S., Spiess, J., 2017. Machine learning: an applied econometric approach. J. Econ. Perspect. 31, 87–106.

Nabavi-Pelesaraei, A., Damgaard, A., 2023. Regionalized environmental damages and life cycle cost of chickpea production using LC-IMPACT assessment. Environ. Impact Asses. 103, 107259.

Nabavi-Pelesaraei, A., Ghasemi-Mobtaker, H., Salehi, M., Rafiee, S., Chau, K., Ebrahimi, R., 2023. Machine learning models of exergoenvironmental damages and emissions social cost for mushroom production. Agronomy 13, 13030737.

Nabavi-Pelesaraei, A., Saber, Z., Mostashari-Rad, F., Ghasemi-Mobtaker, H., Chau, K., 2021. Coupled life cycle assessment and data envelopment analysis to optimize energy consumption and mitigate environmental impacts in agricultural production. In: Ren, J. (Ed.), Methods in Sustainability Science Assessment, Prioritization, Improvement, Design and Optimization. Elsevier, Amsterdam, pp. 227–264.

OECD, 2012. Evaluation of Agri-Environmental Policies: Selected Methodological Issues and Case Studies. OECD Publishing, Paris.

Sauppe, J.J., Jacobson, S.H., 2017. The role of covariate balance in observational studies. Nav. Res. Logist. 64, 323–344.

Saeidi, E., Dehkordi, A.L., Nabavi-Pelesaraei, A., 2022. Potential for optimization of energy consumption and costs in saffron production in central Iran through data envelopment analysis and multi-objective genetic algorithm. Environ. Prog. Sustain. 41, e13857.

Sims, C., 2010. But economics is not and experimental science. J. Econ. Perspect. 24, 59–68.

Stetter, C., Mennig, P., Sauer, J., 2022. Using machine learning to identify heterogeneous impacts of agri-environment schemes in the EU: a case study. Eur. Rev. Agric. Econ. 49, 723–759.

Thomas, F., Midler, E., Lefebvre, M., Engel, S., 2019. Greening the common agricultural policy: a behavioural perspective and lab-in-the-field experiment in Germany. Eur. Rev. Agric. Econ. 46, 367–392.

Tibshirani, J., Athey, S., Friedberg, R., Hadad, V., Miner, L., Wager, S., Wright, M., 2018. Grf: Generalized Random Forests (Beta). https://github.com/grf-labs/grf.Rpackageversion0.10.2.

Vergamini, D., Viaggi, D., Raggi, M., 2020. Evaluating the potential contribution of multi-attribute auctions to achieve agri-environmental targets and efficient payment design. Ecol. Econ. 176, 106756.

Vollan, B., 2008. Socio-ecological explanations for crowding-out effects from economic field experiments in southern Africa. Ecol. Econ. 67, 560–573.

Wang, A., Nianogo, R.A., Arah, O.A., 2017. G-computation of average treatment effects on the treated and the untreated. BMC Med. Res. Methodol. 17, 1–5.

Wang, Y., Schaub, S., Wuepper, D., Finger, R., 2023. Culture and agricultural biodiversity conservation. Food Pol. 120, 102482.

Zimmermann, A., Britz, W., 2016. European farms' participation in agri-environmental measures. Land Use Pol. 50, 214–228.