UNIVERSITÀ POLITECNICA DELLE MARCHE

DIPARTIMENTO DI SCIENZE ECONOMICHE E SOCIALI

THE COEVOLUTION OF POLICY SUPPORT AND FARMERS' BEHAVIOUR.

AN INVESTIGATION ON ITALIAN AGRICULTURE OVER THE 2008-2019 PERIOD

ROBERTO ESPOSTI

QUADERNO DI RICERCA n. 464

March 2022

The views expressed in the articles are those of the authors and do not involve the responsibility of the Department.

Abstract

This paper investigates the coevolution of the CAP expenditure and of the farms' performance and choices to assess whether and to what extent CAP itself satisfies the fundamental requisites of Causal Inference. In order to identify some regularities in this coevolution, the analysis is performed on a constant group of professional and representative farms over a long enough time period. The Italian 2008-2019 FADN balanced sample is here considered. Results question whether CAP expenditure is actually accompanied by any significant farmers' response. An exception may actually concern the support specifically focused on environmental standards. Methodological implications about the applicability of Program Evaluation Methods to CAP assessment are drawn.

KEYWORDS: Common Agricultural Policy, Farmers' Behaviour, Program Evaluation, Panel Data.

JEL class.: Q18, D04

Address:

Roberto Esposti, Department of Economics and Social Sciences - Università Politecnica delle Marche, 60121, Ancona (Italy). Email: r.esposti@staff.univpm.it

The Coevolution of Policy Support and Farmers' Behaviour.

An investigation on Italian agriculture over the 2008-2019 period

Roberto Esposti*

*Department of Economics and Social Sciences - Università Politecnica delle Marche (Ancona, Italy); email: r.esposti@staff.univpm.it

Abstract

This paper investigates the coevolution of the CAP expenditure and of the farms' performance and choices to assess whether and to what extent CAP itself satisfies the fundamental requisites of Causal Inference. In order to identify some regularities in this coevolution, the analysis is performed on a constant group of professional and representative farms over a long enough time period. The Italian 2008-2019 FADN balanced sample is here considered. Results question whether CAP expenditure is actually accompanied by any significant farmers' response. An exception may actually concern the support specifically focused on environmental standards. Methodological implications about the applicability of Program Evaluation Methods to CAP assessment are drawn.

Keywords: Common Agricultural Policy, Farmers' Behaviour, Program Evaluation, Panel Data.

JEL Classification: Q18, D04

"Verum scire est scire per causas"

1. Introduction: main motivation of the study

This paper is inspired by the growing application of Causal Inference (CI) to the assessment of public policies. Though grounded on well-known statistical concepts, CI has become a field in itself in the last two decades and has also significantly affected the application of econometric methods to policy assessment now usually referred to as Program Evaluation Methods (PEM) (Imbens and Wooldridge, 2009; Imbens and Rubin, 2015; Perraillon et al., 2022). In the last decade, also the wide literature about the impact of the Common Agricultural Policy (CAP), of its measures and reforms, on the farming activity has paid much attention to these techniques (Dumangane et al., 2021).

The initial motivation of the paper was to critically review the actual applicability of PEM to CAP assessment focusing on the most challenging issues and on the possible methodological ways out. These methodological challenges will be actually discussed in detail later in this paper together with the indication of some possible recent development that can help in properly dealing with them. Soon, however, this original motivation was replaced by a question that turned out to come first and that should be preliminary to any CI assessment: which empirical support do we really have to consistently and properly apply PEM to CAP assessment?

The key issue is that the CAP and the agricultural sector actually co-evolve. A natural and unambiguous cause-effect direction can be obviously assumed but it is not necessarily a good representation of the world. This poses severe problems for the application of the that Treatment-Effect (TE) logic on which any PEM is grounded (Khagram and Thomas, 2010). Rather than investigating the responsiveness of farms to the evolution of the CAP support, thus assuming that a cause-effect relationship exists, the focus here is on the investigation of the coevolution of the CAP and of the farming sector to which it applies: if no coevolution (i.e., correlation) emerges, a response (i.e., causation) can be severely questioned. The research question thus becomes: does CAP support really generate a response? To empirically answer this questions, the invariance of the field of observation must be granted: a constant group of farms must be followed in its evolution over time together with the CAP support these farms are recipients of. We need a balanced panel of heterogeneous enough professional farms covering the different conditions the CAP itself is asked to confront with. The Farm Accountancy Data Network (FADN) is helpful to perform this investigation, particularly in the Italian case where the FADN-RICA dataset contains most of the required information for the present analysis (Cagliero et al., 2010). Moreover, Italy presents a very diverse agriculture, and it is often considered the most heterogenous agriculture within the EU (Baldoni et al., 2021). Therefore, the 2008-2019 Italian FADN balanced panel is here used.

The rest of the paper is structured as follows. Section 2 overviews the literature and the policy relevance underlying the present empirical investigation. Section 3 presents and discusses the balanced panel used for the analysis. Section 4 illustrates the composition, distribution and evolution of the CAP support within the panel while section 5 investigates the dynamics of the farms' production choices and performance. Section 6 tries to connect these two dynamics assessing whether and how they co-evolve and to what extent one can be considered a response to the other. Section 7 discusses the methodological challenges to be face to carry out causal inference on the relationship between these two dynamics. Section 8 concludes drawing some policy implications.

2. The policy issue

With the EU approaching the first year of application of its n-th CAP reform, expected to enter into force in 2023, the debate among agricultural economists, policy experts and analysts remain essentially the same of the previous reforms. Positions range between two extremes. On the one hand, those (and the EU Commission itself) who support the idea that this reform, as the previous ones, contain substantial novelties and somehow radical changes (European Commission, 2021; Pupo D'Andrea, 2021). On the other hand, others consider it, as the previous ones, essentially a conservation of the same fundamental schemes (same money, same beneficiaries, same modalities,) with only marginal or "cosmetic" changes (ARC2020, 2020; Sotte, 2021a); a sort of "conservative revolution".

What is common between these two opposite views is that both see the CAP as a policy expected to produce an effect on (or a response by) the farming sector (OECD, 2011; Matthews, 2021).[1] Maybe, however, this is not the proper perspective from which the CAP and its reforms have to be evaluated. The very fundamental question is to what extent the CAP really conditions farmers' choices and, therefore, whether it is it really worth to adopt a treatment-effect logic

[1] "Agricultural economists have been more concerned with the how and how well food and agricultural policies should be designed to achieve specific objectives and how policies have succeeded in their aims" (Matthews, 2021, p. 185-186).

(Coderoni, Esposti and Varacca, 2021). The CAP presents three major problematic features in this respect.

First, it is a policy and not a program, that is, is made of a set of interdependent measures (Lassance, 2020). These may be separately assessed (Castaño et al., 2019) but are not, usually, separately delivered to beneficiaries; and beneficiaries know this. In order words, the CAP is not a treatment, but it is a farm-specific (thus heterogeneous) combination of multiple treatments. Consequently, also the evaluation of individual measures should be performed only within a complex multiple-treatment environment.

Secondly, the CAP is not just a set of measures, but it is a menu of measures since beneficiaries (farmers) are not assigned to some measures but voluntarily select among them (Esposti, 2022).[2]

Thirdly, this policy being a menu of measures, it turns out (in fact, it aims) to be a "passive" policy in the sense that is tailored on the existent rather than on inducing a change or a behavioural response. "Active" measures are present, but they may take the form of conditionalities, that is, requirements to be met in order to be eligible to a support. These conditionalities are usually quite weak, if not actually purely apparent, in the sense that most beneficiaries already satisfy them or need just minimum adjustments to satisfy them (Latacz-Lohmann et al., 2019).

The key point here is that neither the CAP nor any CAP reform has a clear and univocal objective or target for which beneficiaries are expected to provide a specific response. CAP it is a sort of "institutional environment" regularly accompanying, and not necessarily inducing, farms' evolution. Eventually, the CAP behaves as a welfare system reserved to the EU farming

[2] The generalized voluntary nature of the CAP can be questioned. Here, voluntariness is intended in confront with the golden standard of randomized experiments where units assigned to the treatment do not choose whether or not to be treated. On the contrary, for all II Pillar measures the treatment is always the consequence of a voluntary choice. In the case of I Pillar direct payments, a difference has to be made between the period before and after 2015. After 2015, in practice all farms (but landless farms) have become entitled to apply for these payments. Before 2015, those farms that did not receive coupled payments before 2005 were not entitled to apply and, therefore, could not voluntary opt for the treatment. In remain true that, even when entitled, farms have to apply (so, to take a decision) and this also implies the respect of the cross-compliance conditions. Consequently, farmers that do not want to accept this conditionality may decide to do not apply even when entitled to do so.

sector. Its universalism (though limited to the farming activity) is expressed by the fact that its menu of measures covers nearly all farms, as well as all their different activities and instances.[3] This does not exclude some more targeted measures, but it remains true that multiple targeted measures ultimately aim to be universalistic. The main consequence of this universalism is that the CAP tends to be conservative and passive in the abovementioned sense. Rather than being one the effect of the other, the CAP and the farming sector actually co-evolve.

The nature of the CAP as an all-encompassing policy is obviously not, *per se*, at odds with the increasingly advocated need for an evidence-based design and implementation (Esposti and Sotte, 2013; Erjavec, 2016). But this evidence concerns an expected effect (and, therefore, effectiveness and efficiency). Since this expected effect is unclear, the need of an evidence-based CAP, inevitably raises the question: evidence about what? Waiting for the implementation of the new CAP reform (for the period 2023-2027), it seems useful to limit this fundamental question to the last 15 years. This is the period under investigation here and it has been interested by two major reforms, implemented in 2005 and 2015, and by some major further adjustments meanwhile (particularly in 2007 and 2008) (Sotte, 2021b). It can be argued that these reform steps share the same three fundamental objectives (Frascarelli, 2020, 2021; Coderoni et al., 2021): farm income support; farm competitiveness through (more) market orientation, i.e., (more) product diversification; larger and better public (mostly environmental) good provision by farms.[4]

[3] This universalism does not conflict with the voluntary nature of most measures. It is rather the opposite: through a large set of voluntary measures, the CAP is able to provide assistance to all different kind of farmers according to their very different kinds of objectives. Voluntariness within universalism is, therefore, the obvious consequence of the large heterogeneity of beneficiaries.

[4] Matthews (2021, pp. 185-191) overviews the evolution of the fundamental objectives of the CAP over time. “Farm income”, “Environment” and “Competitiveness” are among the most persistent. The objective of production diversification and market reorientation can be considered an explicitation of the competitiveness objective. These are not the only objectives of the CAP but are those that directly and exclusively refer to farmers’ behaviour under scrutiny here. Other objectives could actually be added to this short list (European Commission, 2019; Coderoni et al., 2021). In particular, two are worth noticing. One is favouring structural change or adjustment within agriculture. The other is supporting the rural economy. But these objectives are beyond the horizon and, above all, the field of observation of the present study both for the limited time under consideration and for the use of balanced panel of farms (see below) that, evidently, do not cover all socio-economic aspects of the rural economy.

The decoupling of I Pillar support was firstly introduced, in Italy, in 2005 (the so-called Fischler Reform). It has been extended and reinforced in 2007 (with the introduction of the Single Common Market Organization, CMO) and in 2008 (the Health-Check Reform), and then progressively dissociated from historical direct payments in 2015 (the Ciolos Reform) (Sotte, 2021b). Consequently, the period under consideration here (2008-2019) starts from a year in which the full decoupling of direct payments was already under way. Meanwhile, II Pillar support has been strengthened in terms of overall support and of its share on the total CAP budget, but also in terms of progressively stronger orientation towards environmental goods provision.

With respect to the three abovementioned fundamental objectives, the decoupling of support (with the maintenance of the support level) was expected to induce market re-orientation while granting farmers' income (Anton, 2006; Esposti, 2017a,b). Also II Pillar had to faciliate market re-orientation (and structural change) and, at the same time, the environmental good provision especially due to the strengthening of Agro-Environmental Measures (AEM) already introduced in the 1992 reform (MacSharry Reform). Pillar I itself has been designed to contribute to the environmental objectives with the introduction of the environmental conditionality already in 2005, then further enhanced with the novel Greening payments in 2015. Therefore, in principle, this sequence of reforms has been designed to get progressively closer to the abovementioned objectives. In practice, however, their actual implementation might have not consistently moved in the expected direction.

Within the large body of studies on the impact of the CAP, many focus on its economy-wide or society-wide impacts (Lillemets et al., 2022), but most of them disregard through which impacts on farms' behaviour this aggregate effect should be enforced. Another set of studies (see Sotte, 2014, and Terluin and Verhoog, 2018, to mention a few) investigates the evolution of the CAP support, its amount, modalities and distribution at the farm level. They conclude that no much change in the actual distribution of the support can be actually observed and that, ultimately, CAP reforms are mostly cosmetics. The change is so gradual that all reforms become essentially conservative: the amount, the beneficiaries and the distribution among them remained almost the same. There is an often implicit deduction in this latter group of studies: since the distribution of the support did not significantly change, the (reform of the) CAP can not have had an effect. But this is not obvious. Maintaining the distribution but changing the forms and modalities may still induce a response.

Beside the distributional issue, a lot of research work has also been done in order to directly investigate, simulate, estimate the possible impact of the CAP on beneficiaries. This large body of literature is definitely helpful in better understanding the mechanisms through which the CAP operates and, therefore, in better designating and implementing it (Matthews, 2021). But analysing the possible impact of the CAP and its reforms with these approaches does not necessarily correspond to a program evaluation. Most studies are grounded on farm-level structural models used either for ex-ante (simulations) or ex-post (simulations or estimations) assessment (see, for instance, Mack et al., 2019). Within their theoretical structure, these models somehow impose the existence, the form and sometime the direction of the response to policy measures. Consequently, they violate the key CI principles by mixing up correlation with causation due to the structure itself and to the consequent extrapolation implied by models' estimation: the counterfactuals are never observed, and they might not even exist, but the counterfactual case is just extrapolated from the estimated models parameters.

Eventually, the problem remains the lack of a counterfactor evidence. This may also depend on the fact that such an evidence may require observing the farms behaviour over a long-enough period of time with respect to a CAP measure or regime change. . Unfortunately, most studies concentrate their attention on the short period of planning, discussing and negotiating of any CAP reforms up to its approval. After that, most analysts do not take all the needed time to observe the possible longer-term response of the farming sector (Esposti, 2017a), as the attention immediately move to the new upcoming reform.

A final body of studies emerged in the last decade. It assesses the CAP impact explicitly within a TE logic. (Chabé-Ferret and Subervie, 2013; Castaño et al., 2019; Coderoni, Esposti and Varacca, 2021; Esposti 2017a,b, 2022). But, as mentioned, the actual characteristics of the CAP and of its reforms does not necessarily fit the strict requirements of this logic Nonetheless, its suitability to CAP assessment remains unquestioned in most of these studies. The bottom line is that, preliminarily to any TE investigation, it is helpful to find empirical support for the applicability of the logic to the three abovementioned complex objectives. Namely, in order to make the TE logic suitable, which data and indicators can be used? Which correlation emerges and which hypotheses can be formulated in this respect? Answering these questions is the main purpose of the present study.

3. The data: 2008-2019 FADN Italian balanced sample

Another major investigating farms' responsiveness and coevolution with respect to CAP measures concerns the field of observation. Several previous studies work on all farms, but this can introduce a bias as their response is not always fully observable for two reasons for the presence of many very small farms (even "non-farms") (Sotte, 2006; Sotte and Arzeni, 2013): they may not respond at all; their small response may remain unobserved; their response may fall outside the available datasets. There is another reason why this field of observation can introduce a bias. Movements observed within a non-constant group of farms, especially containing many very small (non)farms, are also driven by long-term structural processes that are largely independent on the CAP support. Observed dynamics, therefore, should be purged of this effect before assessing the impact of the CAP. But this filtering is very challenging.

A final limitation of the field of observation of many previous studies is the lack of a long-enough time dimension. Most of them are, in fact, *ex ante* assessments thus they are a-temporal in the sense that are based on current farm-level data possibly on the basis of future scenarios. They seldom take the needed time until the farms' coevolution or response is significantly revealed by data.

Here, we want to focus on a field of observation that take these limitations into account: the Italian 2008-2019[5] FADN balanced panel.[6] As anticipated above, working on the balanced sample may miss some of the implications of CAP and its reforms as changes occurring in non-professional farms, that are numerically prevalent in the Italian context (Sotte, 2006; Sotte and Arzeni, 2013), are missing. Moreover, the structural changes may be also missing. As the non-constant part of the FADN sample is excluded, the dynamics of entry/exit (i.e. deactivation) from the sector, as well as other changes somehow related to the entry/exit from the sample (for instance, change in size due to land acquisition or loss), are at least partially missed. However, none of this possibly missing information is at the core of the CAP objectives here considered. Therefore, given the scope of the present analysis, working on the changes observed within the balanced sample seems to be justified.

Within this field of observation, the empirical analysis is developed in a sequence of three stages. First, the evolution of the CAP support and of its distribution within the sample is investigated, considering both its total amount and its components (I Pillar and II Pillar support; coupled and decoupled I Pillar payments; AEM and other II Pillar measures). Then, the evolution of the farmers' choices (output and input composition) and performance (net income, profitability and productivity) is analysed. Finally, some stylised facts about the coevolution between the two dynamics above are highlighted. This sequence of steps points to some

[5] Even if 2020 data were available, they are going to be problematic in terms of comparability due the effects of the COVID-19 pandemic also on the farming sector. The EU-wide FADN sample could be used instead but the information available over all countries are less comparable and, above all, less detailed than those reported in the Italian RICA-FADN dataset.

[6] This choice also explains why some of the results here presented may also substantially diverge from what obtained in studies working on the same period but on a different fields of observation (European Commission, 2019).

research hypotheses about the applicability of the TE logic to this coevolution. In this respect, the main methodological challenges and the possible solutions are finally reviewed.

4. The evolution of the CAP support

The first question to be answered is whether the CAP support actually changed within the adopted field of observation and how. Figure 1 displays the total and per farm public support considering all the possible sources: CAP payments (both pillars) and national (including regional and local) payments still admitted by the current EU regulation under specific conditions.[7] The total support remains quite regular over the period (always ranging between 23 and 27 million €) with only limited oscillations due to the transition to one CAP regime to another. Overall, we observe an increase in total support (+17% from 2008 to 2019) in nominal terms, but this growth almost entirely vanishes (+4%) in real terms (2010 prices). This emerges clearly expressing the support as per farm average. The average support passes from 14.4 thousand € to 16.9 thousand € per farm, in nominal terms. But in real terms this variation drops from 14.4 thousand € to 15.3 thousand € per farm.

Figure 2 reports the evolution of the composition of the total public and CAP support. As anticipated, the national support represents a very marginal part, always lower than 5% and corresponding to 2% and 1% at the beginning and at the end of the period, respectively. Eventually, this residual part of the support declined by 24% from 2008 to 2019 and remained largely lower than 1 million € with the only exception of 2009 and 2010. For this reason, the national support will be neglected in the rest of the analysis.

The composition of the overall CAP support evolved as a combination of three dynamics. The share of I Pillar and II Pillar has been gradually re-equilibrated with the latter moving from a 13% to 29%. At the same time, I Pillar support shows an initial fall of the coupled payments

[7] Regional co-financing of II Pillar is still included in CAP support.

share on the total I Pillar support from 20% in 2008 to a minimum of 3% in 2012. This rapid decline has to be attributed to the progressive implementation of the Fischler Reform reinforced by the introduction of the Single CMO and Health Check Reform. Nonetheless, after the implementation of the Ciolos reform in 2015, coupled support has progressively recovered its share on I Pillar total payment up to a final 15% in 2019. Therefore, within the field of observation, the process of progressive decoupling of support is more or less stuck at the end of the previous decade, as with the 2015 reform the initial proportion between coupled and decoupled payments has almost restored. It is also interesting to notice that this occurred because, while the decoupled support experienced a gradual decline (as established by the implementation of the 2015 reform), this did not occurred for the coupled payments that remained substantially stable.

Also for the II Pillar support a substantial conservation of the internal distribution across measures can be appreciated. Though the number of measures within the so-called Rural Development Policy is large and varies with the architecture of II Pillar across reforms, it seems more reasonable to focus on the two major streams of action, that is, the AEM and all other measures. Figure 2 shows that they both increase quite regularly over the whole period and their proportions did not change remarkably. In fact, AEM passed from a share of 44% on the total II Pillar support in 2008 to 51% in 2019.

The 2019-2008 growth rate of these four major components of CAP support summarizes these three major dynamics. While the total CAP support grew by 17% in nominal terms, I Pillar declined by 4% and II Pillar grew by 156%. Within I Pillar, decoupled support remained stable (-0.4%) while coupled payments declined by -20%. Within II Pillar, the largest growth concerns AEM payments (+196%) while the other measures increased by 124%.

The huge growth and the increasing relevance of the AEM support deserves some additional investigation. Figure 3 shows how these payments evolved in terms of number of beneficiaries and of average support per beneficiary. The growth of AEM support comes from the combination of two facts. On the one hand, the number of beneficiaries increased by 75% passing from 245 farms (15% of the whole balanced sample in 2008) to 428 units (27% in 2019). On the other hand, the average payment per farm increased almost with the same intensity (+70%) passing from about 5.3 thousand € in 2008 to 9.1 thousand € in 2019. In fact, the growth of the number of beneficiaries is not regular as it shows a fall from 2012 to 2015 and, then, a jump as a consequence of the transition from one regime to another. This sort of bureaucratic cycle is somehow compensated by the countermovement of the average payment per farm that reaches its peak exactly in 2015.

The synthesis that can be drawn from this general picture is that, at least from the farms' perspective, the evolution of CAP support in the 12 years under investigation really represents a sort of "conservative revolution": the different components of the whole expenditure changed significantly, but the support eventually delivered to farmers is more or less the same. Although it may sound paradoxical, the main short-term impact of any CAP reform in terms of amount of support, its composition and distribution is the purely bureaucratic attrition in the transition from one regime to another.

Nonetheless, the key argument of the critics of this alleged conservatism of the CAP consists not so much in the amount of support but in its strongly uneven distribution across farmers. Table 1 reports some year-by-year distributional statistics of the total and CAP support, and of its different components, within the present field of observation. Overall, it is confirmed that values (but the maximum) are quite stable over time. At the same time, the distribution is very disperse with a standard deviation always much higher (at least twice) than the mean value. Moreover, the left tail of the distribution being truncated at 0, the presence of several extreme values generate a remarkable asymmetry with a very long right tail. This is clearly revealed by the difference between the mean and the median (2nd quartile) values, with the former being in all cases more than double than the latter. As anticipated, the maximum payments assume off-the-chart values and also largely oscillate over time. The maximum total CAP support ranges between a minimum of 421 thousand € in 2008 and a maximum of 1.159 thousand € in 2015. High variability and asymmetry is observed in all the different policies but some specificities are worth noticing. In particular, both I Pillar payments and non-AEM II Pillar payments shows a standard deviation that is about five times the respective mean value. For both II Pillar subgroups the observed support is zero until the third quartile indicating that payments concentrate on a very limited number of farms.[8] It can be also concluded, however, that these specific asymmetries tend to compensate, at least partially, as dispersion and asymmetry observed in the total support is significantly lower than what observed in the single components. Evidently, the few farms receiving a large part of two specific supports (for instance, I Pillar coupled support and AEM payments) mostly do not overlap.

To better illustrate these distributional characteristics and their evolution over time, the Lorentz curves of the Pillar I and Pillar II support, respectively, are reported in Figure 4 for years 2008, 2015, 2019. The sharp concentration of the support on a very limited number of farms clearly emerges. As expected, it is higher in the case of II Pillar where 5% and 3% of farms (i.e., 79 and 48 farms) concentrate 50% of the support in 2019 and in 2008, respectively. But this over concentration is only a little lower for I Pillar with 8% and 6% (127 and 95 farms), respectively. Within the adopted field of observation, the sequence of CAP reforms has slightly changed the distribution of the CAP support by making it a little bit more homogenous. But this change remains almost negligible.

However, this stability does not mean that from any individual farm perspective nothing changed in the CAP support. By looking at any single farm % variation of the received support

[8] A similar, in fact more extreme, case can be found in national payments where also time variation is large. These distribution characteristics can be explained by the fact that national payments tend to have an emergency or exceptional nature: they are activated under very special conditions, for very specific farms and for a limited period of time.

from 2008 to 2019 (bottom of Table 1), it emerges that several farms lost all the support (-100%) while for others the growth is maximum (in fact, it can not be computed) simply because the initial value was zero. Between these extreme cases, we find most farms with a change in the support that ranges from a decline (the first quartile is -19%) to a huge increase (the third quartile is +370%). The mean value (the second quartile) indicates a 30% growth which is consistent with the growth of average support commented above. We should thus conclude that the evolution of the CAP over this period significantly redistributed the support across farms but did not make it more homogeneously distributed. Whether or not this redistribution has been consistent with the declared CAP objectives is questionable and requires further investigation (see below).

5. The evolution of the farms' behaviour

5.1. Profitability

In order to assess whether or not the CAP evolution described above had any relevant impact on farms' performance and choices, the first question to be answered concerns farms' profitability. Here we identify the farm's profit with the farm's net income.[9] This latter is simply computed as revenue plus policy support less all costs. Therefore, in order to investigate the evolution of farms' profitability it is worth to analyse the evolution of its components. Figure 5 displays the dynamics of the average revenue and variable costs within the field of observation. A selection of these costs are also shown. They concern what we design here as environment-using costs: fertilizers, pesticides (herbicides included), energy and water.

It firstly emerges that, even though we are exclusively dealing with professional farms, most observations are of limited economic dimension as the average revenue ranges from a minimum

[9] In the FADN terminology what is here refereed to as Net Income corresponds to the Entrepreneurial Income. As most agricultural production units are family farms, this also corresponds, in most observations, to the Family Farm Income (European Commission, 2018a).

of 118 thousand € to a maximum of 141 thousand €. Secondly, a pretty regular increase of both revenue and costs is observed, but with the latter showing a larger growth than the former (+38% and +12%, respectively). It follows that the incidence of variable costs on revenue passes from 38% in 2008 to 47% in 2019. Among costs, environment-using ones maintain a quite constant share, always higher than 20% and lower than 25%. From these figures a quite regular profitability over the period can be deduced. Figure 6 shows that the average farm net income did not significantly change as it remains between 50 and 60 thousand €. A -10% variation is actually observed comparing 2019 with 2008, but this decline can be entirely attributed to the very last year.

If we express net income in real terms, however, a different conclusion can be drawn. Although inflation has been constantly low during this period, in real terms the average farm net income suffered a -20% decline from 2008 to 2019 that becomes a -9% if we stop the comparison at 2018. We should thus rather conclude that, on average, farms actually struggled to defend their profitability over this period. At the same time, however, the number of farms with negative net income did not increase. It amounted to 9% of the whole sample in 2008 and to 7% in 2019, and has remained always between 10% and 5% though with a clear drop after 2009.

Again, however, average values may be uninformative, and even misleading, due to the large heterogeneity occurring within the panel. In this respect, Figure 7 presents the Lorentz curves of the farm net income for selected years 2008, 2015 and 2019.[10] Two aspects are worth noticing. First, as expected, the distribution of net income within the sample is highly asymmetric with very few units concentrating most of the total (positive) net income. Second, no significant change in this distribution can be appreciated moving from 2008 to 2019. Eventually, in 2008 9% of farms concentrated 50% of the total (positive) net income; in 2019, this share has slightly increased to 11%.

---

[10] These curves are obtained considering only farms with a positive net income in the respective year.

Table 2 illustrates further how during these twelve years the farm net income dispersion and asymmetry maintained the same basic features with no appreciable evidence of a more uniform distribution. As obvious, extreme values oscillate a lot over years. The minimum net income is always a negative value and ranges between -402 thousand € in 2013 and -66 thousand € the year before (2012). The maximum net income ranges between 3691 thousand € in 2016 (the 4.3% of the total positive net income) and 1815 thousand € the year after (2.1%). Such large dispersion is confirmed by the standard deviation. It is always around the double of the mean or more, but it also shows a noticeable decline in the last three years under observation. The same does not occur for the asymmetry that remains large and constant over the whole period, with a very long right tail that motivates why the mean value is always more than double than the median value (2nd quartile): the median/mean ratio ranges from 0.43 in 2008 to 0.45 in 2019.

5.2. Factor use and structural change

The fact that farm profitability did not change much over the period does not exclude that the behaviour and choices of farmers significantly responded to the change of external conditions (CAP included). In order to more deeply investigate this response is useful to assess whether factor endowment, use and intensities significantly changed within the adopted field of observation. Four fixed (or quasi-fixed) factors are considered: land (UAA); labour (AWU) also including the farm family labour (FAWU); Machinery (KW); Livestock (LSU) (Sahrbacher et al., 2008).

Figure 8 exhibits the evolution of these factors' endowment over the 2008-2019 period. To facilitate interpretation and comparison, values have been indexed with respect to the initial level (i.e., 2008=100). For all factors a positive trend can be appreciated whose slope seems to be dependent on the respective degree of fixity. From 2008 to 2019 the average land endowment increased by only 6%, while the growth has been of 10%, 15% and 23% for AWU, LSU and

KW, respectively. In fact, livestock endowment is the only case showing significant oscillations and, more importantly, an apparent trend reversal after 2015.

What emerges here points to a substantial intensification in the use of these factors (in fact, the same was observed for the variable inputs). Whether or not this pattern has to do with the CAP evolution remains to be investigated. But it definitely has important implications on the overall farms' performance. Combining it with the profitability dynamics, a decline of factors' productivity is observed. Figure 9 displays the evolution the farm net income per unit of (family) labour over the 2008-2019 period. Labour productivity (or profitability) declined by 25% from 2008 to 2019, but most of the decline occurs in the very first years of the period. Nonetheless, two aspects deserve further consideration in this respect. On the one hand, if the real term values are considered, the decline is more pronounced (-34%) and occurs quite regularly up to 2014. On the other hand, if productivity (or profitability) is computed only on family labour, the decline disappears in nominal terms (+0.4%) and resizes at -11% in real terms.

To better investigate the nature of this factors' intensification, Table 3 reports the distributional characteristics of the factor intensities per labour unit (AWU) together with labour profitability. It firstly emerges that these structural characteristics remain quite stable over time as could be expected considering that adjustments in (quasi)fixed factors' endowment take time and may have a cost (Esposti, 2017a). It emerges a small reduction in the incidence of family labour on the total farm's labour use (-3.2%). Also the land endowment per unit of labour slightly declines (-4.8%). But for the other production factors, it emerges a gradual intensification with a 11% increase of machinery endowment, a 8% increase of the livestock endowment and, above all, a 18% increase of environment-using costs per unit of labour.

Although these ratios should get rid of the size effect, with the only exception of the FAWU/AWU ratio, they show a remarkable heterogeneity. Also for these structural characteristics and their evolution, a major dispersion (as expressed by the standard deviation/mean ratio) and asymmetry (as expressed by the median/mean ratio) emerges within the field of observation. For instance, in the case of land endowment, we range from no-land farms to observations with hundreds of hectares per unit of labour. The bottom line of this large heterogeneity is expressed by the net income per unit of labour reported in the final rows of Table 3. Here we also find negative values and this makes the dispersion even more evident. Values range from a minimum of -345 thousand € per unit of labour in 2008 to a maximum 2372 thousand € per unit of labour in 2009. Only a little decline of dispersion of asymmetry is observed in the post 2015 period. More importantly, the mean value significantly declines over the 2008-2019 period (-13% in nominal terms; -22% in real terms) and this reveals a significant redistribution in favour of the more profitable farms: while 1st and 2nd quartiles decline by 15% and 20% respectively, the 3rd quartile declines by only 6% and the maximum value increases by 8%.

It is finally interesting to assess whether this evolution in terms of factor endowment, intensities and profitability is associated to other structural adjustments concerning farm holders, their turnover and attitudes. Figure 10 reports the presence of female and young (<40 years old) farmers within the sample. It is worth noticing that this field of observation may significantly underestimate the holders' turnover. As entry and exit dynamics are excluded by definition within a balanced panel, here only the internal replacements are captured, that is, the possible substitution of the holder within the same farm.[11]

What emerges, here, is a sharp decline of young holders (from 18% in 2008 to 6% in 2019) and a substantial stability of the presence of female holders (from 15% to 17%). This latter evidence seems in contrast with what observed in the Italian agriculture as a whole where both the share

[11] Although partial, however, this may still be a reliable representation of the actual structural change occurring within the professional farming sector. Considering agriculture as a whole may misrepresent the presence of female and young farmers as numbers are affected by the presence of very small (non)farms. In the specific Italian case, in particular, both the presence of female and of elder holders has been always influenced by the persistence of these marginal (non)farms (Iacoponi, 2021).

of female agricultural workers and the share of active farms with female holders are declining (Selmi, 2021). Moreover, there is no evidence, overall, of a correspondence between young and female holders as the average age of female and male holders is substantially the same (Giampaolo et al., 2021). It thus seems difficult to interpret these figures as an unquestionable evidence of a progressive emergence of a new generation of farmers within the adopted field of observation. Nonetheless, the share of farmers settled by succession significantly increased from 30% in 2008 to 43% in 2019. This would indicate that 13% of farms experienced a succession during the period of observation. However, this succession is not apparently associated with the takeover of young and female farmers. In addition, most of these successions occurred between 2010 and 2012, thus it may be questioned whether it is real or it is just an artefact due to data collection or some other administrative reason.

It may be argued that, beside structural turnover of farm holders, what really matters is the emergence of a different attitude especially in terms of long-term production orientation. Some indicators may be informative in this respect like, for instance, the remarkable growth of organic farming within the field of observation (from 5% to 13%; see Figure 10). The evolution of production orientation, however, requires a more careful investigation as observed changes might not reveal a change in farmers' attitude but rather be the direct consequence of the implementation of specific policy measures. Next section will deal with these aspects more in detail.

5.3. Production choices

A final aspect of the evolution of farmers' behaviour concerns their production choices. This investigation is not trivial as agriculture typically is a multioutput activity, with productions that may be technically interdependent both across space and over time (e.g., crop rotation). Therefore, expressing production choices with some synthetic indicator is challenging. The information provided within the FADN dataset can be helpful in finding this kind of metric. First of all, the classification of agricultural holdings by Type of Farming (TF) can be used.[12] FADN classifies farms in eight TF categories: five main groups of specialist agricultural holdings and three mixed groupings.[13] Therefore, the first indicator of a production response is expressed by the TF dynamics: a switch from one TF to another evidently expresses the farmer's decision to change production orientation or specialization.

Figure 11 exhibits the evolution of the TF categories over the 2008-2019 period. The most frequent categories are field crops (TF1), permanent crops (TF3) and grazing livestock (TF4). None of the other Types of Farming (TFs) exceeds a 10% share. Overall, shares remain quite constant over time: TF1 remains at 26% even though a slight decline is observed between 2010 and 2016; TF3 remains constant at 30% up to 2014 and then slightly declines to 28%; TF4 starts from 21% and experiences an increase in the first years but then comes back to 22% in 2019. All other TFs show a very limited variation of their share (always lower than 2%) even though more significant movements are observed from 2009 to 2010. Even the combination of these TFs does not express any significant structural dynamics. For instance, TFs with livestock activities (TF4, TF5, TF7 and TF8) combined show the same share in 2008 and 2019 (31%) with minimum changes over the period.

Even though relatively few transitions from one TF to another are observed, it remains interesting to investigate further where these transitions occurs and speculate on the possible motivations. Figure 12 orders the farms per number of TF changes over the 2008-2019 period. For 1079 units (68% of the sample) no change is observed. For other 166 farms (about 10%) only one change is observed. It means that these are genuine switches, namely, in these observations a real change in production orientation has taken place. For all other units, multiple

[12] The TF of an agricultural holding is determined by the relative importance of each production activity on the total farm Standard Output (SO).

[13] These groups are defined as follows: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

switches are observed during the period. In most cases, they are back-and-forth movements, that is, these farms are momentarily associated to another TF but then go back to the original category. In few farms a switch from one TF to another occurs almost every year or about any two years. Arguably, this peculiar behaviour does not express any relevant change in production farmers' choices but it can be interpreted as physiological oscillations of production activities in borderline farms between two TFs.

In order to only focus on real changes in production orientation, we limit our attention to those switches that make the initial TF of farm differ from the final one. These switches concern 187 farms (12% of the sample). These movements are positioned in a Source-Destination matrix by TF category (Table 4).[14] As could be expected, flows mostly concern two kind of movements: one occur across the main TFs, (TF1, TF3 and TF4); the other concerns movements from more specialized TFs to the mixed ones (TF6, TF7 and TF8). Nonetheless, no prevalent migration emerges and this confirms that, over the period of observation, there is no prevalent evolutionary dynamic expressing a generalised reorientation of the farmers' production choices. However, the switch of TF may be a poor indicator of farm production orientation because of the abovementioned "instability" but also of the rough information provided by the TFs themselves. The slow, gradual and smooth movements that are likely to occur within an agricultural context might not surface properly. At the same time, there could be more radical changes in farmer's output mix that are not captured by the TF classification. It is the case of the activation of unconventional farm activities usually designated as multifunctional diversification: farms combining agricultural production with market or non-market services (multifunctional farms). The FADN dataset provides information about the so-called "Other

[14] Therefore, the diagonal elements indicate the non-switching units.

gainful activities", also defined as "agriculture-related activities" ("*attività connesse*") in Italian regulation.[15]

Figure 13 displays the evolution of the number of farms with other gainful activities, as well as their incidence on standard output both in the whole sample and in these multifunctional farms. It is worth noticing that for both the number of farms and the incidence on the whole sample a sharp drop is observed between 2009 and 2010. After that, the trend regularly and consistently reverts to the initial 2008-2009 variation. It can be argued that this 2009-2010 drop is an artefact due to some changes in data collection. This interpretation is corroborated by the incidence of these activities within these multifunctional farms: it does not show any drop and it increases quite regularly, at least up to 2016.

Therefore, if compared to the 2010 level, in 2019 we observe a 3% growth in the number of multifunctional farms within the sample (from 14% to 17%), a 1.4% growth in the incidence of these activities within the full sample, and a 5% growth in the incidence within multifunctional farms. Therefore, the observed progress of multifunctional activities seems slow overall and it looks like more an increasing specialization of a limited group of farms. Eventually, it appears as a gradual and spontaneous structural evolution driven more by the market conditions than by some change in the policy support (see below).

6. The coevolution

This section derives from the analysis above some stylised facts about nature and extent of the coevolution of CAP support and farm behaviour. This derivation is separately performed on the three abovementioned major policy objectives: income support; production diversification; environmental goods provisions.

[15] They include agritourism and rural tourism, educational farms, active subcontracting, aquaculture, transformation of farm products, production of renewable energy, environmental services, agro-craft activities.

6.1. Farm income and CAP support

Is there any evidence supporting the hypothesis that CAP payments really protected the farm's net income in both level and variability? An income-support effect should imply a negative relationship between the level of CAP support and the farms net income, that is, a larger support for farms showing higher income difficulties. These latter can be expressed by a negative net income, by a net income that would be negative without the CAP payment (i.e., the ratio between CAP support and net income is >1) or, more generally, by a low labour profitability (i.e., net income per unit of labour). But they could be also be intended as larger income variability. If CAP support were higher for these farms, it could be concluded that it really contributes to prevent these farms from exiting the sector.

In order to assess these hypotheses, it is worth measuring the intensity of support per unit of family labour (FAWU) both to eliminate the size effect and to focus on the actual farmers' objective variable. Table 5 provides detailed information about the evolution of the CAP support per unit of net income and of AWU and, above all, about its distribution within the sample. Figure 14 displays the CAP support and number of farms with a CAP support larger than the net income (included net income<0). Five major facts seem to emerge and are worth noticing.

- The support per unit of net income significantly oscillates due to the oscillations of the net income itself but, overall, it remains stable over time: 39% in 2008 and 40% in 2019, with a maximum of 66% in 2018 and minimum of 24% in 2014. In any case, the CAP support represents, on average, a significant contribution as it ranges between one fourth and two third of farms' net income.[16]
- The support per unit of FAWU increased by 21% in nominal terms (8% in real terms) from 2008 to 2019. Also in this case oscillations matter with 2008 assuming a quite low value. If

[16] These figures confirm what emerged in previous studies also for Italian agriculture (European Commission, 2018b).

comparison is made between 2009 and 2019, the increase falls to 4% in nominal terms and becomes a decline (-7%) in real terms.

– The distribution of the support is very sparse and asymmetric. For both CAP support per unit of net income and per AWU, the median is largely lower than the mean. This depends on the presence of few farms with very high level of unit support. In the case of net income this dispersion may depend on the presence of negative incomes,[17] while in case of FAWU, right-tail boundary cases are more extreme as the maximum value is always above 500 thousand € per unit.

– The correlation between the CAP support per unit of FAWU and the respective unit net income is significantly positive and quite high. This correlation ranges between a minimum of 0.36 in 2009 and a maximum of 0.67 in 2018, and it slightly reinforces over time. It indicates that the incidence of the CAP support on net income per unit of labour tends to be stronger in farms that need it less as they show an higher labour profitability.

– The number of farms with a CAP support greater than net income (negative net income included) is quite stable (around 20%). They receive an almost proportional share of support (between 20% and 30%) and the average support to these farms increased by 11% in nominal terms but remained constant in real terms (-0.6%).

– The growth of unit CAP support[18] shows a weak but significantly positive correlation with family labour profitability. At the same time, a positive but much stronger correlation is observed between unit support and the variability the family labour profitability.

It can be concluded that a quite contradictory evidence emerges about the consistency of the CAP as an income support policy. On the one hand, CAP support may have really supported the farms' income as its incidence is high. On the other hand, however, support and support

[17] In computing this indicator, farms with negative net income are attributed the highest incidence observed in the rest of the sample.
[18] For farms with a zero initial CAP support, the attributed growth rate corresponds to observed maximum finite value.

growth, though very disperse, go more towards farms that need less, i.e., more profitable farms. Therefore, there is no clear indication that this policy is selective in favour of most problematic units but, at the same time, support itself is strongly oriented towards cases showing higher income variability. More than an income support policy, CAP thus seems to behave like an income stabilization policy at whatever income level a farm is.

6.2. Production diversification and CAP support

Is there any evidence supporting the hypothesis that change in CAP payments, either the decoupling of I Pillar payments and the increase of II Pillar II payments, induced production diversification? To assess a diversification-inducing effect to occur we need a metric to measure production diversification. Here we follow the analogy with ecological studies where diversity is often measured using the Shannon (or Shannon-Wiener) and the Simpson indexes (Keylock, 2005). These indexes are here adapted to compute the farm-level Diversification Index for any i-th farm at any time t (DI_{it}) (Coderoni, Esposti and Varacca, 2021):

(1) Shannon $DI_{it} = -\sum_{c=1}^{C}\left[share_{it,c} * \ln\left(share_{it,c}\right)/\ln 2\right]$, $\forall i, \forall t, \forall c \in C$

(2) Simpson $DI_{it} = \sum_{c=1}^{C}\left(share_{it,c}\right)^2$, $\forall i, \forall t, \forall c \in C$

where c indicates a generic crop/animal species of the set of all observed crops/animal species C. For both indexes, the larger is DI_{it} the larger is the observed diversity. The main difference between the two is that the Shannon index ranges between 0 and $\ln C/\ln 2$, while Simpson index ranges between 0 and 1. These indexes are separately computed on crops (on the basis of the share on the total farm's UAA) and on animals (on the basis of the share on the total farm's LSU), and then averaged weighting by the respective share of crop and livestock products on farm revenue. Eventually, more diversified farms are expected to show larger indexes and, more importantly, an increased production diversification within the sample is expressed by an higher average diversity index.

Figure 15 shows the evolution of the average Shannon and Simpson diversity indexes within the adopted field of observation. The two indexes behave similarly though the Shannon index evolves a little more smoothly: from 2008 to 2019, the Shannon index increased by 12%, the Simpson index by 10%. But this growth of diversification only started in 2011 after two years of substantial stability. As usual, these average values may hide a major heterogeneity within the sample. To investigate this aspect, Figure 16 exhibits Shannon and Simpson diversity indexes ordered by increasing values for the two extreme years (2008 and 2019). Again, a similar behaviour emerges. In both cases, the 2019 distribution is a little more homogenous than 2008, but the difference is minor. In both indexes we observe a significant number of farms with no diversity and then a quite regular growth up to a very limited number of extremely high values.

The distribution of these two diversity indexes within the sample over time can be better appreciated by looking at the descriptive statistics reported in Table 6. In both cases, the dispersion and the asymmetry are limited compared to most variables investigated above. Standard deviation is always lower than the mean, while the median is always quite close to the mean itself. The growth of the lower quartiles is more intense than the higher ones, thus indicating that not only diversification increased, but also that it distributed more uniformly within the sample.

More importantly, the bottom of Table 6 reports the correlation coefficients between these indexes and the CAP support per unit of FAWU. As expected, the two diversity indexes behave very similarly; therefore, respective results can be commented on together. CAP support by itself shows a little linkage with diversity indexes, at least until 2016 when a positive relationship started to emerge. Apparently, this emerging relationship can be attributed to both the II Pillar support and to the I Pillar decoupled support, for which, in fact, the positive linkage emerges from the beginning of the period.

A similar analysis can be performed for another set of indicators of production diversification. In this case, it is not an "horizontal" diversification (more crops or livestock activities) but a "vertical" diversification, that is, higher production quality as expressed by process and production certifications and or by the activation of other gainful activities. Table 7 reports the correlation coefficients between CAP support (and its different components) per unit of FAWU and four indicators of this "vertical" diversification.[19] All these indicators can be expression of a generalized tendency of farmers to look for an improved allocation efficiency, i.e., to find the best output mix given the market conditions. In turn, this tendency can be affected by the CAP and its reform in two ways. On the one hand, the progressive decoupling of I Pillar support should enable this market reorientation (Esposti, 2017a,b). On the other hand, it can be also the consequence of the II Pillar support itself, as certifications and diversification activities are incentivized by several II Pillar measures.

Correlation coefficients reported in Table 7, however, only weakly support the linkage between the unit CAP support and these diversification indicators. Three major facts are worth noticing.

– The total CAP support is positively correlated with the organic farming certification (but this linkage is statistically significant only in the last four years) and negatively correlated with product quality certification. This evidence holds true also for decoupled I Pillar support, while any kind of statistically significant relationship seems to vanish when only coupled I Pillar support is considered.

– II Pillar unit support shows a very strong positive linkage with organic farming that only slightly weakened from 2009 to 2014. A little weaker and more volatile, but still positive and mostly statistically significant, is the linkage with all environmental certifications. With only few exceptions concentrated in the initial years of the period, the correlation with II Pillar

[19] Three has to do with certifications: organic farming certification; any kind of environmental certification (organic farming included); any product quality certification but organic certification (for instance, designation of origin). The last indicator is the already discussed multifunctional diversification, that is, the share of other gainful activities on farm's SO.

support statistically disappears when we move to product quality certification and multifunctional diversification.

– A more robust correlation is found between some indicators of production diversification and the Shannon crop diversity index discussed above. Environmental certifications are positively and significantly linked to an higher diversity index. On the contrary, this linkage is statistically negative for product quality certification. This can explained by the fact that this certification is often associated to very specialised farms (for instance, wine production). No significant correlation is finally found between the diversity index and the presence of multifunctional activities.

It can be concluded that there is some linkage between the increasing II Pillar support, the progressive decoupling of I Pillar support and production reorientation. However, this linkage should not be necessarily interpreted as a cause-effect relationship (Khagram and Thomas, 2010). It can be again interpreted as a coevolution between market-driven production choices and the path-dependent CAP support. Its negative linkage with product quality certifications, for instance, can be simply explained by the fact that most of these highly specialised farms were historically recipients of poor support. And of this remains a trace in both decoupled and coupled payments.

Nonetheless, it can not be excluded that Pillar I decoupling may have indirectly helped diversification through two combined processes. On the one hand, it induced farms towards crops' extensification and diversification that progressively opened the door to new productions and in-farm activities or businesses. On the other hand, it combined with II Pillar measures that incentivized these new production or activities. Whether or not decoupling actually caused diversification according to these complex and gradual processes evidently requires appropriate assessment exercises.

6.3. Environmental goods and CAP support

A final question about the coevolution of CAP support and farmers' behaviour is whether the change in the CAP support and composition (II Pillar in particular) accompanied a greater provision of environmental goods. Also in this case, for an environmental-good-provision effect of the CAP to occur we need to find an appropriate metric, i.e., appropriate indicators (Janssen et al., 2010). This is a challenging task because environmental indicators often require detailed physical information that are hardly available at the farm level and only partially included in the FADN dataset.[20] The diversity indexes discussed above may represent proxies of the provision of some environmental services, like the protection of biodiversity within the agro-ecological context. But they seem rough indicators of the provision of otther environmental goods. At the same time, however, an explicit indication of the achievement of higher environmental standards comes from the abovementioned environmental certifications. Therefore, it is worth investigating further the linkage between these certifications and the CAP support.

Figure 17 shows the evolution of the share of farms with organic and environmental certifications. For the sake of comparison, also product quality certifications are reported. It emerges that all certifications significantly grew over the whole period with a +162% for organic farming, +52% for all environmental certifications and +47% for product quality certifications. However, these latter grew more regularly while in the case of environmental certifications growth is limited to the extreme years of the period. In general terms, if we exclude organic farming, environmental certifications seem substantially stagnant compared to product quality certifications. Eventually, organic farming has become the prevalent form of

[20] As part of "the Farm to Fork strategy", the European Commission has recently announced its intention to convert the FADN into a Farm Sustainability Data Network (FSDN) to expand the scope of the current FADN network by collecting farm level data also on environmental and social farming practices.

environmental certifications over time as it was just 34% on the total in 2008 and reached 58% in 2019.

In order to connect this dynamics with the policy evolution, Table 7 presents the correlation coefficients between the two categories of II Piilar CAP support (AEM and other measures) per FAWU and the different certifications. As could be expected, it emerges a strongly positive and significant linkage between AEM payments and environmental certifications, in particular organic farming. On the contrary, there is no evidence of a regular and significant relationship between other II Pillar measures, product quality certifications and multifunctional diversification. Even for these measures, the only evidence concerns the linkage with environmental certification, organic farming in particular.

It could thus be concluded that a robust evidence on the impact of the AEM support on organic farming and, more generally, environmental certifications actually emerges. But this interpretation requires major caution as this linkage may be just apparent or, to be more precise, just a tautology. As a matter of fact, certification is not the consequence of a treatment (i.e., a II Pillar measure), but it is the treatment itself: untreated units cannot be certified whereas treated units are automatically certified. Therefore, the TE logic might not work properly because the treatment does not leave any behavioural trace, namely, it does not induce any observable behavioural response. In fact, the only behavioural trace is the farmer's voluntary choice of the treatment itself which inevitably implies certification.[21]

7. Causal inference and CAP assessment

We can now go back to the original question of the present study, i.e., the actual applicability of the TE logic and PEM to CAP assessment. There has been a significant change over time in

[21] For this same reason also the rhetoric generated by the diffusion of certifications should be taken with caution. Italian agriculture might be considered "the greenest agriculture in Europe" (Symbola, 2016) only because of the largest presence of certifications, i.e. very often, of the associated II Pillar measures.

the forms of CAP support, but from the perspective of a professional farm this might have changed quite a little in the overall amount of support and its distribution across beneficiaries. It is thus legitimate to argue that the CAP gradual change has favoured, if not induced, some of change in farmers' behaviour. But we can not exclude that this latter change would have occurred in any case and the CAP and its reform just accompanied it.

So, the fundamental question remains the same: how much of the farmers' behavioural changes can be attributed to the CAP, namely, it can be considered a response to the policy? A rigorous assessment in this respect requires an appropriate quasi-experimental design in order to implement the appropriate "what-if" logic.[22] This design requires, in turn, appropriate data and estimation approaches but, more importantly, it must fit the common framework underlying any CI investigation. Almost all CI studies are based on the so-called Potential Outcome (PO) framework (Rubin, 1974; Imbens and Wooldridge, 2009; Imbens and Rubin, 2015). Within this theoretical framework, the empirical identification of the TE depends on the identification of counterfactuals mimicking the outcome variable of a treated unit in the case it were not treated (and the other way round) (Perraillon et al., 2022). However, empirical identification and estimation of the TE within this conceptual framework is grounded on three major assumptions. The first is the *Conditional Independence Assumption* (CIA, or Unconfoundedness) that postulates the independence between the potential outcomes and the treatment conditional on a set of pre-treatment (exogenous) variables, or confounders.[23] The second assumption is the *overlap* (also known as balance, or positivity, or common support) *condition* that empirically implies that there must be at least one treated unit and one control unit at each possible value of all confounders. The third condition is the *Stable Unit Treatment Value Assumption* (SUTVA) that rules out any interference of an individual's

[22] Here we refer to "quasi-experimental design" with the same meaning given by Perraillon et all. (2022) to "research design" on observational units, that is, the overall strategy used to answer a research question with non-experimental data.

[23] As stressed by Perraillon et al. (2022), in classical linear regression models the CIA is incorporated in the conventional assumption of spherical disturbances.

treatment status on another individual's potential outcome. If these conditions are satisfied, observational data can be regarded as generated by a "natural experiment".

On the basis of the characteristics of the CAP, of the farming activity and of the empirical evidence above, the validity of all these three assumptions and, consequently, the applicability of the TE logic to CAP assessment can be seriously. Seven orders of problems can be pointed out. Not only they may be all encountered in CAP assessment exercises; more importantly, they may occur simultaneously. Following the order of discussion below, the first problems are general and have progressively found viable methodological solutions (sections 7.1-7.3). Two are still general but are more serious in the CAP case; viable solutions are still under investigation and are at the frontier of the research in this field (sections 7.4-7.5). Finally, two other issues seem quite specific of the CAP case and, therefore, ask for specific solutions (sections 7.6-7.7).

7.1. Heterogeneity

Farms under investigation (treated or not) are characterized by a very large heterogeneity. This has to do with their size (economic and physical) and their structural and geographical characteristics, but also with farmer's personal motivations. While the former features may be observed, the latter remain unobserved and can only be indirectly revealed by the observable farmer's behaviour (Esposti, 2022). Controlling for this heterogeneity requires many confounders, thus highly dimensional datasets that, in turn, imply remarkable computational complexity (the so-called *curse of dimensionality*). The alternatives are to reduce the number of confounders, but then selection on unobservables is likely to occur, or to adopt estimation strategies that mitigate the curse of dimensionality.

Literature in the field has proposed several solutions (Abadie, 2021). That with the largest use is the Propensity Score Marching (PSM), but under large heterogeneity and many confounders this approach is likely to incur in the violation of the overlap condition. To overcome this issue, when treated units are few, synthetic controls can be identified and used (like in the Synthetic Control Method, SCM). Alternative estimation approaches have also been proposed (like, for instance, Lasso[24] estimation; see Koch et al., 2018; STATA, 2021).

But farm heterogeneity is challenging also for another, and more fundamental, reason: the TE itself may be strongly heterogeneous. Although the average TE (ATE) is correctly identified and consistently estimated, it simply remains uninformative. Estimating quantile TE is not particularly useful as it simply provides some additional statistics, beyond the mean, of the TE distribution (Esposti 2017b). Under strong TE heterogeneity, estimating the group or the individual TE (GTE, ITE) is needed for policy assessment and learning (Esposti, 2022). But GTE and ITEs identification and estimation requires approaches that are non-linear, non-parametric and take many covariates into account. Recently proposed Machine Learning (ML) approaches seems interesting in this respect (Coderoni, Esposti and Varacca, 2021; Esposti, 2022). But they are also computationally demanding and complex making their outcome not always transparent and results not fully reliable (Knaus et al., 2021). As a consequence, these approaches also requires a lot of additional validation work (Athey and Imbens, 2017).

7.2. Multivalued treatments

Most CI approaches have been designed and applied in a binary treatment context. But many programs and policies consist in interventions whose intensity varies across discrete or continuous range of possible values (i.e., they are *multivalued treatments*). As discussed, this is definitely the case of almost CAP measures. A multivalued treatment can be still represented within an augmented PO framework but the empirical implications can be severe.

[24] Least absolute shrinkage and selection operator.

Imbens (2000) and Hirano and Imbens (2004) developed an extension of PO framework to continuous multivalued treatments and proposed an estimation approach based on the generalization of the PSM estimation (Generalised Propensity Score, GPS, estimation) (Esposti, 2017a). Hirano-Imbens' approach provides consistent estimates only under the CIA, that is, whenever the treatment assignment can be considered exogenous once all confounders have been taken into account. However, with unobserved confounders, treatment endogeneity might not be excluded. The approach proposed by Cerulli (2015) admits this possibility of treatment endogeneity and the respective results are consistent even under this circumstance.

The application of both approaches, however, may encounter several practical problems for the computational complexity and, above all, for the likely violation of the overlap condition. Alternative non-parametric (or semi-parametric) estimation strategies can be helpful to overcome these issues, but they only apply to discrete (or categorical) multiple treatments (Cattaneo, 2010; Cattaneo et al., 2013; Athey and Imbens, 2017; Esposti, 2017b). Therefore, they may require an arbitrary discretization of continuous treatments.

7.3. Treatment timing

When panel data are available, as in the present case, units can be observed before and after the treatment. This allows TE identification and estimation via widely used approaches like the Difference-in-Differences (DID) estimation or the Two-Way Fixed Effects estimation (de Chaisemartin and D'Haultfœuille, 2020). However, though powerful, these approaches still require counterfactuals, with all the abovementioned complications, and imply an additional assumption (parallel trend assumption) that excludes time as an additional confounder. Since the effect of time on both treatment assignment and the treatment outcome is unobservable, this assumption may be itself problematic especially in those activities where time matters a lot but it also operates differently across observations. Agriculture definitely is among these activities.

Extensions of the conventional DID approach have been recently proposed is order to overcome these difficulties. Some aim to account for treatment heterogeneity (Chan and Kwok, 2022; Cho et al., 2022), also by combining different estimation strategies. For instance, the Synthetic DID estimation combines attractive features of DID and SCM approaches (Arkhangelsky et al., 2021). But what really makes the timing of the treatment a challenging issue in CAP assessment is that it may differ (in fact, it usually differs) across the treated units: they enter the treatment in different moments of time (asynchronous policy adoption). Recent generalizations of the DID approach tackle this issue under more than one pre- and post-treatment periods, but still a fixed treatment time (Cerulli, 2019), as well as and under many post- and pre-intervention times and with the treatment itself that varies over time (Cerulli and Ventura, 2019; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

As discussed above, CAP magnifies these issues. Even though, in principle, CAP reforms start at the same time for all farms (at least within a specific EU member state), their actual implementation can differ across space (for instance, regions) and farms may apply in different moments. Moreover, several measures are reiterated across successive CAP programming periods. Consequently, dealing with time-varying treatments is even more challenging because treatment itself may be reiterated on the same units in different periods of time melded with periods without the treatment.

7.4. Multiple treatments

Almost all CI studies and PEM concentrates on single treatments. As shown, however, in the CAP case treated farms usually receive multiple treatments. Identifying and consistently estimating the TE of any single treatment with the conventional approaches is possible only under the assumption of treatment independence. But this assumption is quite unrealistic as interdependence is likely to occur both in terms of treatment assignment and in terms of outcome variable. Within the CAP both interdependencies may evidently occur also between I and II Pillar measures. In this respect, it could be interesting to assess whether treatments reciprocally interfere by magnifying or offsetting the respective TE. At present, however, a viable empirical solution to this issue has not yet emerged (Frolich, 2004; Athey and Imbens, 2017).

7.5. Spatial interference

When samples are spatially explicit, contiguous treated units may interfere due to economic factors (like imitation or competition) or environmental/physical processes (external effects) (Lobianco and Esposti, 2010). This interference may concern both the treatment assignment (or choice) and the outcome variable. Eventually, this interference violates the SUTVA assumption. Consequently, conventional PEM may provide inconsistent TE estimates thus generating wrong policy conclusions.

This behavioural interference is very likely to occur among farms as illustrated by Baldoni and Esposti (2021) in the specific case of Italian agriculture. Therefore, it should be appropriately taken into account in any farm-level CAP assessment. Almost all TE studies, however, disregard this aspect also because its implications for consistent TE estimation remain to be fully investigated. Some solutions have been recently proposed (Kolak and Anselin, 2020) but empirical applications to CAP measures are still lacking.

7.6. Voluntary and universalistic treatments

As discussed at the beginning of this paper, CAP measures are tendentially universalistic and adoption is mostly voluntary. All or most farms can apply for these measures and, therefore, the treatment status can not be considered exogenous. This poses fundamental problems in finding suitable counterfactuals as they may not exist at all. Even when non-treated units are present and observable, they are so peculiar that can not be confronted with the treated ones:

their peculiarity actually is the main reason for their exclusion (either voluntary or not) from the treatment. The key point, therefore, is that this issue goes beyond the violation of the overlap condition but invests the validity of the CIA itself. Some strategy (like the SCM) can help with respect to the former concern but it can not overcome the unavoidable presence of a selection bias (Coderoni, Esposti and Varacca, 2021). This makes the application of the TE logic to CAP assessment seriously questionable.

Any possible way out of this problem does not rely on alternative or adapted TE estimation approaches. It has rather to do with a proper quasi-experimental design. A proper definition of the treatment variable, of the treated and non-treated samples, of the outcome variable may help restoring the validity of abovementioned assumptions. A pre-condition to make this effort successful is an appropriate theoretical background representing the farmer's behaviour (the treatment choice included) as it can drive the proper design of the quasi-experimental setting.[25]

7.7. Outcome variable

The point above is also associated to a final issue raised by the application of the TE logic to the CAP assessment. It has to do with the outcome variable to be considered. On the one hand, for many CAP measures a policy target variable is simply neither explicit nor univocal. On the other hand, when measures are very clearly targeted (several II Pillar measures, for instance), the outcome variable is clear or univocal but it is just a tautology: the treatment adoption itself implies the outcome variable which automatically takes zero value for the non-treated units. This is the case, for instance, of certifications' adoption.

An outcome variable may not exist, may be unobservable, may be multiple or may be tautological. In any case, this poses a fundamental practical challenge for the consistent application of PEM to CAP assessment. Also in this case, the solution does not depend on some

[25] For a theoretical and empirical investigation on how farmers select the policy and change their behaviour in order to take advantage of it within an utility-maximizing framework, see Esposti (2022).

methodological adaptation or alternative to conventional TE estimation approaches. It rather requires a well suited quasi-experimental design based on a conceptualization of farmers' behaviour that eventually leads to the identification of the most appropriate outcome variable to be considered in the analysis.

8. Some concluding remarks

Assessing the farm-level impact of CAP measures and reforms with a Causal Inference logic is potentially informative thus highly desirable. Unfortunately, it is also highly challenging. Major theoretical and methodological problems are more often overlooked that explicitly tackled. In this respect, a deeper and more critical discussion within the profession would be desirable. This discussion should develop on a sequence of three levels. The present paper is structured along this sequence of steps and is motivated by the need of further research effort in each of them.

The first general level concerns the initial (and usually implicit) question that motivates any policy assessment: is that policy a good policy? Is it working? Answering this question assumes that the analysist knows what a "good policy" is, that is, what the policy is expected to do. In many cases, and in particular when the CAP is under investigation, this assumption is not obvious and should deserve a much deeper examination before any assessment is attempted. On the contrary many studies on CAP measures and reforms do not even consider their objectives or take them for granted while, in fact, they are often not clear at all (Matthews, 2021). This hinders the actual capacity of the analyst to convert the policy assessment into a clear CI research question (Perraillon et al. 2022).

Once the target of the policy to be investigated is clearly focused, the second level of discussion concerns the empirical background such an assessment requires. This firstly means making sure that appropriate datasets are available. Secondly, and more importantly, it means to investigate the coevolution of the policy instruments and of the potentially beneficiating units, that is, farmers' behaviour in the specific case of the CAP. This coevolution is expected to provide enough support to the existence of a possible cause-effect relationships and to the feasibility of its investigation. Though it is true that correlation is not causation, it is also true that the lack of some form of correlation makes the investigation of a causation relationship highly problematic if not unfeasible (Perraillon et al., 2022).

On the basis of these empirical pre-requisites we could even conclude that the CAP has really moved in the right direction, that is, consistently with the declared objectives and the farmers' behaviour changed as well. But this does not mean that the policy induced the expected effect, that is, the expected farmers' response. Therefore, once these empirical pre-requisites are satisfied, the third level of discussion concerns the methodological toolkit we need to perform CAP assessment within a TE logic. This means acknowledging the main challenges the CAP poses in this respect and, consequently, that widely used approaches may be inappropriate in this specific case. An acritical adoption of these approaches may not only lead to wrong policy conclusions but also procrastinates the search for more suited solutions. Moreover, it may divert the attention from what seems really critical in this field, that is, setting up appropriate quasi experimental design with the consequent appropriate datasets and theoretical representation of farmers' choices.

Table 1 – Distribution of the public support (CAP included) within the Italian 2008-2019 FADN balanced sample (€).

	2008	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
TOTAL SUPPORT												
Mean	14449	14848	16642	15802	16700	16846	16870	17158	16614	16381	16510	16856
Standard deviation	31844	31258	41230	38001	39722	38967	42899	42205	41005	40174	36552	34645
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	755	1014	1666	1860	1924	1844	1904	1508	1501	1532	1804	2325
2nd Quartile (Median)	5065	5498	5920	6341	6545	6536	6329	6470	5941	6185	6449	6826
3rd Quartile	14824	15904	17100	16878	17634	17607	17431	18625	17807	16971	17813	18489
Max	420574	505280	859158	834940	737493	720471	894886	1158547	972158	911073	834179	756761
NATIONAL SUPPORT												
Mean	245	573	708	473	373	437	469	255	276	294	296	185
Standard deviation	1883	4874	8621	4410	3126	3396	4983	2219	2408	2233	1974	2379
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	0	0	0	0	0	0	0	0	0	0	0	0
Max	32072	102854	213984	119430	66942	69493	145670	60900	56491	59487	36800	74000
TOTAL CAP												
Mean	14204	14275	16106	15329	16327	16410	16401	16903	16338	15753	16286	16599
Standard deviation	31763	30850	38511	37724	39512	38714	42579	42135	40897	37516	36501	34463
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	724	947	1622	1840	1892	1750	1814	1491	1461	1497	1770	2286
2nd Quartile (Median)	4957	5144	6395	6125	6478	6325	6130	6340	5727	5955	6257	6701
3rd Quartile	14611	15320	17745	15969	17132	17157	16961	18337	17253	16514	17417	18245
Max	420574	505280	805154	834940	737493	717971	894886	1158547	972158	911073	834179	752234
CAP I PILLAR – DECOUPLED												
Mean	9961	9954	11211	11178	12750	12536	12886	11541	11340	10883	10291	9922
Standard deviation	21774	21001	33082	31119	35614	34153	36599	32735	30054	26924	24078	21307
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	98	215	507	768	886	830	878	739	925	1028	1204	1242
2nd Quartile (Median)	3477	3483	4015	4199	4231	4171	4068	3568	3614	3644	3682	3830
3rd Quartile	10715	10992	11718	11772	12412	12095	12179	11040	11008	10519	10445	10378
Max	317849	319288	801933	724970	720596	680898	759890	862371	631221	558244	528809	417296
CAP I PILLAR – COUPLED												
Mean	2374	2380	1923	1577	567	631	776	1726	1883	1744	1736	1889
Standard deviation	11566	12675	8401	8003	3357	3786	5307	8515	9999	10320	8860	9275
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	690	794	0	0	0	0	0	975	1087	1034	1221	1120
Max	237355	340652	122828	124584	90000	108794	134996	293872	338633	352829	305370	312498
CAP II PILLAR – AEM												
Mean	826	931	1100	1127	1602	1620	1366	1946	1940	1917	2279	2450
Standard deviation	2991	3300	4132	4430	5390	5585	5043	6552	6674	6555	7528	7862
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	0	0	0	0	0	1	0	0	0	0	0	1401
Max	38115	51974	77603	77603	77598	99500	100000	73863	77341	92541	92541	120010
CAP II PILLAR – OTHERS												
Mean	1043	1010	1872	1447	1408	1622	1373	1690	1175	1208	1980	2339
Standard deviation	6853	5388	8962	7567	8536	8343	7605	7330	5035	4720	8287	7854
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	0	0	0	0	0	0	0	0	0	0	0	0
2nd Quartile (Median)	0	0	0	0	0	0	0	0	0	0	0	0
3rd Quartile	0	0	0	0	1	1	0	0	0	0	1047	1860
Max	184212	140000	133700	149093	240000	215000	240000	110000	87000	83265	176513	161758

	Min	1st Quartile	2nd Quartile	3rd Quartile	Max
% Δ CAP support (2019-2008)	-100%	-19%	+30%	+370%	-

Table 2 – Distribution of the farm net income within the Italian 2008-2019 FADN balanced sample (€).

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	57056	53945	55907	55703	55380	54253	51358	54100	54186	55072	57512	51440
Standard deviation	139843	134874	135000	142913	127696	119818	123255	132212	133324	109159	106696	106542
Min	-160758	-124741	-143652	-184265	-66484	-402051	-181687	-165917	-205180	-229603	-121842	-255091
1st Quartile	8969	6542	9042	9147	9669	9702	8423	9399	9172	9573	10065	8424
2nd Quartile (Median)	24802	21723	25506	24741	25537	25001	23146	23966	24972	25785	26229	23154
3rd Quartile	58698	52296	58763	57760	59681	58205	53101	57595	62726	61431	65008	58063
Max	2429572	2075403	2333829	2228093	1983041	2019809	2100850	3368715	3691632	1815441	1939388	1930918

Table 3 –Factor use and profitability per labour unit within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
FAWU/AWU												
Mean	0.71	0.68	0.73	0.71	0.70	0.70	0.70	0.69	0.73	0.71	0.72	0.69
Standard deviation	0.31	0.31	0.29	0.30	0.30	0.29	0.29	0.30	0.30	0.30	0.29	0.31
Min	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
1st Quartile	0.43	0.40	0.48	0.46	0.44	0.46	0.45	0.43	0.49	0.44	0.48	0.41
2nd Quartile (Median)	0.80	0.72	0.79	0.80	0.76	0.73	0.74	0.74	0.85	0.79	0.81	0.73
3rd Quartile	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
UAA/AWU (ha)												
Mean	18.5	18.5	17.8	17.4	17.4	17.3	17.5	18.3	17.7	17.8	18.1	17.6
Standard deviation	26.6	25.6	24.3	23.7	24.4	23.9	24.4	31.5	22.9	22.9	23.2	21.9
Min	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.1
1st Quartile	3.8	3.9	3.9	4.0	3.9	3.9	3.9	4.0	4.0	4.1	4.0	4.0
2nd Quartile (Median)	9.5	9.6	9.6	9.4	9.4	9.2	9.2	9.6	9.7	9.3	9.6	9.7
3rd Quartile	23.0	22.9	22.3	22.4	21.8	21.7	21.6	21.6	22.3	22.2	22.1	21.9
Max	486.4	387.3	387.3	421.8	421.8	421.8	387.3	803.6	274.5	200.5	192.4	179.1
KW/AWU (hp)												
Mean	113.1	112.4	112.2	112.7	114.0	114.0	116.4	124.0	120.3	123.0	123.7	125.7
Standard deviation	117.1	104.8	110.3	100.7	98.2	98.1	100.3	241.8	109.4	115.8	117.3	121.4
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1st Quartile	45.3	47.7	50.0	50.2	51.8	50.9	51.5	51.8	52.2	51.2	53.0	53.6
2nd Quartile (Median)	80.8	82.9	82.1	82.8	86.1	87.3	88.0	90.0	92.4	90.3	91.2	90.6
3rd Quartile	137.8	143.6	143.5	145.9	143.7	144.3	148.1	148.2	151.9	155.6	155.4	155.5
Max	1341.5	1010.0	2010.0	812.2	798.3	925.8	845.9	8560.0	1488.0	1122.7	1488.0	1488.0
LSU/AWU												
Mean	12.3	12.4	14.2	14.3	13.7	15.1	14.4	14.5	15.8	14.8	13.6	13.2
Standard deviation	36.4	41.3	44.5	57.8	40.7	55.1	46.8	56.3	62.4	56.2	43.6	46.9
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1st Quartile	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2nd Quartile (Median)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3rd Quartile	11.1	11.9	13.0	12.7	12.5	12.3	13.0	12.0	11.5	10.6	10.1	9.4
Max	528.1	1031.5	992.4	1782.4	580.1	880.8	860.3	1041.6	1124.6	1291.5	604.5	722.7
Environment-using Costs/AWU (€)												
Mean	5498	5432	5501	5920	6197	6033	6223	6908	6419	6602	6398	6488
Standard deviation	8373	7237	8036	7993	8199	7813	8101	19089	9226	11042	9776	9830
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	1452	1444	1543	1737	1856	1827	1938	1873	1669	1688	1670	1705
2nd Quartile (Median)	3068	3184	3199	3484	3598	3634	3743	3678	3602	3608	3691	3764
3rd Quartile	5940	6072	5957	6428	6838	6635	6914	6960	7002	6927	7031	7018
Max	102031	64425	84848	75441	92735	73174	82336	671360	119471	189599	154697	132348
Net Income/AWU (€)												
Mean	33991	34658	33194	33845	31891	31971	29003	29232	31445	30749	32729	29628
Standard deviation	78467	96969	81619	93450	72083	80916	85630	67193	77978	64547	70778	63762
Min	-345243	-114033	-62508	-60077	-45493	-127082	-122912	-104936	-123965	-155465	-49852	-136698
1st Quartile	4479	3346	4630	4501	4974	4664	3959	4556	4455	4831	4963	3820
2nd Quartile (Median)	14190	11500	13726	13303	13803	13181	11190	12294	12503	12793	13746	11406
3rd Quartile	34085	30944	32888	32817	32397	32365	29211	29891	33712	33185	34799	31881
Max	1100695	2371566	1480981	1644227	879534	1889753	2135670	1317088	1446709	1089877	1488212	1196382

Table 4 – Source-Destination matrix for TF category within the Italian 2008-2019 FADN balanced sample (in grey >10 elements).

SOURCE / **DESTINATION**	TF 1	TF 2	TF 3	TF 4	TF 5	TF 6	TF 7	TF 8	Total
TF 1	294	10	20	35	6	57	3	36	460
TF 2	10	96	22	0	0	14	0	0	142
TF 3	20	10	375	4	2	47	2	12	471
TF 4	33	0	5	272	2	6	17	46	382
TF 5	5	0	3	2	28	2	3	5	48
TF 6	55	6	58	5	3	9	0	5	141
TF 7	2	0	2	13	4	0	0	0	22
TF 8	35	0	15	36	7	6	2	5	105
Total	455	122	501	366	52	141	26	110	1772

Legend: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

Table 5 – Evolution of the CAP support per unit of net income and of AWU within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A) CAP support/Net Income (%)												
Mean	39%	29%	54%	40%	43%	33%	24%	49%	47%	51%	66%	40%
Standard deviation	387%	1207%	408%	270%	805%	628%	810%	363%	953%	11234%	732%	266%
Min	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1st Quartile	0%	0%	3%	4%	5%	4%	4%	3%	2%	3%	4%	5%
2nd Quartile (Median)	17%	21%	24%	24%	24%	22%	25%	25%	22%	22%	24%	25%
3rd Quartile	55%	64%	61%	60%	60%	61%	62%	64%	62%	60%	61%	63%
Max	9868%	16679%	8601%	3553%	21479%	17270%	6455%	9591%	27578%	2388%	23517%	3902%
B) CAP support/FAWU (€)												
Mean	13660	15954	14701	14041	14789	16774	16627	16239	14330	15240	14561	16534
Standard deviation	33102	45784	40671	32212	34684	53774	61150	43461	36434	42160	37633	39940
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	556	800	1096	1244	1470	1330	1350	1164	1043	1175	1386	1754
2nd Quartile (Median)	4038	4802	4519	4525	5165	5369	5238	5303	4414	4893	4954	5592
3rd Quartile	12498	14468	13835	13489	15083	14765	15201	16545	14457	13841	14328	16522
Max	647037	973039	781053	533976	597378	1233624	1413233	1053225	883780	828248	1005035	886387
Correlation coefficient between B) and net income/FAWU	0.38*	0.36*	0.60*	0.39*	0.52*	0.64*	0.65*	0.51*	0.50*	0.46*	0.67*	0.54*
Correlation coefficient between net income/FAWU and the CAP support 2019-2008 growth rate										0.06*		
Correlation coefficient between avg. 2019-2008 CAP support/FAWU and standard deviation of net income/FAWU										0.52*		

[a] Farms with Net Income<0 are excluded
*Statistically significant at 5% confidence level

Table 6 – Evolution of the Shannon and Simpson diversity indexes within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A) Shannon diversity index (>1)												
Mean	1.34	1.35	1.35	1.32	1.33	1.36	1.38	1.42	1.45	1.45	1.47	1.49
Standard deviation	0.94	0.96	0.93	0.94	0.94	0.95	0.97	0.95	0.98	0.98	0.99	1.00
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1st Quartile	0.66	0.66	0.66	0.62	0.64	0.65	0.65	0.72	0.76	0.73	0.74	0.75
2nd Quartile (Median)	1.27	1.31	1.31	1.30	1.31	1.37	1.40	1.44	1.45	1.43	1.44	1.48
3rd Quartile	1.94	1.96	1.96	1.92	1.94	1.99	2.02	2.04	2.09	2.10	2.12	2.14
Max	5.50	5.60	4.85	6.18	5.29	4.97	5.31	5.01	4.80	4.85	5.12	5.50
B) Simpson diversity index (0-1)												
Mean	0.37	0.38	0.38	0.37	0.38	0.38	0.38	0.40	0.41	0.40	0.40	0.41
Standard deviation	0.26	0.26	0.26	0.26	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1st Quartile	0.12	0.11	0.11	0.08	0.09	0.09	0.10	0.15	0.16	0.15	0.17	0.17
2nd Quartile (Median)	0.42	0.44	0.44	0.43	0.44	0.44	0.44	0.47	0.47	0.47	0.47	0.47
3rd Quartile	0.60	0.61	0.61	0.60	0.61	0.61	0.61	0.63	0.63	0.63	0.62	0.64
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Correlation coefficient btw A) and CAP support per FAWU	0.01	-0.02	0.03	0.01	0.00	0.03	0.05	0.04	0.09*	0.05*	0.11*	0.03
Correlation coefficient btw B) and CAP support per FAWU	-0.03	-0.03	0.02	-0.03	0.00	0.02	0.03	0.01	0.06*	0.04	0.09*	0.04
Correlation coefficient btw A) and I Pillar decoupled support per FAWU	0.05*	0.03	0.08*	0.07*	0.02	0.03	0.04	0.04	0.08*	0.06*	0.11*	0.04
Correlation coefficient btw B) and I Pillar decoupled support per FAWU	0.01	0.01	0.07*	0.04	0.02	0.01	0.03	0.01	0.07*	0.04	0.10*	0.06*
Correlation coefficient btw A) and II Pillar support per FAWU	0.01	-0.02	0.03	0.01	0.00	0.03	0.05	0.04	0.09*	0.05*	0.11*	0.03
Correlation coefficient btw B) and II Pillar support per FAWU	-0.01	-0.01	-0.02	0.00	-0.02	0.05*	0.04	0.05*	0.08*	0.02	0.06*	0.02

Table 7 – Correlation coefficients between CAP support per unit of FAWU and different certifications within the Italian 2008-2019 FADN balanced sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Total CAP support/FAWU												
Organic Farming	0.03	0.01	0.03	0.02	0.00	0.00	0.01	0.02	0.07*	0.09*	0.09*	0.08*
Environmental Certification (organic included)	0.01	-0.03	-0.01	0.00	-0.03	0.01	0.00	-0.01	0.02	0.00	0.03	0.04
Product Quality Certification (organic excluded)	-0.01	-0.03	-0.06*	-0.08*	-0.08*	-0.07*	-0.08*	-0.07*	-0.07*	-0.08*	-0.07*	-0.06*
% of other gainful activities	-0.03	-0.01	-0.03	-0.03	0.01	-0.01	-0.03	-0.02	-0.03	-0.02	-0.03	-0.04
Decoupled I Pillar support/FAWU												
Organic Farming	0.00	0.00	-0.01	-0.01	-0.02	-0.03	-0.02	-0.02	0.05*	0.05*	0.05*	0.02
Environmental Certification (organic included)	0.00	-0.04	-0.03	-0.03	-0.04	-0.02	-0.02	-0.04	-0.03	-0.01	-0.01	0.01
Product Quality Certification (organic excluded)	-0.04	-0.04	-0.06*	-0.08*	-0.08*	-0.08*	-0.07*	-0.08*	-0.09*	-0.10*	-0.08*	-0.07*
% of other gainful activities	-0.04	-0.01	-0.03	-0.03	-0.03	-0.02	-0.03	-0.03	-0.04	-0.04	-0.03	-0.04
Coupled I Pillar support/FAWU												
Organic Farming	-0.02	-0.02	-0.04	-0.04	-0.03	-0.02	-0.01	-0.03	0.00	-0.02	-0.01	-0.03
Environmental Certification (organic included)	-0.03	-0.03	-0.04	-0.05*	-0.03	-0.01	-0.01	-0.03	0.02	-0.03	-0.03	-0.03
Product Quality Certification (organic excluded)	0.02	-0.03	-0.05*	-0.08*	-0.03	-0.03	-0.03	0.00	-0.01	-0.03	-0.04	-0.03
% of other gainful activities	-0.04	-0.03	-0.03	-0.02	0.01	0.01	-0.01	-0.03	-0.03	-0.02	-0.02	-0.04
II Pillar support/FAWU												
Organic Farming	0.19*	0.08*	0.14*	0.10*	0.07*	0.10*	0.07*	0.16*	0.20*	0.13*	0.19*	0.18*
Environmental Certification (organic included)	0.11*	0.04	0.10*	0.07*	0.03	0.12*	0.05	0.13*	0.17*	0.06*	0.16*	0.12*
Product Quality Certification (organic excluded)	0.05*	0.02	-0.01	0.00	0.00	-0.04	-0.03	0.02	0.00	-0.02	0.01	-0.01
% of other gainful activities	0.06*	0.04	0.01	0.00	0.08*	0.01	0.01	0.02	0.01	0.01	0.01	0.02
AEM II Pillar support/FAWU												
Organic Farming	0.30*	0.17*	0.16*	0.14*	0.15*	0.11*	0.13*	0.19*	0.18*	0.19*	0.20*	0.19*
Environmental Certification (organic included)	0.23*	0.08*	0.13*	0.11*	0.08*	0.06*	0.09*	0.14*	0.15*	0.09*	0.14*	0.13*
Product Quality Certification (organic excluded)	0.08*	0.02	0.02	0.04	0.02	-0.01	-0.01	0.04	0.02	-0.01	0.02	-0.02
% of other gainful activities	0.03	0.00	-0.02	0.00	0.01	0.00	0.00	-0.01	-0.01	-0.01	0.00	-0.03
Other II Pillar support/FAWU												
Organic Farming	0.03	-0.01	0.06*	0.04	-0.01	0.03	0.03	0.06*	0.12*	0.04	0.11*	0.10*
Environmental Certification (organic included)	-0.02	-0.01	0.03	0.02	-0.01	0.12*	0.02	0.06*	0.12*	0.00	0.12*	0.06*
Product Quality Certification (organic excluded)	0.00	0.01	-0.02	-0.03	-0.02	-0.05*	-0.04	-0.01	-0.02	-0.03	-0.01	0.01
% of other gainful activities	0.06*	0.05*	0.01	0.00	0.10*	-0.02	-0.01	0.03	0.01	0.00	-0.01	-0.01
Shannon Index												
Organic Farming	0.15*	0.12*	0.13*	0.13*	0.12*	0.12*	0.09*	0.08*	0.10*	0.09*	0.08*	0.07*
Environmental Certification (organic included)	0.23*	0.21*	0.19*	0.19*	0.15*	0.15*	0.13*	0.13*	0.13*	0.12*	0.08*	0.11*
Product Quality Certification (organic excluded)	-0.06*	-0.01	0.01	-0.04	-0.07*	-0.08*	-0.09*	-0.09*	-0.07*	-0.07*	-0.07*	-0.06*
% of other gainful activities	0.00	0.04	0.02	0.00	0.01	0.02	0.03	0.02	0.03	0.03	0.02	0.02

*Statistically significant at 5% confidence level

Figure 1 – Total and per farm public support within the Italian 2008-2019 FADN balanced sample.

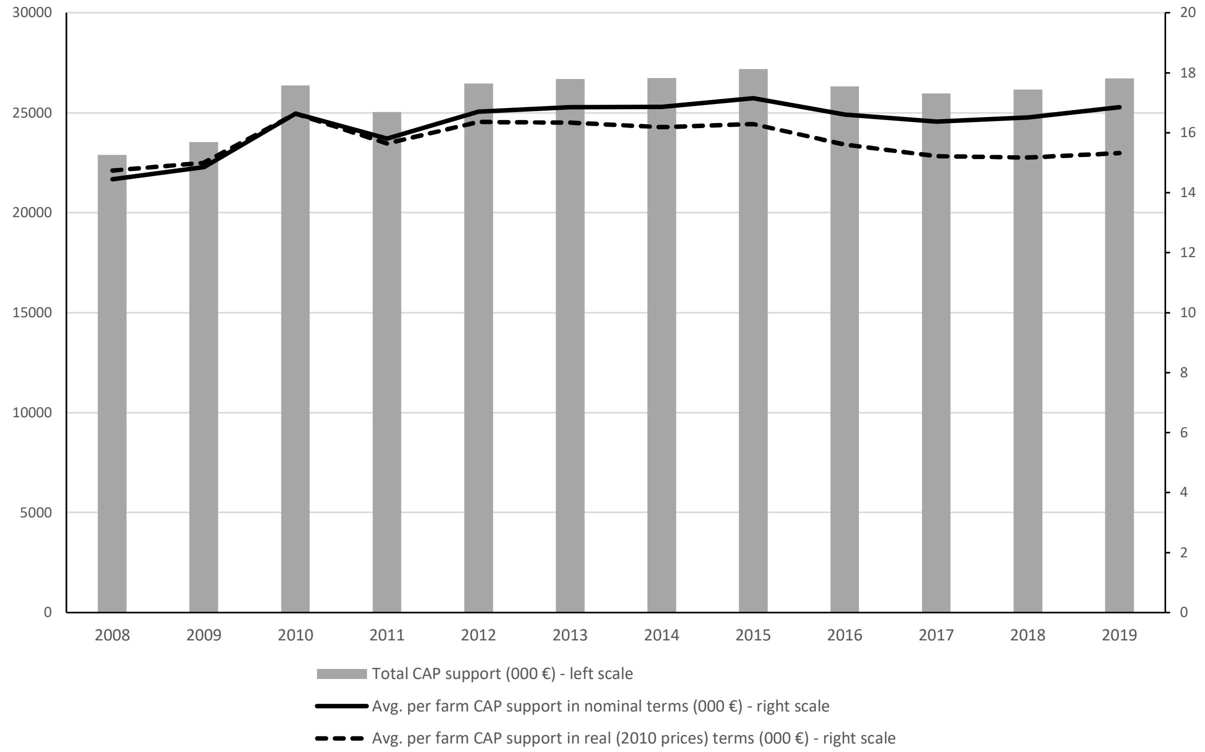
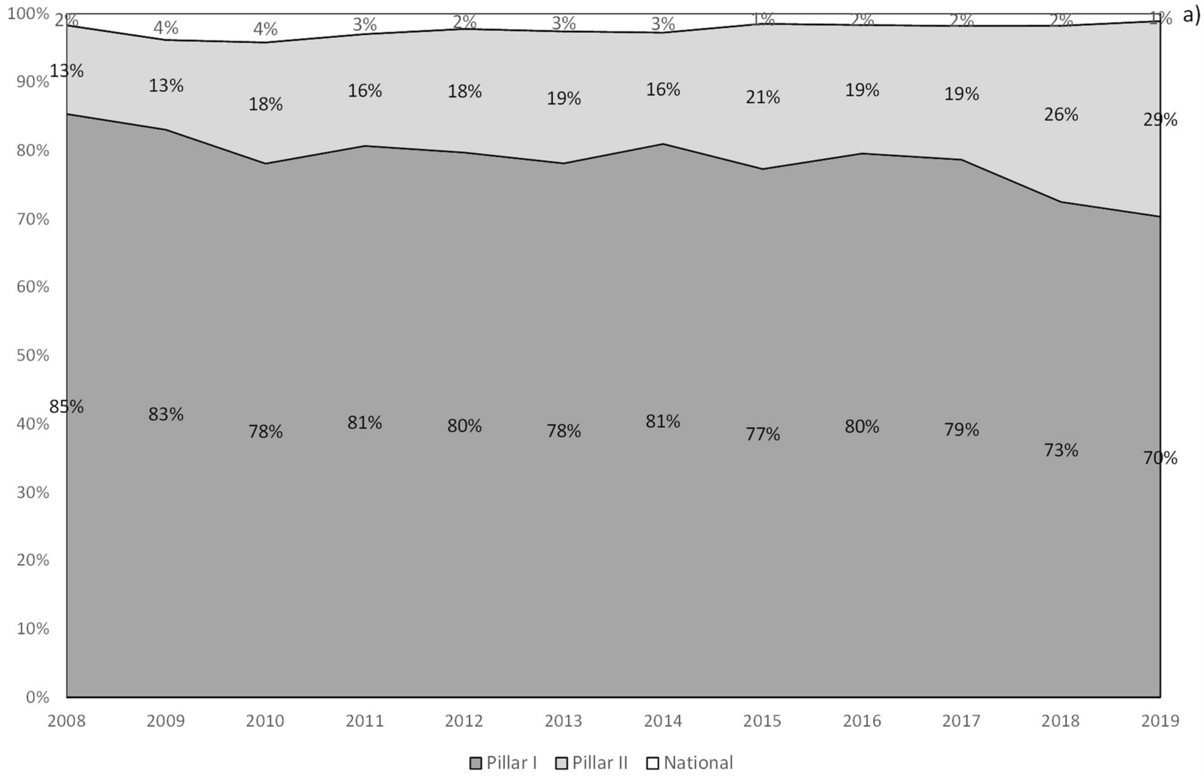


Figure 2 – Composition of the total public (a) and CAP (b) support within the Italian 2008-2019 FADN balanced sample.



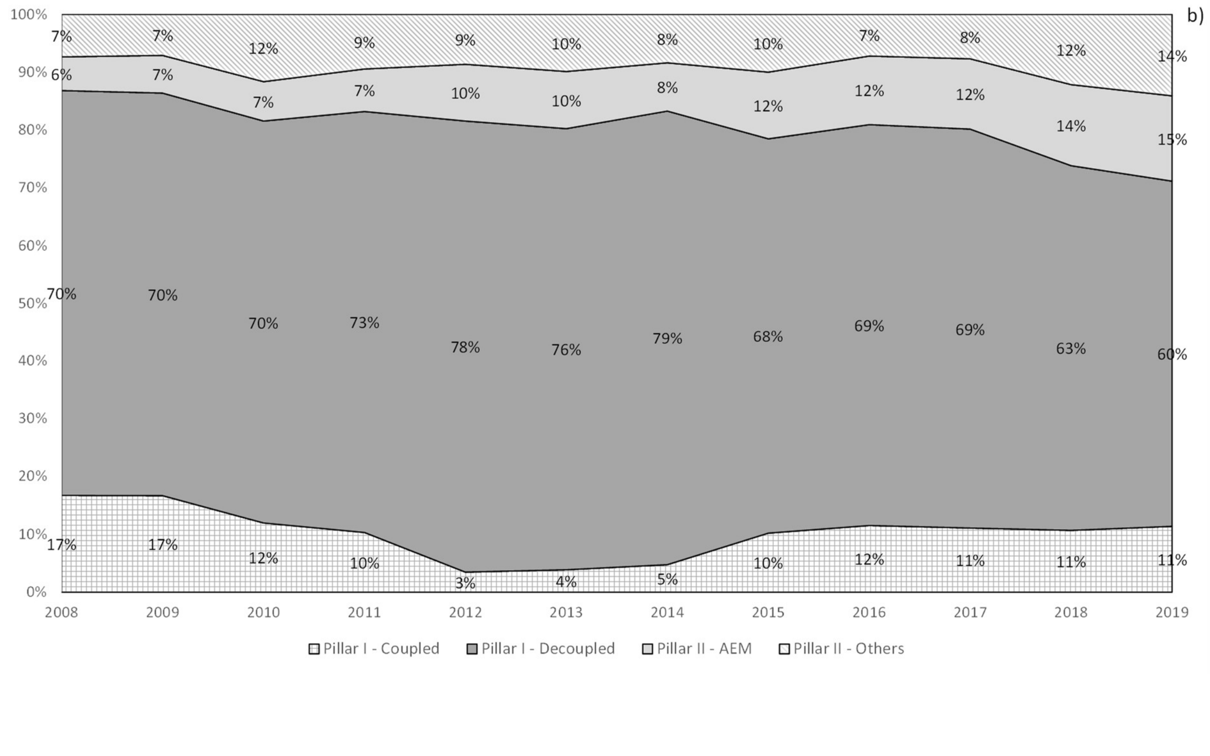


Figure 3 – Evolution of the Agro-Environmental Measures (AEM) support within the Italian 2008-2019 FADN balanced sample: number of beneficiaries, total support and average support per beneficiary.

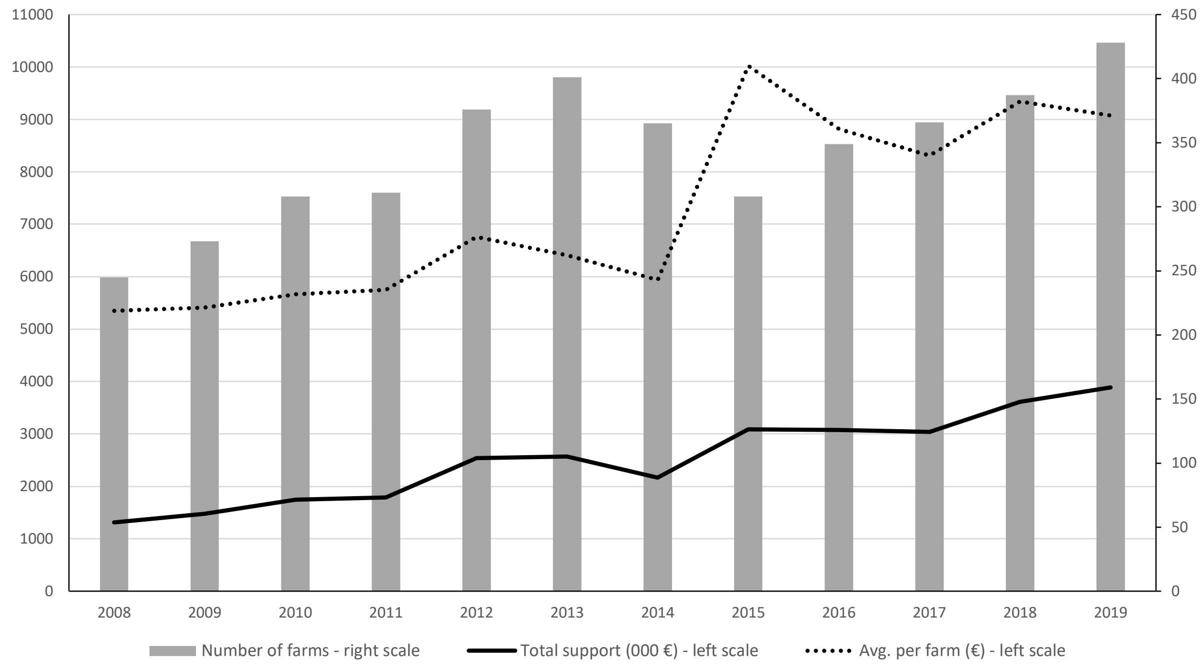


Figure 4 – Lorentz curves of the Pillar I (a) and Pillar II (b) support within the Italian 2008-2019 FADN balanced sample: years 2008, 2015, 2019.

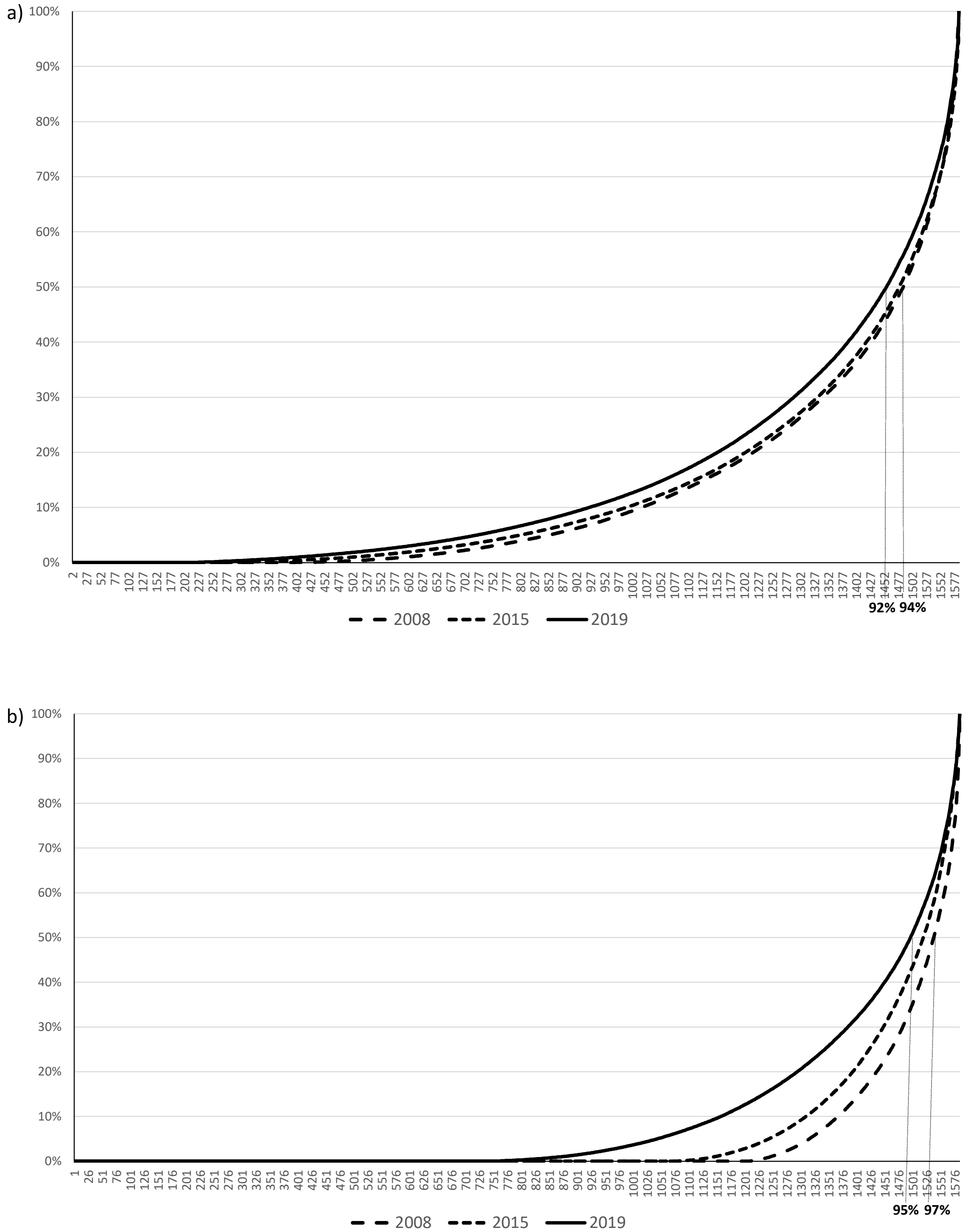


Figure 5 – Avg..revenue, variable costs and environment-using costs (fertilizers, pesticides, energy, water) (€) over the 2008-2019 period within the Italian FADN balanced sample.

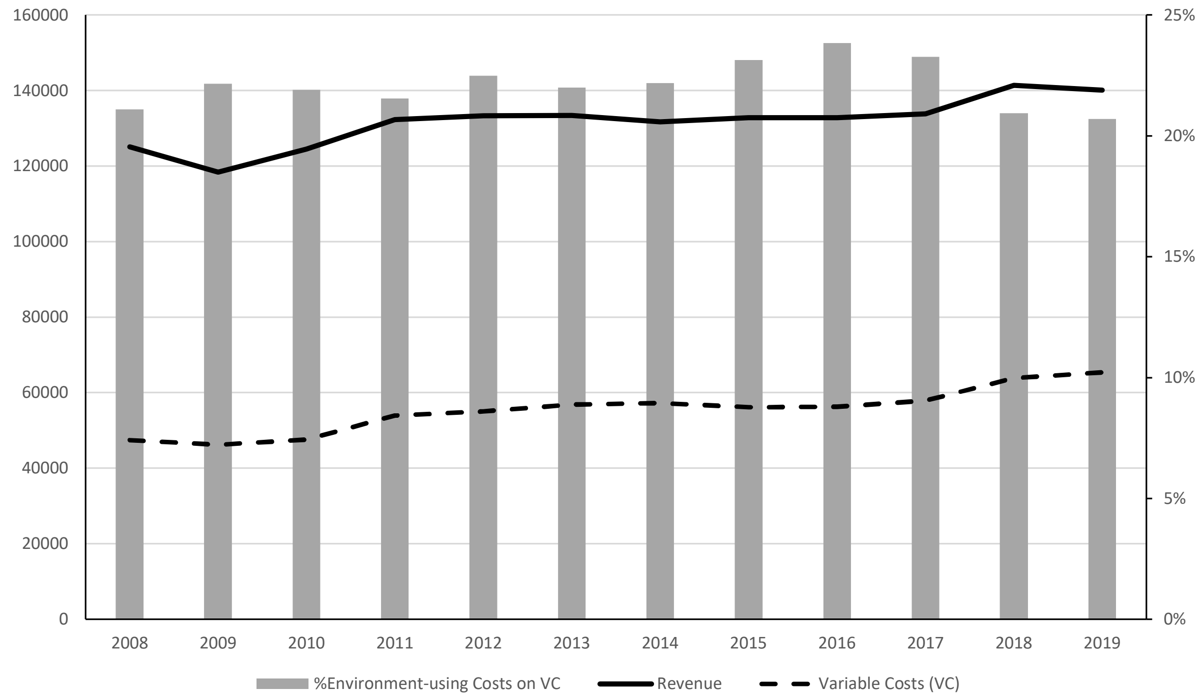


Figure 6 –Average farm net income (€) over the 2008-2019 period within the Italian FADN balanced sample.

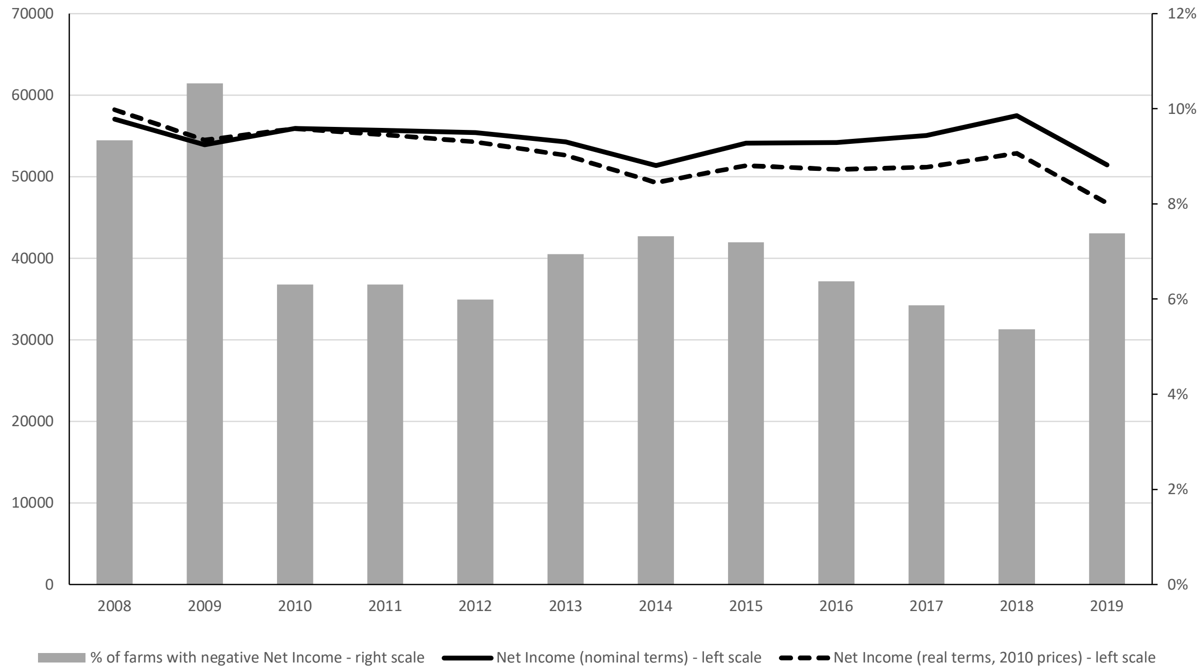


Figure 7 – Lorentz curves of the (positive) farm net income within the Italian 2008-2019 FADN balanced sample: years 2008, 2015, 2019.

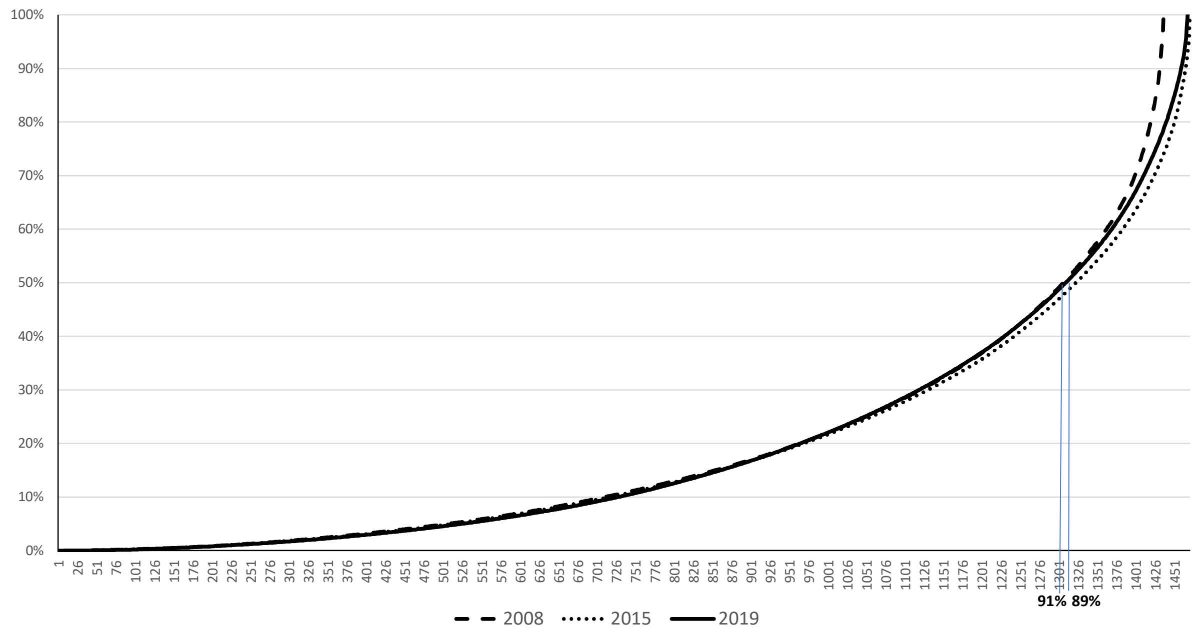


Figure 8 – Evolution of main factors' average endowment (2008=100) over the 2008-2019 period within the Italian FADN balanced sample.

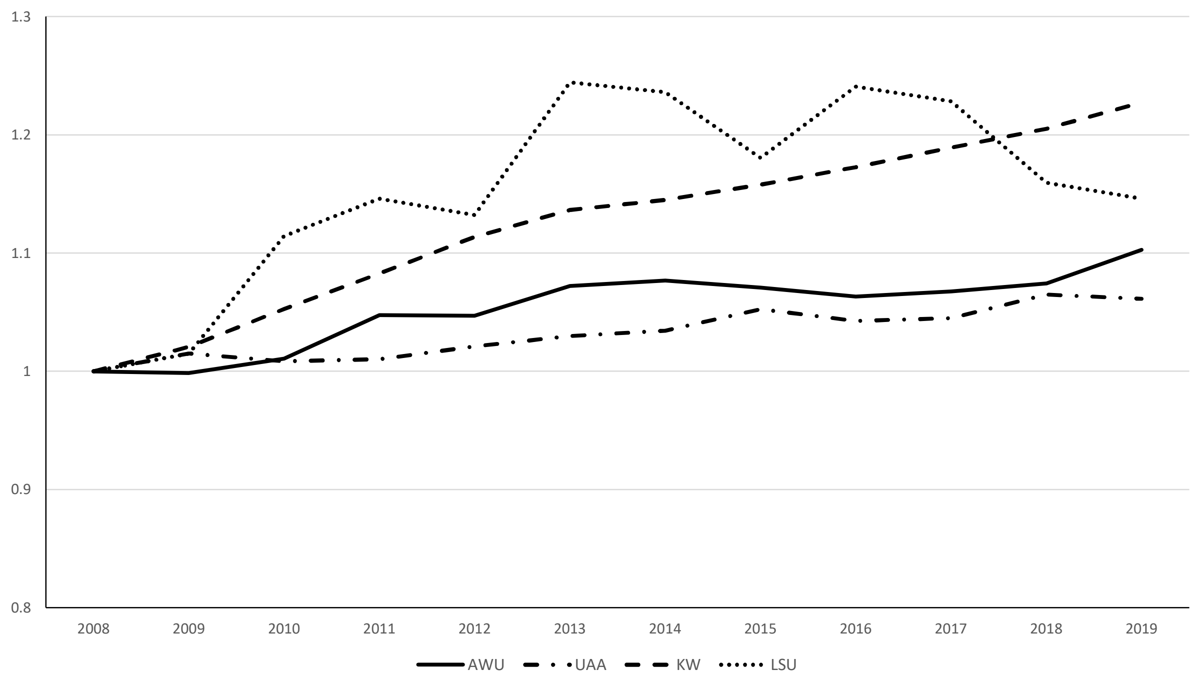


Figure 9 – Evolution the farm net income per (F)AWU over the 2008-2019 period within the Italian FADN balanced sample.

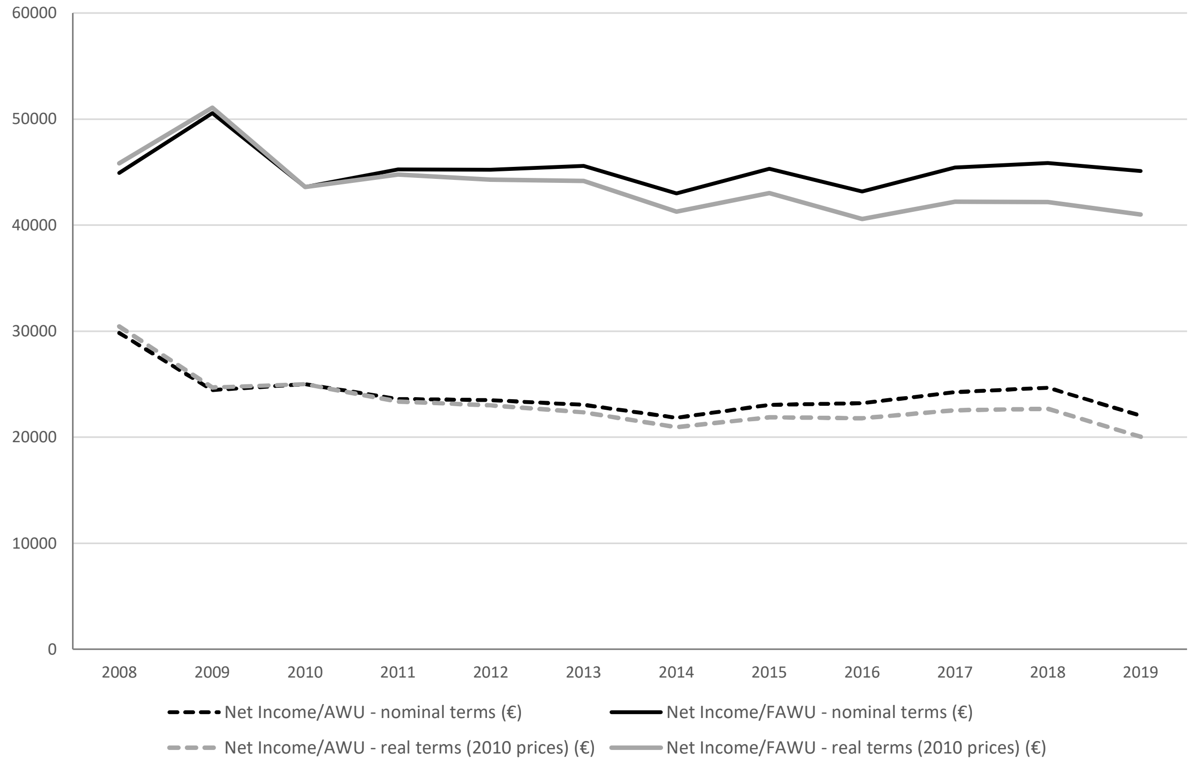


Figure 10 – Evolution of the presence of the female, young and organic farmers over the 2008-2019 period within the Italian FADN balanced sample.

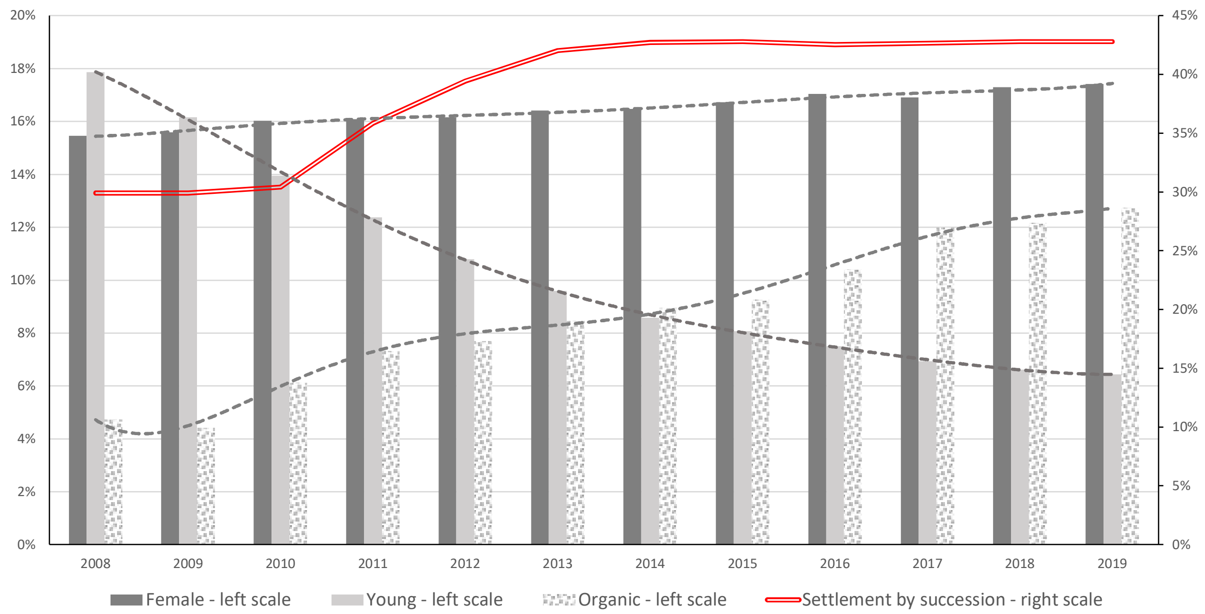
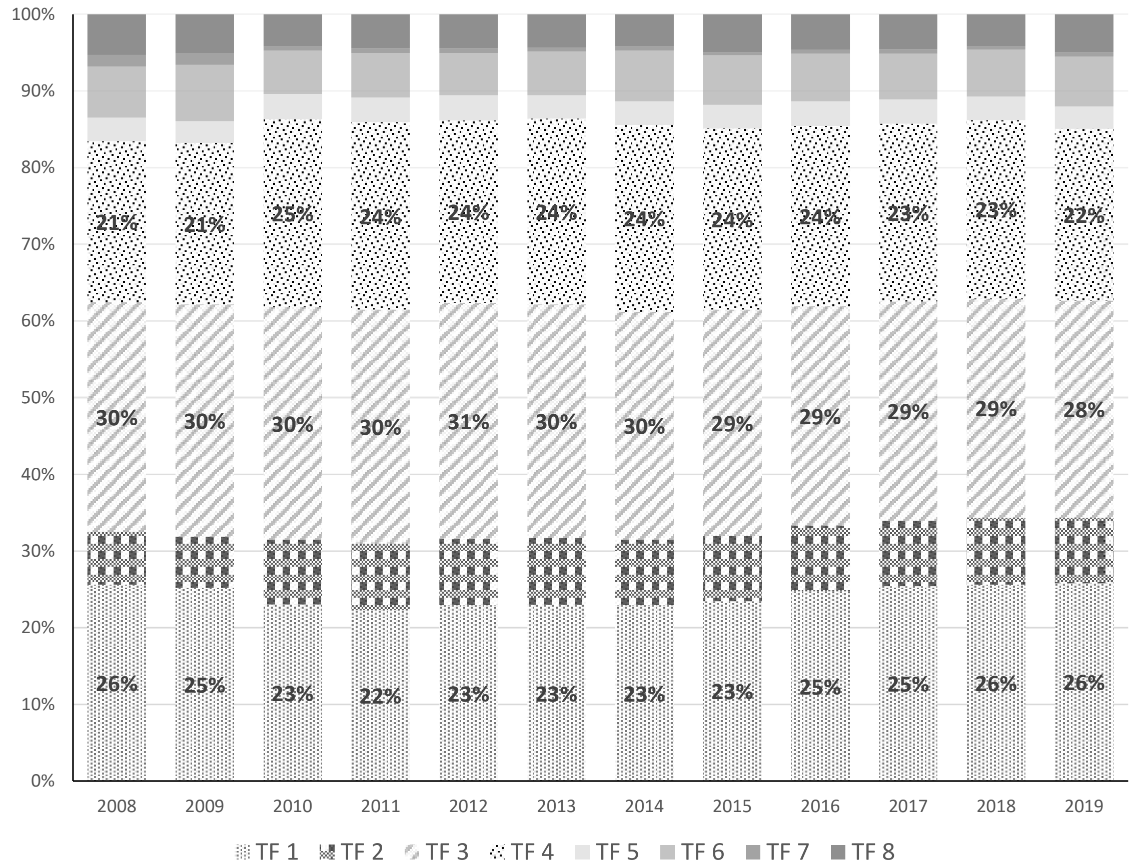


Figure 11 – Evolution of the Type-of-Farming (TF) categories over the 2008-2019 period within the Italian FADN balanced sample (% is indicated only for FT >10%,).



Legend: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

Figure 12 – Farms per number of TF changes over the 2008-2019 period within the Italian FADN balanced sample.

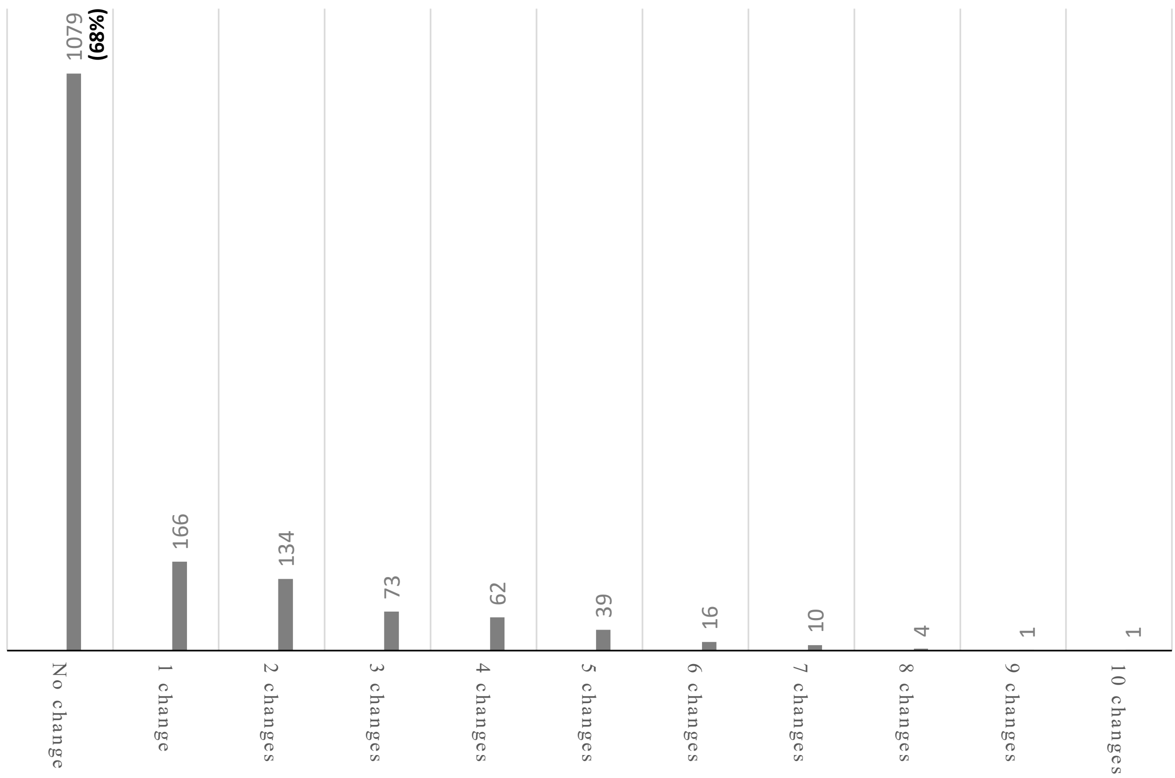


Figure 13 – Evolution of the farms and of the incidence on farm standard output of other gainful activities within the Italian FADN balanced sample.

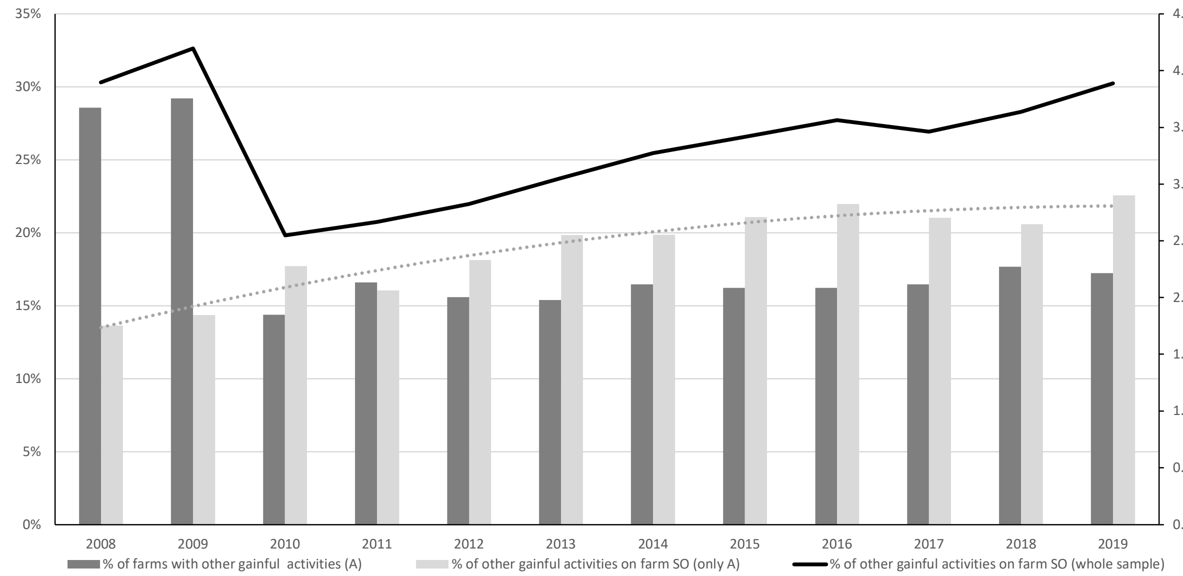


Figure 14 – CAP support and number of farms with CAP support > net income (included net income < 0) within the 2008-2019 Italian FADN balanced sample.

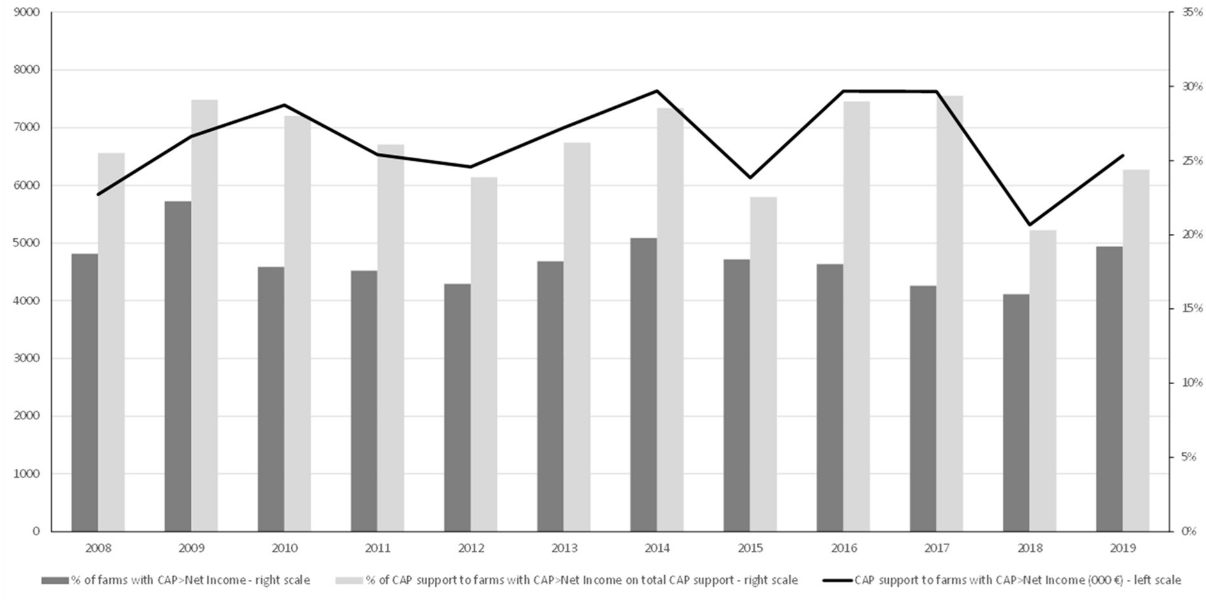


Figure 15 – Evolution of the average Shannon and Simpson diversity indexes within the Italian 2008-2019 FADN balanced sample.

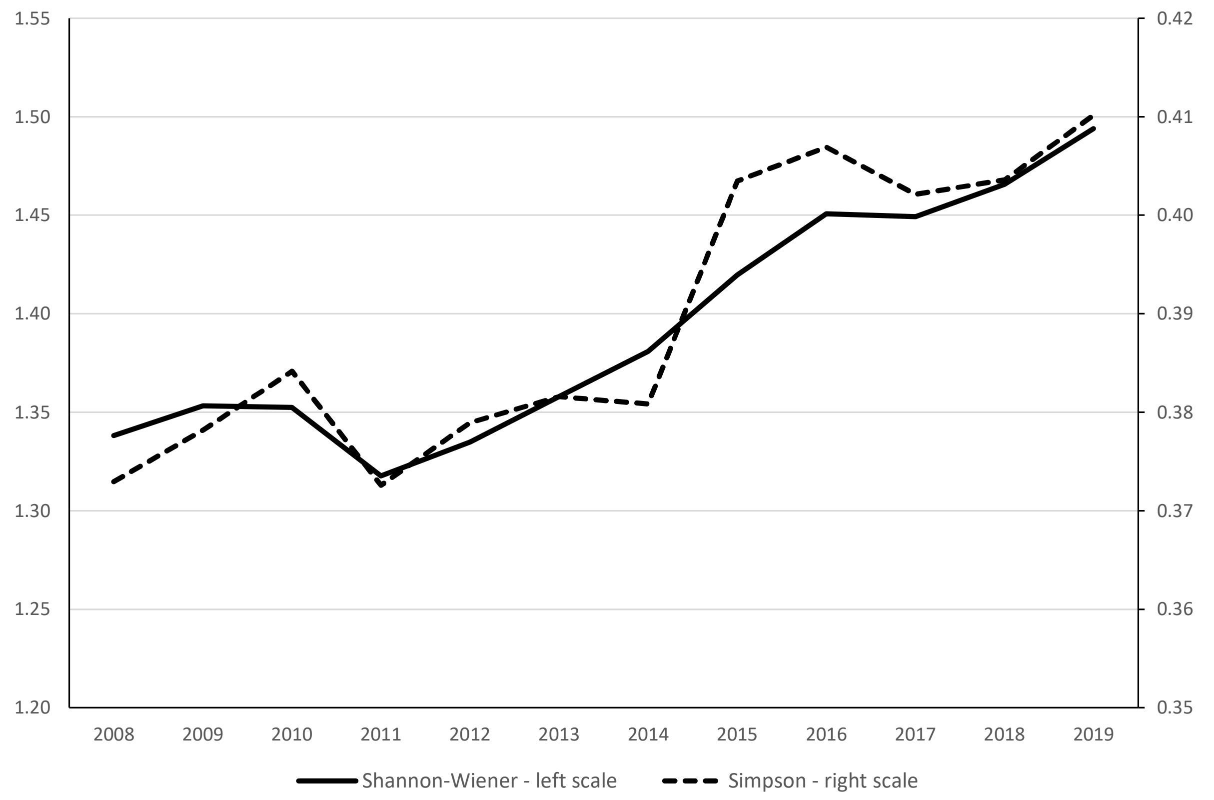


Figure 16 – Shannon and Simpson diversity indexes ordered by increasing values within he Italian 2008-2019 FADN balanced sample: years 2008 and 2019.

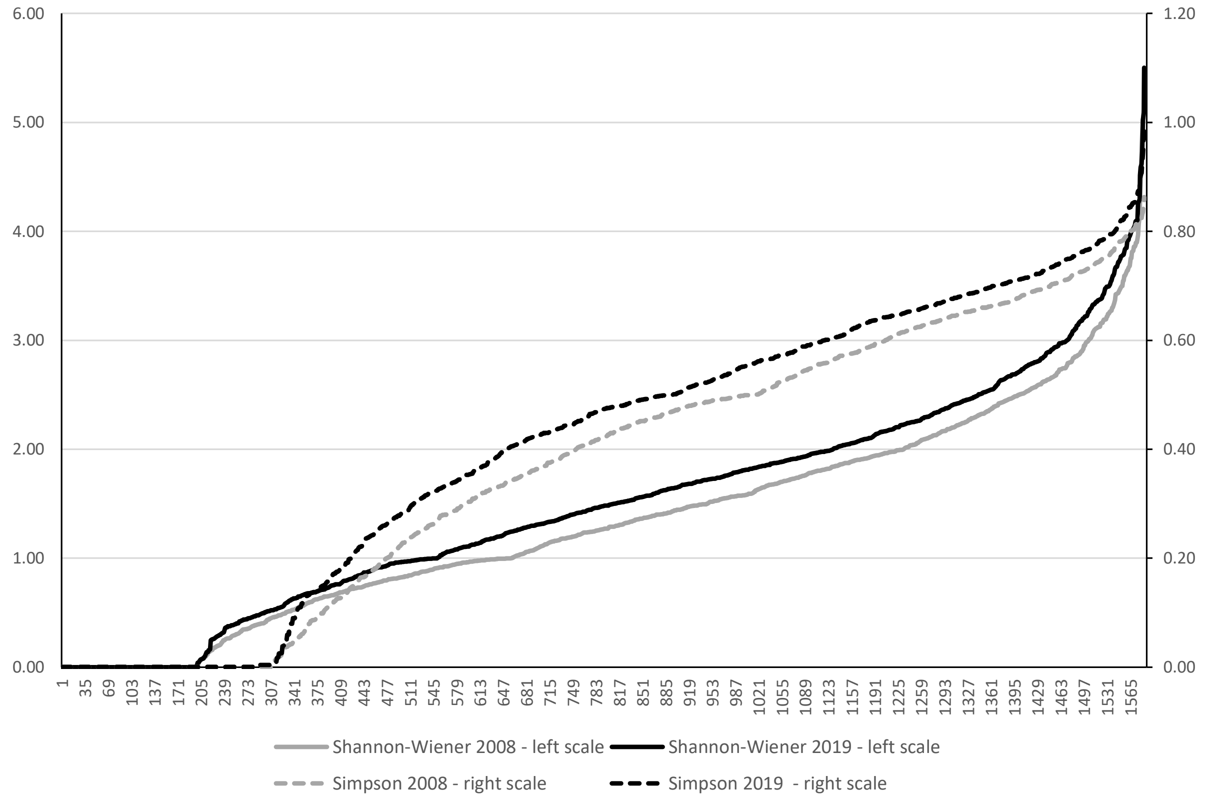
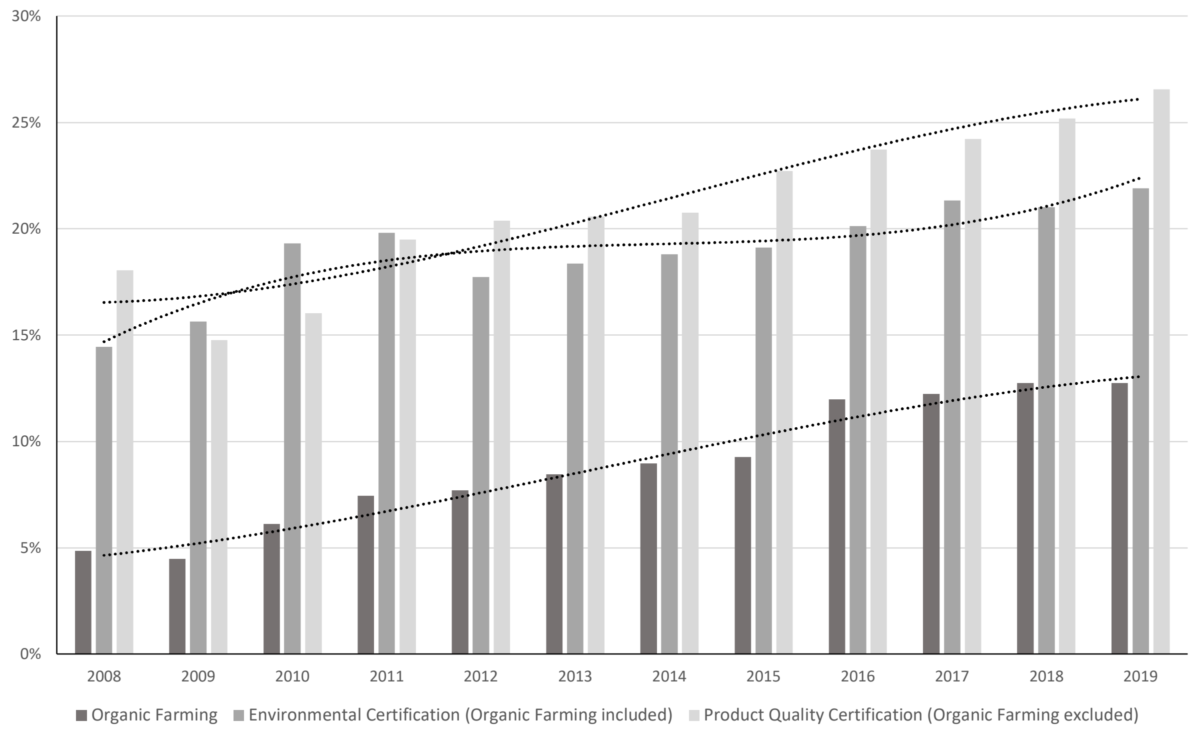


Figure 17 – Evolution of the share of farms with certifications within the Italian 2008-2019 FADN balanced sample.



References

Abadie, A. (2021). Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. *Journal of Economic Literature* 59(2): 391–425.

Arkhangelsky, D., Athey, S., Hirshberg, D.A., Imbens, G.W., Wager, S. (2021). Synthetic Difference-in-Differences. *American Economic Review* 111(12): 4088–4118

Anton, J. (2006). Modeling production response to 'more decoupled' payments. *Journal of Agricultural International Trade and Development* 2(1): 109–126.

ARC2020 (2020). CAP reform post 2020: lost in ambition? Final Report, Agricultural and Rural Convention, Brussels.

Athey, S., Imbens, G.W. (2017). The State of Applied Econometrics: Causality and Policy Evaluation. *Journal of Economic Perspectives* 31(2): 3–32.

Baldoni, E., Coderoni, S., Esposti, R. (2021). Immigrant workforce and agriculture productivity: Evidence from Italian farm-level data. European Review of Agricultural Economics 48 (4): 805–834.

Baldoni, E., Esposti, R. (2021). Agricultural Productivity in Space: an Econometric Assessment Based on Farm-Level Data. *American Journal of Agricultural Economics* 103(4): 1525-1544.

Cagliero, R., Cisilino, F. and Scardera, A. (2010). L'utilizzo Della RICA per la Valutazione di Programmi di Sviluppo Rurale. Roma: Rete Rurale Nazionale.

Callaway, B., Sant'Anna, P.H.C. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics* 225(2): 200-230.

Castaño, J., Blanco, M., Martinez, P. (2019). Reviewing Counterfactual Analyses to Assess Impacts of EU Rural Development Programmes: What Lessons Can Be Learned from the 2007–2013 Ex-Post Evaluations? *Sustainability* 11, 1105: 1-22.

Cattaneo, M.D. (2010). Efficient semiparametric estimation of multi-valued treatment effects under ignorability. *Journal of Econometrics* 155(2): 138–154.

Cattaneo, M.D., Drukker, D.M., Holland, A.D. (2013). Estimation of multivalued treatment effects under conditional independence. *The Stata Journal* 13(3): 407–450.

Cerulli, G. (2015). ctreatreg: command for fitting dose-response models under exogenous and endogenous treatment. *The Stata Journal* 15(4): 1019–1045.

Cerulli, G., Ventura, M. (2019). Estimation of pre- and posttreatment average treatment effects with binary time-varying treatment using Stata. *The Stata Journal* 19(3): 551-565.

Cerulli, G. (2019). TFDIFF: Stata module to compute pre- and post-treatment estimation of the Average Treatment Effect (ATE) with fixed binary treatment. Statistical Software Components, Boston College Department of Economics.

Chabé-Ferret, S. and Subervie, J. (2013). How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching. *Journal of Environmental Economics and Management* 65: 12–27.

Chan, M.K., Kwok, S.S. (2022). The PCDID approach: difference-in-differences when trends are potentially unparallel and stochastic. *Journal of Business & Economic Statistics* (forthcoming).

Cho, R., Desbordes, R., Eberhardt, M. (2022). Too Much Finance... For Whom? The Causal Effects of the Two Faces of Financial Development. CEPR Discussion Paper Series, DP17022, Centre for Economic Policy Research. London.

Coderoni, S., Helming, J., Pérez-Soba, M., Sckokai, P., Varacca, A. (2021). Key policy questions for ex-ate impact assessment of European agricultural and rural policies. *Environmental Research Letters* 16, 090444.

Coderoni, S., Esposti, R., Varacca, A. (2021). How differently do farms respond to agro-environmental policies? A Machine-Learning approach. Department of Agricultural and Food Economics, Università Cattolica del Sacro Cuore (Piacenza, Italy), unpublished manuscripts.

de Chaisemartin, C., D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. American Economic Review 110(9): 2964–2996

Dumangane, M., Freo, M., Granato, S., Lapatinas, A., Mazzarella, G. (2021). An Evaluation of the CAP impact: a Discrete policy mix analysis. EUR 30880 EN, Publications Office of the European Union, Luxembourg.

Erjavec, E. (2016). Back to the CAP's future: an interest- or evidence-based policy? CAP reform. 1 March 2016. http://capreform.eu/. Accessed on 1st April 2016.

Esposti, R. (2017a). The empirics of decoupling: Alternative estimation approaches of the farm-level production response. *European Review of Agricultural Economics* 44 (3): 499–537.

Esposti, R. (2017b). The heterogeneous farm-level impact of the 2005 CAP-first pillar reform: A multivalued treatment effect estimation. *Agricultural Economics* 48 (3): 373–386.

Esposti, R. (2022). Non-Monetary Motivations of Agro-Environmental Policies Adoption. A Causal Forest Approach. Quaderno di Ricerca n. 459, Dipartimento di Scienze Economiche e Sociali, Università Politecnica delle Marche.

Esposti, R., Sotte, F. (2013). Evaluating the Effectiveness of Agricultural and Rural Policies: An Introduction. *European Review of Agricultural Economics* 40(4): 535-539.

European Commission (2018a). Agricultural and farm income. Directorate-Generale for Agriculture and Rural Development, European Commission, Brussels.

European Commission (2018b). CAP explained Direct Payments for farmers 2015-2020. Directorate-Generale for Agriculture and Rural Development, European Commission, Brussels.

European Commission (2019). Analytical factsheet for Italy: Nine objectives for a future Common Agricultural Policy. Directorate-Generale for Agriculture and Rural Development, European Commission, Brussels.

European Commission (2021). Factsheet – a greener and fairer CAP. Directorate-Generale for Agriculture and Rural Development, European Commission, Brussels.

Frascarelli, A. (2020). Direct Payments between Income Support and Public Goods. *Italian Review of Agricultural Economics* 75(3): 25-32.

Frascarelli, A. (2021). Direct Payments between Income Support and Public Goods. *Italian Review of Agricultural Economics* 75(3): 25-32.

Giampaolo, A., Scardera, A., Carè, V. (2021). Le imprenditrici agricole. Una fotografia dei dati RICA. Rete Rurale Nazionale, *RRN Magazine*13: 26-29.

Hirano, K., Imbens, G. W. (2004). The propensity score with continuous treatment. In: A. Gelman and X. L. Meng, *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*. West Sussex: Wiley InterScience, 73–84.

Iacoponi, V. (2021). L'agricoltura delle donne. Rete Rurale Nazionale, *RRN Magazine*13: 7-10.

Imbens, G.W (2000). The Role of the Propensity Score in Estimating Dose-Response Functions. *Biometrika* 87(3): 706–710.

Imbens, G.W., Rubin, D.B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Imbens, G.W., Wooldridge, J.M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* 47(1): 5–86.

Janssen, S., Louhichi, K., Kanellopoulos, A., Zander, P., Flichman, G., Hengsdijk, H., Meuter, E., Andersen, E., Belhouchette, H., Blanco, M. Borkowski, N., Heckelei, T., Hecker, M., Li, H., Oude Lansink, A., Stokstad, G., Thorne, P., van Keulen, H., van Ittersum, M.K., (2010). A Generic Bio-Economic Farm Model for Environmental and Economic Assessment of Agricultural Systems. *Environmental Management* 46: 862–877.

Khagram, S., Thomas, C.W. (2010). Toward a Platinum Standard for Evidence-Based Assessment. *Public Administration Review*. Supplement to Vol. 70: S100-S106.

Keylock, C.J. (2005), Simpson diversity and the Shannon–Wiener index as special cases of a generalized entropy. *Oikos* 109: 203-207.

Koch, B., Vock, D.M., Wolfson, J. (2018). Covariate selection with group lasso and doubly robust estimation of causal effects. *Biometrics* 74: 8–17.

Kolak M, Anselin L. (2020). A Spatial Perspective on the Econometrics of Program Evaluation. *International Regional Science Review* 43(1-2):128-153.

Knaus, M.C., Lechner, M., Strittmatter, A. (2021). Machine learning estimation of heterogeneous causal effects: Empirical Monte Carlo evidence. *The Econometrics Journal* 24 (1): 134–161.

Lassance, A. (2020). What Is a Policy and What Is a Government Program? A Simple Question With No Clear Answer, Until Now. Social-Science Research Network (SSRN), https://ssrn.com/abstract=3727996 or http://dx.doi.org/10.2139/ssrn.3727996. Accessed on 31st December 2021.

Latacz-Lohmann, U., Balmann, A., Birner, R., Christen, O., Gauly, M., Grethe, H., Grajewski, R., Martínez, J., Nieberg, H., Pischetsrieder, M., Renner, B., Röder, N., Schmid, J.C., Spiller, A., Taub, F., Voget-Kleschin, L., Weingarten, P. (2019). Designing an effective agri-environment-climate policy as part of the post-2020 EU Common Agricultural Policy. Berichte über Landwirtschaft, Sonderheft 227.

Lillemets, J., Fertő, I., Viira, A-H (2022). The socioeconomic impacts of the CAP: Systematic literature review. *Land Use Policy* 114, 105968.

Lobianco, A. and Esposti, R. (2010). The Regional Multi-Agent Simulator (RegMAS): an open-source spatially explicit model to assess the impact of agricultural policies. *Computers and Electronics in Agriculture* 72(1): 15–26.

Mack, G., Ferjani, A., Möhring, A., von Ow, A., Mann, S. (2019). How did farmers act? Ex-post validation of linear and positive mathematical programming approaches for farm-level models implemented in an agent-based agricultural sector model. *Bio-based and Applied Economics* 8(1): 3-19.

Matthews, A. (2021). The contribution of research to agricultural policy in Europe. *Bio-based and Applied Economics* 10(3): 185-205.

OECD (2011). Evaluation of Agricultural Policy Reforms in the European Union. Paris: OECD Publishing.

Perraillon, M.C., Lindrooth, R.M., Hedeker, D. (2022). *Health Services Research and Program Evaluation: Causal Inference and Estimation*. Cambridge University Press (forthcoming).

Pupo D'Andrea, M.R. (2021). Le novità della PAC 2023-2027. *Agriregionieuropa*, Numero Speciale - Agricalabriaeuropa n. 1, 2-6.

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology* 66(5): 688–701.

Sahrbacher, C., Kellermann, K., Balmann, A. (2008). Winners and Losers of Policy Changes – What Is the Role of Structural Change? Paper presented at the 107th EAAE Seminar, European Association of Agricultural Economists, January 30-February 1, Sevilla, Spain.

Selmi, U. (2021). Parità di genere e agricoltura, il modello è la multifunzionalità. Rete Rurale Nazionale, *RRN Magazine*13: 17-20.

Sotte, F. (2006). Imprese e non-imprese nell'agricoltura Italiana. *Politica Agricola Internazionale* 1/2006: 13–30.

Sotte, F. (2014). La geografia della nuova PAC in Italia. *Agriregionieuropa* 38: 11-15.

Sotte, F. (2021a). Riflessioni sulla futura politica agricola europea. *Agriregionieuropa*, Numero Speciale - Agricalabriaeuropa n. 1, 7-11.

Sotte, F. (2021b). La politica agricola europea. Storia e analisi. *Collana Economia Applicata,* Agriregionieuropa - Associazione Alessandro Bartola, Ancona.

Sotte, F. and Arzeni, A. (2013). Imprese e non-imprese nell'agricoltura italiana. *AgriRegioniEuropa* 32: 65–70.

Stata (2021). Treatment-effects estimation using lasso. New in STATA 17, StataCorp LLC, https://www.stata.com/new-in-stata/causal-inference-treatment-effects-lasso/. Accessed on 31st December 2021.

Sun, L., Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics 225: 175–199

Symbola (2016). GreenItaly. Rapporto 2016. Una risposta alla crisi, una sfida per il futuro. Unioncamere — Fondazione Symbola, Roma.

Terluin, I., Verhoog, D. (2018). Distribution of CAP pillar 1 payments to farmers in the EU. Wageningen University & Research, Wageningen Economic Research report 2018-039b.