BAE
Bio-based and Applied Economics

AIEAA
ASSOCIAZIONE ITALIANA DI ECONOMIA AGRARIA E APPLICATA

OPEN ACCESS

Citation: R. Esposti (2022). The co-evolution of policy support and farmers behaviour. An investigation on Italian agriculture over the 2008-2019 period. *Bio-based and Applied Economics* 11(3): 231-264. doi: 10.36253/bae-12912

Received: March 17, 2022
Accepted: September 7, 2022
Published: November 4, 2022

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Davide Menozzi.

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The co-evolution of policy support and farmers behaviour. An investigation on Italian agriculture over the 2008-2019 period

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Abstract. This paper investigates the co-evolution of the CAP expenditure and of the farms' performance and choices to assess whether and to what extent CAP assessment itself meets the requisites of Causal Inference. In order to identify some regularities in this co-evolution, the analysis is performed on a constant group of professional farms over a long enough time period. The Italian 2008-2019 FADN balanced sample is here considered. Results points to two major empirical implications. First of all, they question whether CAP expenditure is actually accompanied by any significant farmers' response. An exception may actually concern the support specifically focused on environmental standards. Secondly, they raises some major methodological issues about the applicability of the Treatment Effect logic to CAP assessment.

Keywords: Common Agricultural Policy, Farmers' Behaviour, Program Evaluation, Panel Data, Co-evolution.
JEL Codes: Q18, D04.

"Verum scire est scire per causas"

1. INTRODUCTION: TWO TOPICS, ONE OBJECTIVE

This paper deals with two distinct research topics and aims to join them into a unique research objective. The first topic consists in analysing the evolution of the Common Agricultural Policy (CAP) support, of the farmers' production choices and of their possible interdependence (henceforth, the *co-evolution*). The second topic has to do with the growing use of the so-called Program Evaluation Methods (PEM) (Imbens and Wooldridge, 2009) in assessing the impact of the CAP, its measures and reforms, on the farming activity (Dumangane *et al.*, 2021). The research objective that brings these two topics together is understanding whether and under which conditions investigating the farms' response to CAP support can be performed with the cause-effect logic implied by these PEM.

PEM have progressively emerged as the application of the general principles of Causal Inference (CI) to the assessment of public policies (Imbens

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and Rubin, 2015; Perraillon *et al.*, 2022). These methods are thus grounded on sound statistical concepts but, at the same time, they imply specific preconditions for an appropriate application to policy assessment (Khagram and Thomas, 2010). The bottom line is that an unambiguous cause-effect direction must occur between a well-defined policy measure (the *Treatment*) and a well-defined response (the *Treatment Effect*, or TE).

Such a direction (TE logic, henceforth) can be obviously assumed but it is not necessarily a good representation of the world especially in the case of many CAP measures. In particular, a correlation between some CAP measures (or reforms) and farmers' behaviour does not automatically make the latter a response to the policy. Not only because, as well known, correlation is not causation (Angrist and Pischke, 2009). More importantly, as stressed by the literature on the political economy applied to the CAP decision making process (Swinnen, 2015; Collantes, 2020), a potential endogeneity may occur within this process. The main aftermath of such endogenous relationship is that CAP and farmer's behaviour rather co-evolve, so the observed correlation might express a cause-effect relationship whose direction, in fact, is not clearly identifiable.

It follows that this paper is an empirical work but it is not an empirical application of some PEM to some CAP assessment. The empirical analysis rather aims to investigate the extent and nature of the abovementioned co-evolution in order to assess whether and how it is compatible with the application of the TE logic. The main research question underlying this study is thus the following: which empirical support do we really have to interpret farmers' behaviour as a response to CAP measures and, thus, to consistently and properly apply the TE logic to CAP assessment?

To answer these questions, the invariance of the field of investigation must be granted: a constant group (i.e., a balanced panel) of heterogeneous enough professional farms followed in its evolution over time together with the different CAP support they are recipients of. 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 abovementioned logic of the study also justifies its structure. 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. Sections 4 examines the evolution of both CAP support and farms' production choices and performance. Then, section 5 presents the co-evolution hypothesis by connecting these two dynamics and wondering to what extent one can be considered a response to the other. Section 6 derives the main consequences of this co-evolution in terms of the methodological challenges in adopting the TE logic in this field. Section 7 concludes drawing some methodological 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 remains 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 really worth to adopt a TE logic (Coderoni, Esposti and Varacca, 2021). In particular, the CAP presents three major problematic features in this respect.

First, CAP 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

[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).

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).[3]

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 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 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.[4] 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 seem to actually co-evolve.[5]

The nature of the CAP as an all-encompassing policy is not, *per se*, at odds with an evidence-based design and implementation (Esposti and Sotte, 2013; Erjavec and Erjavec, 2015; Erjavec, 2016; Ehlers *et al.*, 2021). 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 (period 2023-2027), it seems useful to limit this 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). It can be argued that these reform steps share the same three fundamental objectives (Frascarelli, 2020, 2021; Coderoni *et al.*, 2021): farm income support (or protection); farm competitiveness through (more) market orientation, i.e., (more) product diversification; larger and better public (mostly environmental) good provision by farms.[6]

In Italy, the decoupling of I Pillar support (the so-called Fischler Reform) was firstly introduced in 2005. 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

[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. It remains 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.

[3] There may be significant exceptions to this conclusion due to large heterogeneity of agricultural systems across EU and Italy. For instance, in farming systems showing the prevalence of monoculture the introduction of green payments, and the consequent compliance, had a relevant impact on farmers' choices and behaviour (Bertoni *et al.*, 2018; 2021).

[4] 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.

[5] This is the empirical counterpart of the political economy argument on the endogeneity of the CAP (Swinnen *et al.*, 2015) which suggests that its design may depend on farmers' choices and behaviour more than the other way round.

[6] 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. In fact, 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 investigation 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.

in terms of a 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; Ciliberti *et al.*, 2022). Also II Pillar had to facilitate market re-orientation (and structural change) and, at the same time, the environmental goods 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 not have generated a major impact.[7]

A lot of research work has been done in order to directly investigate, simulate, estimate the impact of these CAP reform steps 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.

Eventually, the problem is the lack of a counterfactual evidence. In most of these studies the counterfactuals are never observed, and they might not even exist, but the counterfactual case is just extrapolated from the estimated models parameters. The search of such counterfactual evidence may explain the emergence, in the last fifteen years, of a consistent body of empirical studies whose aim is to explicitly assess the CAP impact within a TE logic (just to mention a few: Chabé-Ferret and Subervie, 2013; Castaño *et al.*, 2019; Coderoni, Esposti and Varacca, 2021; Ciliberti *et al.*, 2022; Esposti 2017a,b, 2022). This research effort is commendable and promising. As mentioned, however, the actual characteristics of the CAP and of its reforms do not necessarily fit the strict requirements of this TE logic. In most of these recent studies its suitability for CAP assessment is given for granted and never really questioned. In principle, preliminary to any TE investigation, it would be desirable to scrutinize the empirical support about the applicability of this logic to the three abovementioned key objectives. Looking for this empirical support is the main purpose of the present study.

3. THE DATA: 2008-2019 FADN ITALIAN BALANCED SAMPLE

Another major issue in the investigation of farms' responsiveness and co-evolution with respect to CAP measures concerns the field of investigation. Several previous studies work on all farms, but this can introduce a bias as their response may be not fully observable for the presence of many very small farms (even "non-farms") (Sotte, 2006; Sotte and Arzeni, 2013) and may be also driven by long-term structural processes that are largely independent on the CAP support. A further limitation of the field of investigation 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' co-evolution or response is significantly revealed by data.

Here, we focus on a sample that take these issues into account: the Italian 2008-2019 FADN balanced panel.[8] A constant field of observation is clearly needed to investigate the co-evolution of the CAP support a farmers choice in order to get rid of the spurious effects simply generated by the change in the sample composition. This choice, however, may also have limitations and two of them are worth noticing here. The first limitation is that working on the FADN sample may miss some of the

[7] Studies on the distribution of the CAP support across regions and farms (see Sotte, 2014, and Terluin and Verhoog, 2018, to mention a few) have mostly concluded that the beneficiaries and the allocation among them did not change significantly over time. This can be considered an implicit demonstration that the (reform of the) CAP might not have had an effect. But this is not obvious. Maintaining the distribution of support but changing the forms and modalities may still induce a response.

[8] This balanced panel consists of 1585 farms observed over 12 years, thus 19020 total observations. 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. The choice of working with a balanced panel 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 investigation (European Commission, 2019).

implications of CAP and its reforms as changes occurring in non-professional farms, numerically prevalent in the Italian context (Sotte, 2006; Sotte and Arzeni, 2013), remain unobserved as these units are excluded from the FADN field of survey. Structural changes may be also missing in the balanced panel. 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 three CAP objectives here considered.

The second limitation concerns the possible lack of representativeness of the adopted balanced panel with respect to whole Italian agriculture even when only professional farms are considered (Mari, 2020; Vrolijk and Poppe, 2021).[9] Representativeness is evidently sacrificed when a balanced panel is extracted over a long-enough period since the FADN sample is rotating just in order to maintain representativeness over time. It is thus informative to make explicit how much the adopted dataset may over or under-represent some farms category compared to the whole Italian agriculture. Table A1 in the Annex compares the distribution of farms by Type of Farming (TF) and Economic Size class (ES) in the adopted sample (in year 2010) with the Italian 2010 agricultural Census.[10] For the sake of comparison, Census data are reported in two forms: the whole farm population and the population corresponding to the FADN field of survey, that is farms with a Standard Output (SO) higher than 8 thousand € (also called professional or market-oriented farms).[11]

It firstly emerges that the FADN sample always somehow misrepresents the whole Italian agriculture as about 63% of the farm population is excluded from the FADN field of survey. But limiting the attention to professional farms, the distribution of farms within the balanced FADN panel in terms of TF does not differ much from what observed in the Census data, even though a slight over-representation of grazing livestock activities (TF4) and under-representation of permanent crop farms (TF4) is observed. A more important bias concerns the ES as the balanced panel evidently self-select larger farms, in economic terms. This bias has to be taken in mind in commenting the following results and any generalization to the whole Italian agriculture requires caution.

However, it is worth stressing here that there is no feasible solution to this representativeness issue whenever a balanced FADN panel is adopted.[12] Even the vector of individual weights that accompany the FADN sample cannot be helpful in this respect. These weights allow to carry over the sample-level evidence to the population, at least for those dimensions for which the FADN sample is representative (Mari, 2020). Therefore, weights are useful to compute population-level aggregates, given representativeness, but it is not suitable to recreate this representativeness. Moreover, these weights refer to the whole FADN sample and not to the balanced FADN sample. They also vary any year and have to be redefined any time the underlying sampling scheme is changed as occurred, in particular, with the change of the professional farm threshold in Italy in 2014 and with the change of the TF classification in 2010. Applying these weights to the balanced panel over 12 years would incur the risk of generating an uncontrollable distortion rather than correcting for an observed misrepresentation.

Considering that working on a constant sample is a strict condition to properly investigate the co-evolution of CAP support and farms' behaviour, we prefer here to sacrifice representativeness rather than to generate artefacts in the attempt to correct for it. Also because representativeness is not a major concern with the respect of the major objective of the present paper. Evidently, any policy conclusion based on these data should be taken with major caution (Vrolijk and Poppe, 2021, p.10). But the main interest, here, is rather on the methodological implications of the co-evolution of CAP support and farms' behaviour. It may be the case that such co-evolution does not perfectly correspond to what observed in the whole Italian agriculture and may slightly overvalue the incidence of the outliers (in particular, farms with very high payments).[13] However, evidence here reported remains valid within the adopted field of investigation and, more importantly, with respect to its main methodological implications.

Within this sample, the empirical analysis is developed in a sequence of three steps. First, the evolution of the CAP support and of its distribution is investigated, considering both its total amount and its components (section 4.1). Then, the evolution of the farmers' choic-

[9] We wish to thank two anonymous referees for their helpful suggestions and remarks on this aspect.

[10] Together with the geographical district (regions in Italy), these are the two levels for which the representativeness of the FADN sample is granted (Mari, 2020).

[11] In Italy, this threshold was 4 thousand € up to 2014.

[12] In any case, it has been already noticed that also within the Italian FADN sample the full representativeness on the three abovementioned dimensions is more theoretical than actual (Mari, 2020, Tables 2 and 3).

[13] In the present case, however, what could be considered outliers are actually real farms. They might be peculiar and, for this reason, they are recipients of a very high CAP support. But this does not mean that they represent anomalous or aberrant cases.

es and performance is analysed (section 4.2). Finally, some stylised facts about the co-evolution of these two dynamics are derived (section 5).

4. THE EVOLUTION OF THE CAP SUPPORT AND FARMS' BEHAVIOUR

4.1. CAP support

The first question to be answered is whether the CAP support actually changed within the adopted field of investigation and how. Figure 1 displays the total and per farm public support considering all the possible sources.[14] 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).[15] Consequently, the per farm 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 CAP support. It evolved as a combination of three dynamics:

1. I Pillar declined by 4% and II Pillar grew by 156% and this has made the share of I Pillar and II Pillar be gradually re-equilibrated with the latter moving from a 13% to 29% of total CAP support.

2. Within I Pillar, decoupled support remained stable (-0.4%) while coupled payments declined by -20% up to a final 15% in 2019 on total Pillar I payments (corresponding to 11% on total CAP support). The process of progressive decoupling of support actually stopped in 2012 since for the rest of period the shares of coupled and decoupled support remained quite stable.

3. Within II Pillar, the largest growth concerns AEM payments (+196%) while the other measures increased by 124% with AEM support passing from a share of 44% on the total II Pillar support in 2008 to 51% in 2019. The huge growth and the increasing relevance of the AEM support is investigated further in the Annex (Figure A1).

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. 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 sample. 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 than the mean value as indicated by a greater than two Coefficient of Variation (CV). Moreover, the left tail of the distribution being truncated at 0, the presence of several extreme values generates 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.

High variability and asymmetry is observed in all the different policies but some specificities are worth noticing. In particular, both coupled I Pillar payments and non-AEM II Pillar payments show very high CV values. 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.[16] 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 are significantly lower than in the single components.

This apparent stability of the CAP support distribution over time does not mean that from any individual farm perspective nothing changed. By looking at the single farm percentage variation of the received support 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 is 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

[14] Regional co-financing of II Pillar is included in CAP support. The remaining national support represents a very marginal part, always lower than 5%. For this reason, the national support will be neglected in the rest of the analysis.

[15] Following Matthews (2000), real values are computed using the official Italian GDP deflator released by the National Institute of Statistics (ISTAT).

[16] 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.

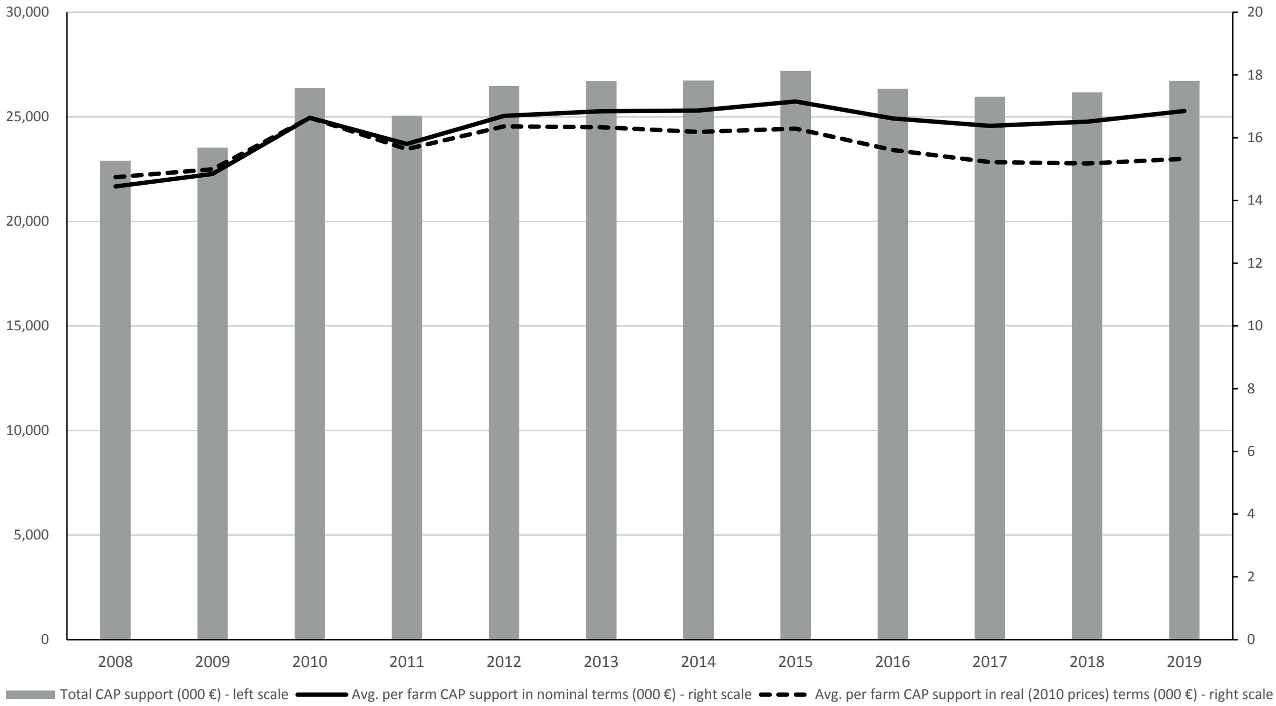

Figure 1. Total and per farm public support within the Italian 2008-2019 FADN balanced sample.

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.

4.2. Farms' behaviour

4.2.1. Profitability

In order to assess whether or not this CAP evolution had any relevant impact on farms' performance and choices, the first question to be answered concerns farms' profitability. Here we proxy the farm's profit with the farm's net income simply computed as revenue plus policy support less all costs.[17] Therefore, in order to investigate the evolution of farms' profitability it is worth to analyse the evolution of its components. Figure 3 displays the dynamics of the average revenue and variable costs within the field of investigation. A selection of these costs is also shown. They concern what we design here as environment-using costs: fertilizers, pesticides (herbicides included), energy and water.

It firstly emerges a regular increase of both revenue and costs, 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 4 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,

[17] In the FADN terminology what is here referred to as Net Income corresponds to the Entrepreneurial Income. As most agricultural production units are family farms, this also corresponds, for many units, to the Family Farm Income (European Commission, 2018a). The difference between net farm income and farm profit is that the former is defined as farm revenue, plus policy support, less all external costs; the latter as the difference between net farm income and the opportunity cost of factors of production (labour, land and capital) provided by the family farm. We wish to thank an anonymous referee for an helpful clarification on this point.

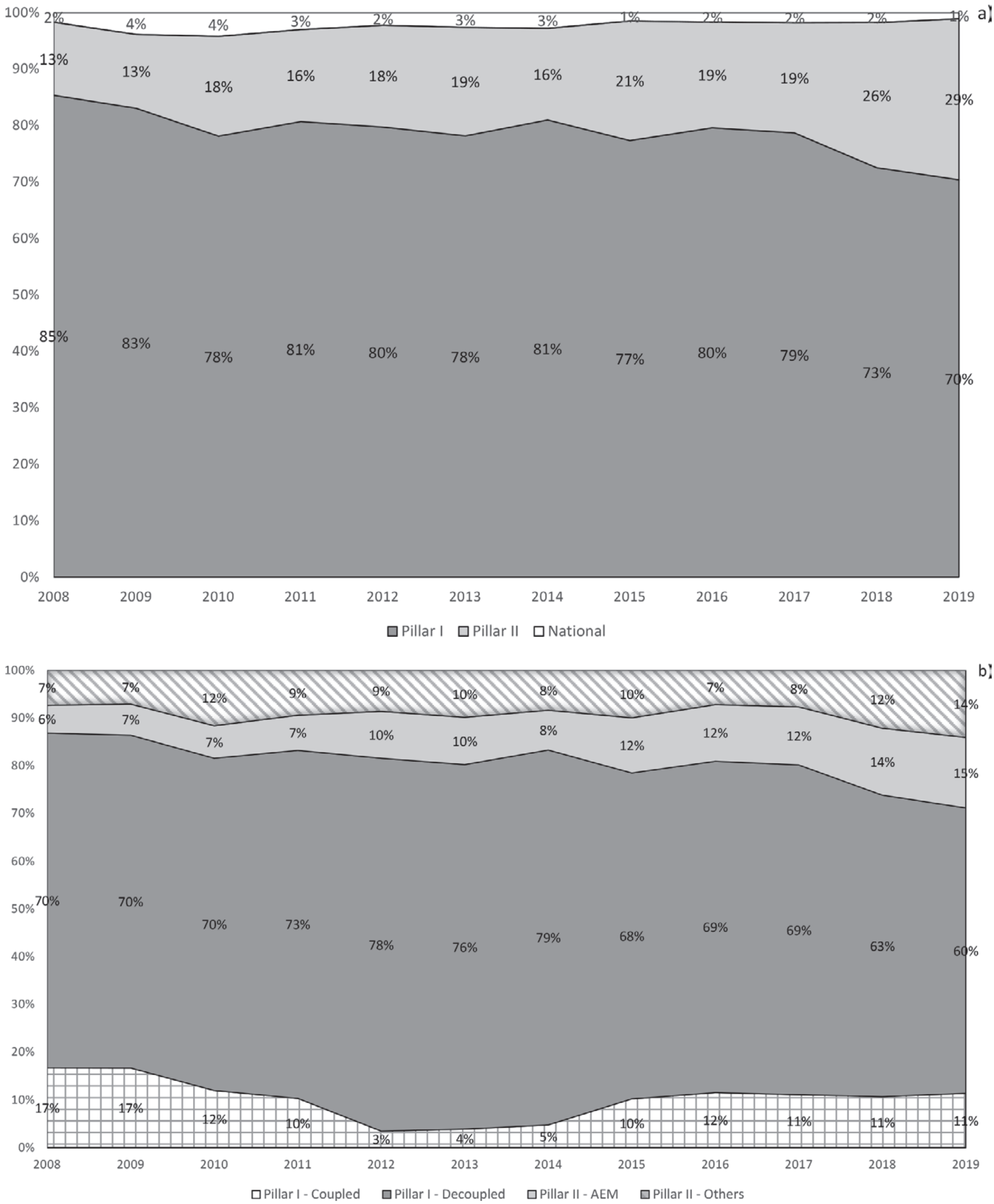

Figure 2. Composition of the total public (a) and CAP (b) support within the Italian 2008-2019 FADN balanced sample.

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	14,449	14,848	16,642	15,802	16,700	16,846	16,870	17,158	16,614	16,381	16,510	16,856
Standard deviation	31,844	31,258	41,230	38,001	39,722	38,967	42,899	42,205	41,005	40,174	36,552	34,645
Coefficient of Variation	2.2	2.1	2.5	2.4	2.4	2.3	2.5	2.5	2.5	2.5	2.2	2.1
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	755	1,014	1,666	1,860	1,924	1,844	1,904	1,508	1,501	1,532	1,804	2,325
2nd Quartile (Median)	5,065	5,498	5,920	6,341	6,545	6,536	6,329	6,470	5,941	6,185	6,449	6,826
3rd Quartile	14,824	15,904	17,100	16,878	17,634	17,607	17,431	18,625	17,807	16,971	17,813	18,489
Max	420,574	505,280	859,158	834,940	737,493	720,471	894,886	1,158,547	972,158	911,073	834,179	756,761
NATIONAL SUPPORT												
Mean	245	573	708	473	373	437	469	255	276	294	296	185
Standard deviation	1,883	4,874	8,621	4,410	3,126	3,396	4,983	2,219	2,408	2,233	1,974	2,379
Coefficient of Variation	7.7	8.5	12.2	9.3	8.4	7.8	10.6	8.7	8.7	7.6	6.7	12.9
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	32,072	102,854	213,984	119,430	66,942	69,493	145,670	60,900	56,491	59,487	36,800	74,000
TOTAL CAP												
Mean	14,204	14,275	16,106	15,329	16,327	16,410	16,401	16,903	16,338	15,753	16,286	16,599
Standard deviation	31,763	30,850	38,511	37,724	39,512	38,714	42,579	42,135	40,897	37,516	36,501	34,463
Coefficient of Variation	2.2	2.2	2.4	2.5	2.4	2.4	2.6	2.5	2.5	2.4	2.2	2.1
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	724	947	1,622	1,840	1,892	1,750	1,814	1,491	1,461	1,497	1,770	2,286
2nd Quartile (Median)	4,957	5,144	6,395	6,125	6,478	6,325	6,130	6,340	5,727	5,955	6,257	6,701
3rd Quartile	14,611	15,320	17,745	15,969	17,132	17,157	16,961	18,337	17,253	16,514	17,417	18,245
Max	420,574	505,280	805,154	834,940	737,493	717,971	894,886	1,158,547	972,158	911,073	834,179	752,234
PILLAR I - DECOUPLED												
Mean	9,961	9,954	11,211	11,178	12,750	12,536	12,886	11,541	11,340	10,883	10,291	9,922
Standard deviation	21,774	21,001	33,082	31,119	35,614	34,153	36,599	32,735	30,054	26,924	24,078	21,307
Coefficient of Variation	2.2	2.1	3.0	2.8	2.8	2.7	2.8	2.8	2.7	2.5	2.3	2.1
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	98	215	507	768	886	830	878	739	925	1,028	1,204	1,242
2nd Quartile (Median)	3,477	3,483	4,015	4,199	4,231	4,171	4,068	3,568	3,614	3,644	3,682	3,830
3rd Quartile	10,715	10,992	11,718	11,772	12,412	12,095	12,179	11,040	11,008	10,519	10,445	10,378
Max	317,849	319,288	801,933	724,970	720,596	680,898	759,890	862,371	631,221	558,244	528,809	417,296
PILLAR I – COUPLED												
Mean	2,374	2,380	1,923	1,577	567	631	776	1,726	1,883	1,744	1,736	1,889
Standard deviation	11,566	12,675	8,401	8,003	3,357	3,786	5,307	8,515	9,999	10,320	8,860	9,275
Coefficient of Variation	4.9	5.3	4.4	5.1	5.9	6.0	6.8	4.9	5.3	4.9	5.1	4.9
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	1,087	1,034	1,221	1,120
Max	237,355	340,652	122,828	124,584	90,000	108,794	134,996	293,872	338,633	352,829	305,370	312,498
PILLAR II – AEM												
Mean	826	931	1,100	1,127	1,602	1,620	1,366	1,946	1,940	1,917	2,279	2,450
Standard deviation	2,991	3,300	4,132	4,430	5,390	5,585	5,043	6,552	6,674	6,555	7,528	7,862

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Coefficient of Variation	3.6	3.5	3.8	3.9	3.4	3.4	3.7	3.4	3.4	3.4	3.3	3.2
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	1,401
Max	38,115	51,974	77,603	77,603	77,598	99,500	100,000	73,863	77,341	92,541	92,541	120,010
PILLAR II – OTHERS												
Mean	1,043	1,010	1,872	1,447	1,408	1,622	1,373	1,690	1,175	1,208	1,980	2,339
Standard deviation	6,853	5,388	8,962	7,567	8,536	8,343	7,605	7,330	5,035	4,720	8,287	7,854
Coefficient of Variation	6.6	5.3	4.8	5.2	6.1	5.1	5.5	4.3	4.3	3.9	4.2	3.4
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	1,047	1,860
Max	184,212	140,000	133,700	149,093	240,000	215,000	240,000	110,000	87,000	83,265	176,513	161,758
% Variation CAP support (2019-2008)		Min		1st Quartile		2nd Quartile		3rd Quartile		Max		
		-100%		-19%		+30%		+370%		-		

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.[18]

More generally, average values may be uninformative, and even misleading, due to the large heterogeneity occurring within the panel as also detailed in the Annex (Figure A3). Table 2 illustrates how during these twelve years the farm net income dispersion and asymmetry maintained the same basic features with no major evidence of a more uniform distribution. Such large dispersion is confirmed by a CV always around two or more, though it also shows a 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).

4.2.2. 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 investigation. 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 5 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 (2008=1). 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

[18] A classical issue in the analysis of farm profitability concerns whether the farming activity can grant agricultural workers and families a comparable income with respect to the rest of the economy. This issue has generated a long debate among agricultural economists, particularly in Italy (Rocchi *et al.*, 2012). Present results may provide some indication in this respect even though, as discussed, the net farm income here considered does not correspond, *stricu sensu*, to the family farm income for all units. In addition, as discussed, the adopted sample only consider commercial farms and tends to be biased upward, i.e., to have a little overrepresentation of larger farms in economic terms. Nonetheless, for the sake of comparison, it can be noticed that the mean net farm income in the last year of observation (51,440 €) is significantly higher than the average family income resulting, for the same year, from the Italian Statistics on Income and Living Conditions (SILC) (33,653 €). This remains true even when only families with prevalent autonomous work are considered (42,340 €). However, it should be also noticed that this positive gap can be a further consequence of the asymmetry within the sample. If the median net farm income is considered (23,154 €) the gap seems to be actually reversed. Moreover, while the average (or median) net farm income observed within the sample shows a decline in real terms over the period under analysis, the average real-term family income resulting from the SILC data show a very slight increase (+0.4%).

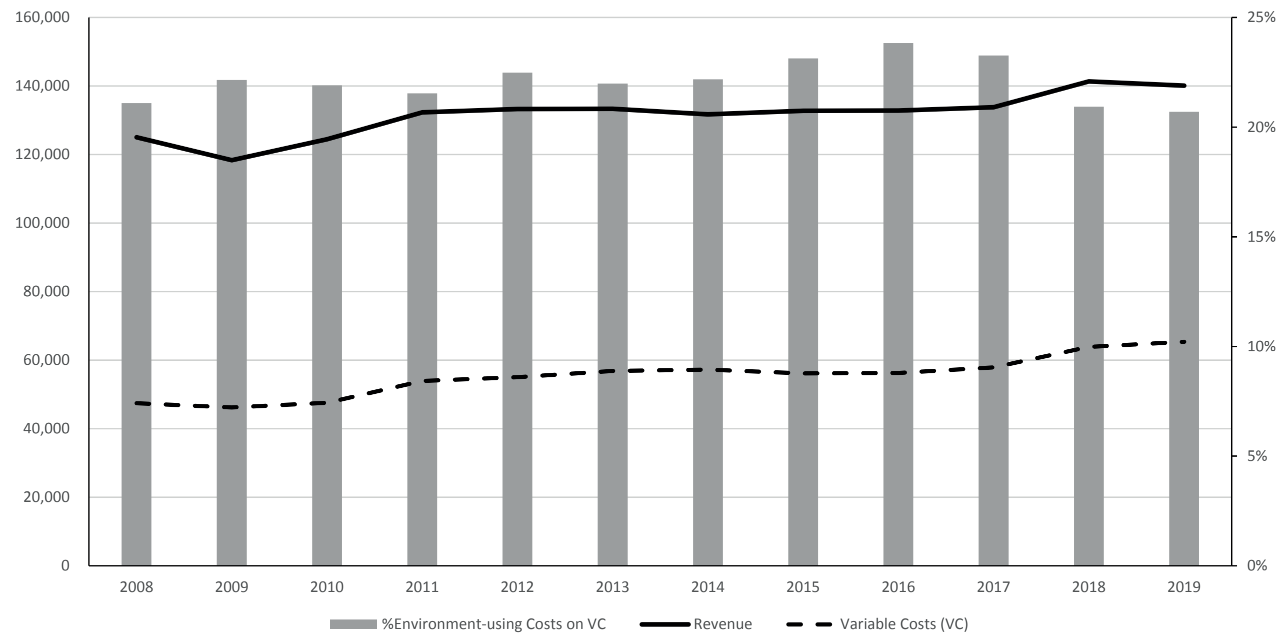

Figure 3. Average revenue, variable costs and environment-using costs (fertilizers, pesticides, energy, water) (€) over the 2008-2019 period within the Italian FADN balanced sample.

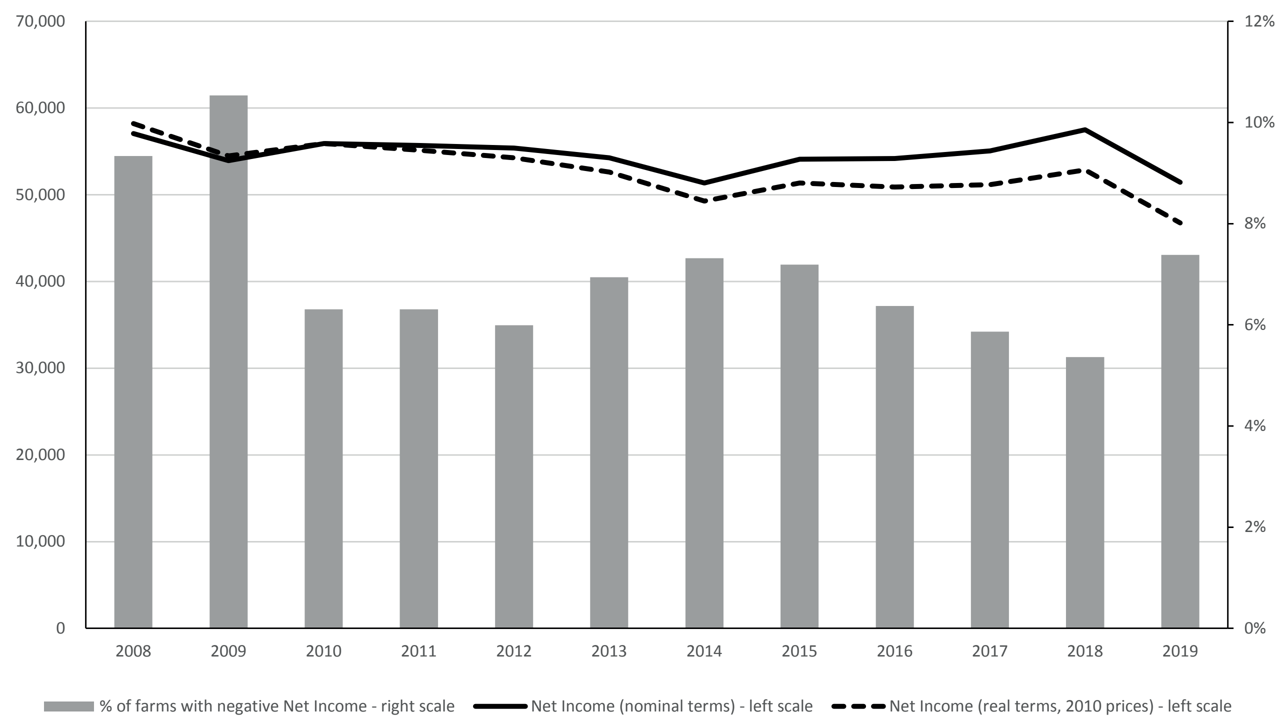

Figure 4.Average farm net income (€) over the 2008-2019 period within the Italian FADN balanced sample.

oscillations and, more importantly, an apparent trend reversal after 2015.

What emerges points to a substantial intensification in the use of these factors (in fact, the same was observed for the variable inputs). A more detailed analysis of the nature of this factors' intensification is available in the Annex (Table A2). It is worth emphasizing here that, combining the evolution of factors' use with

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	57,056	53,945	55,907	55,703	55,380	54,253	51,358	54,100	54,186	55,072	57,512	51,440
Standard deviation	139,843	134,874	135,000	142,913	127,696	119,818	123,255	132,212	133,324	109,159	106,696	106,542
Coefficient of Variation	2.5	2.5	2.4	2.6	2.3	2.2	2.4	2.4	2.5	2.0	1.9	2.1
Min	-160,758	-124,741	-143,652	-184,265	-66,484	-40,2051	-18,1687	-165,917	-205,180	-229,603	-121,842	-255,091
1st Quartile	8,969	6,542	9,042	9,147	9,669	9,702	8,423	9,399	9,172	9,573	10,065	8,424
2nd Quartile (Median)	24,802	21,723	25,506	24,741	25,537	25,001	23,146	23,966	24,972	25,785	26,229	23,154
3rd Quartile	58,698	52,296	58,763	57,760	59,681	58,205	53,101	57,595	62,726	6,1431	65,008	58,063
Max	2,429,572	2,075,403	2,333,829	2,228,093	1,983,041	2,019,809	2,100,850	3,368,715	3,691,632	1,815,441	1,939,388	1,930,918

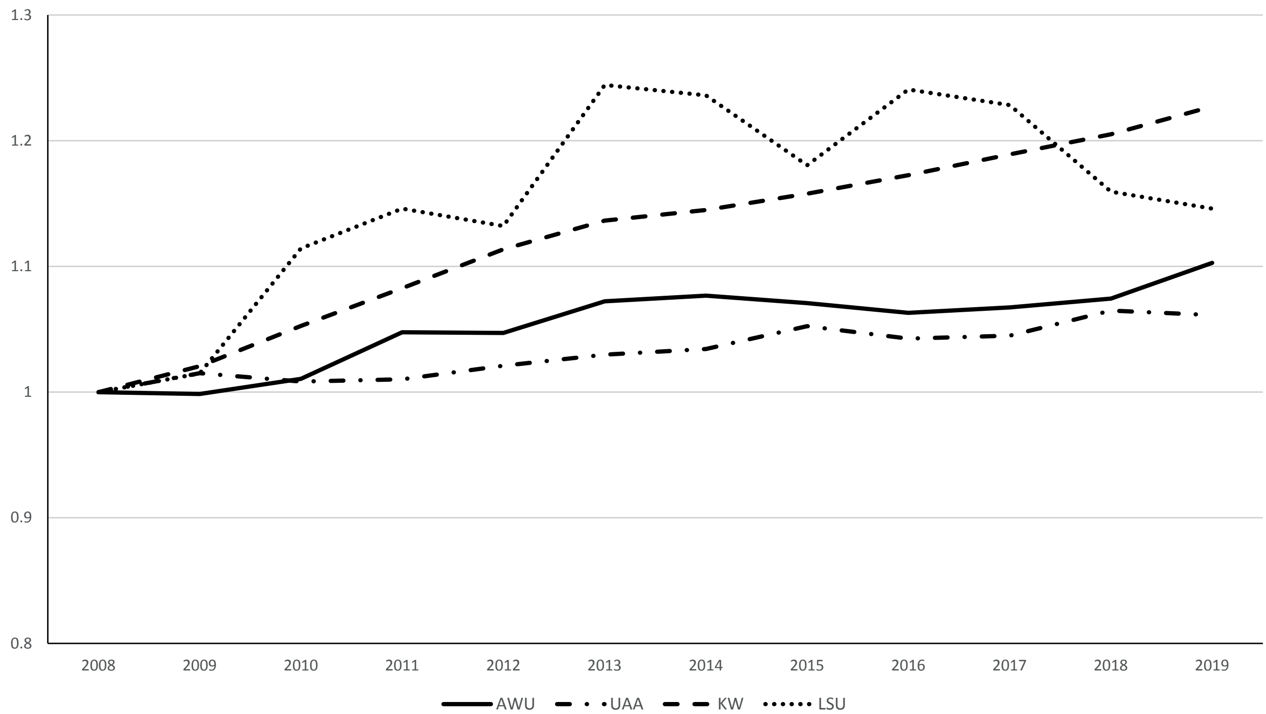

Figure 5. Evolution of main factors' average endowment (2008=1) over the 2008-2019 period within the Italian FADN balanced sample.

the profitability dynamics, a decline of factors' productivity is observed. Figure 6 displays the evolution of the farm net income per unit of labour. Labour productivity (or profitability) declined by 25% from 2008 to 2019, though most of the decline occurs in the very first years of the period. However, if the real term values are considered, the decline is more pronounced (-34%) and occurs quite regularly up to 2014.

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 7 reports the presence of female and young (<40 years old) farmers within the sample.[19] What emerges 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%). Moreover, there is no

[19] It is worth noticing that this sample 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. 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 Italian case, in particular, both the presence of female and of elder holders has been always altered by the persistence of these marginal (non)farms (Iacoponi, 2021).

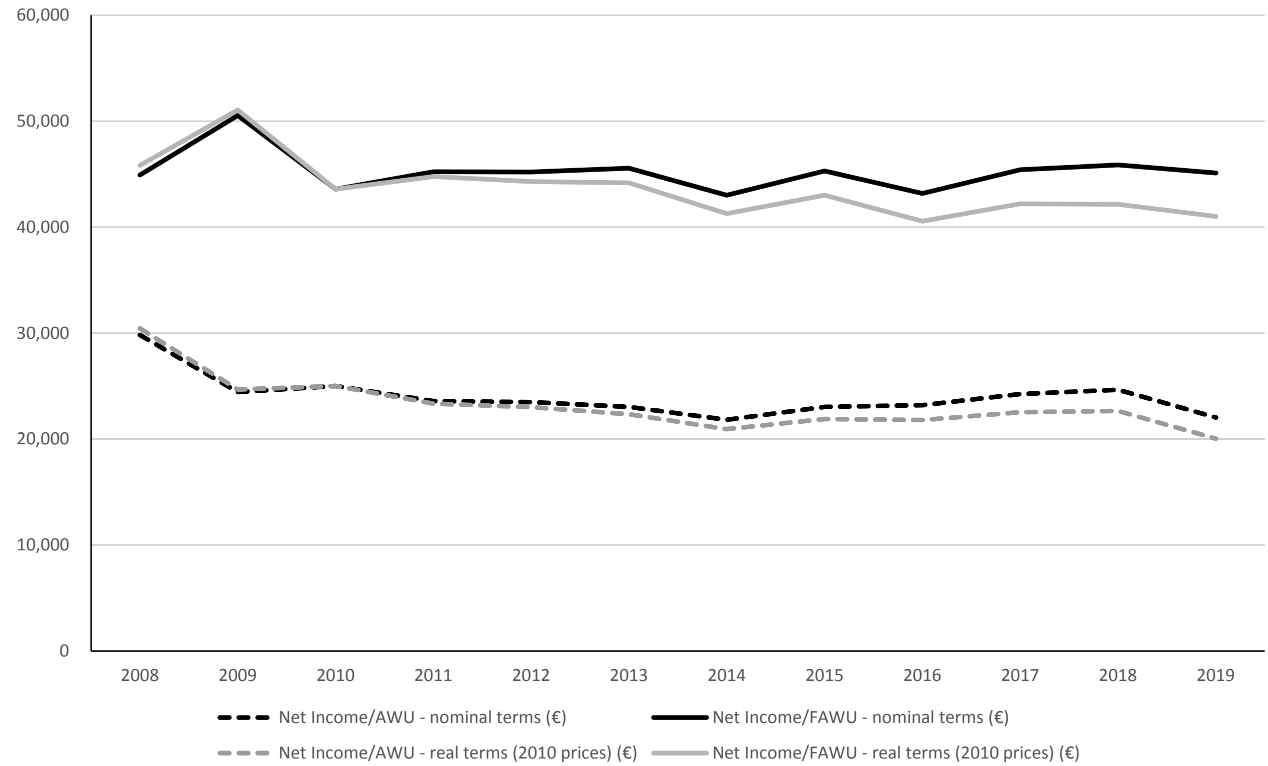

Figure 6. Evolution the farm net income per (F)AWU over the 2008-2019 period within the Italian FADN balanced sample.

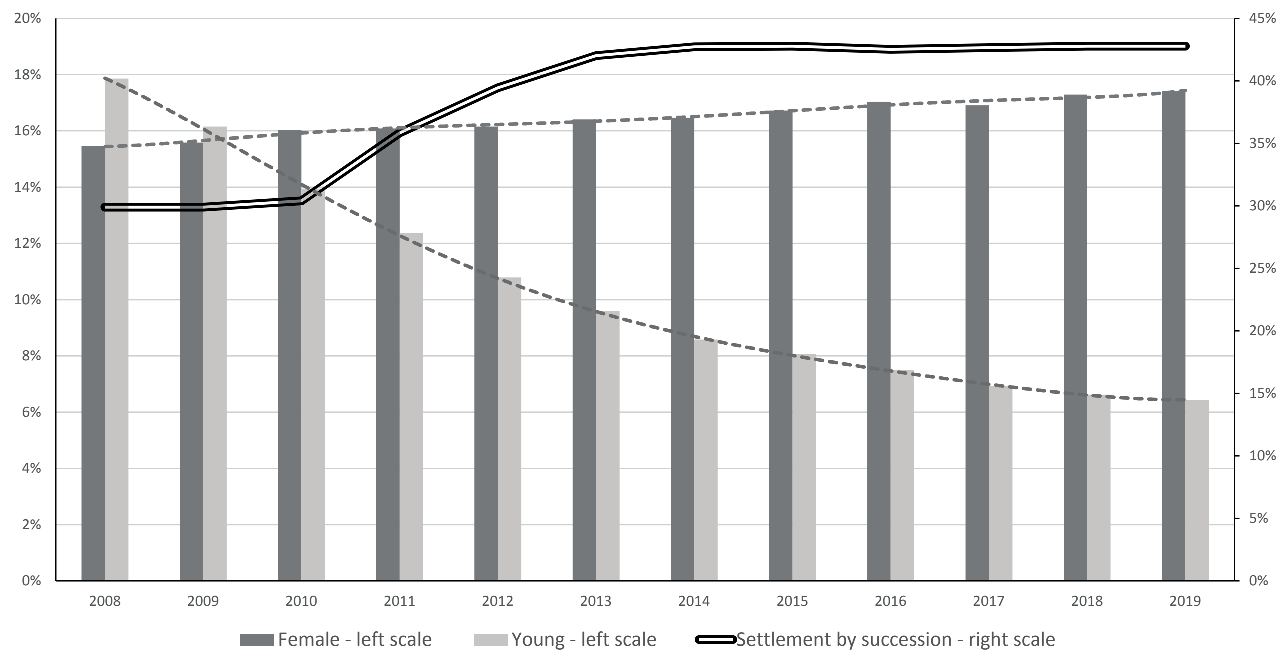

Figure 7. Evolution of the presence of the female, young and organic farmers over the 2008-2019 period within the Italian FADN balanced sample.

evidence of a correspondence between young and female holders as the average age of female and male holders is substantially the same.[20]

It thus seems difficult to interpret these figures as the progressive emergence of a new generation of farmers within the adopted sample. 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.

4.2.3. Production choices

A final aspect of the evolution of farmers' behaviour concerns their production choices. The classification of agricultural holdings by Type of Farming (TF) can be informative in this respect. FADN classifies farms in eight TF categories: five main groups of specialist agricultural holdings and three mixed groupings.[21] 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 8 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 the combination of these TFs does not express any significant structural dynamics. For instance, TFs with livestock activities combined (TF4, TF5, TF7 and TF8) 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 may be interesting to investigate further where these transitions occurs and speculate on the possible motivations. The Annex (Table A3) provides more details on the observed TF switches. Here, it seems interesting to define the proper dimension of this event. Figure 9 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 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. Arguably, this peculiar behaviour does not express any relevant change in production farmers' choices. It can be interpreted as physiological oscillations of production activities in borderline farms between two TFs.

However, the switch of TF may be a poor indicator of farm production re-orientation. 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 gainful activities", also defined as "agriculture-related activities" ("*attività connesse*") in Italian regulation.[22]

Figure 10 displays the evolution of the number of farms with other gainful activities, as well as their incidence on the SO both in the whole sample and in these multifunctional farms. 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 as 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 mul-

[20] See also Giampaolo *et al.* (2021) and Selmi (2021) for a comparison with analogous evidence on the whole Italian agriculture.

[21] The TF of an agricultural holding is determined by the relative importance of each production activity on the total farm SO. The eight 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.

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

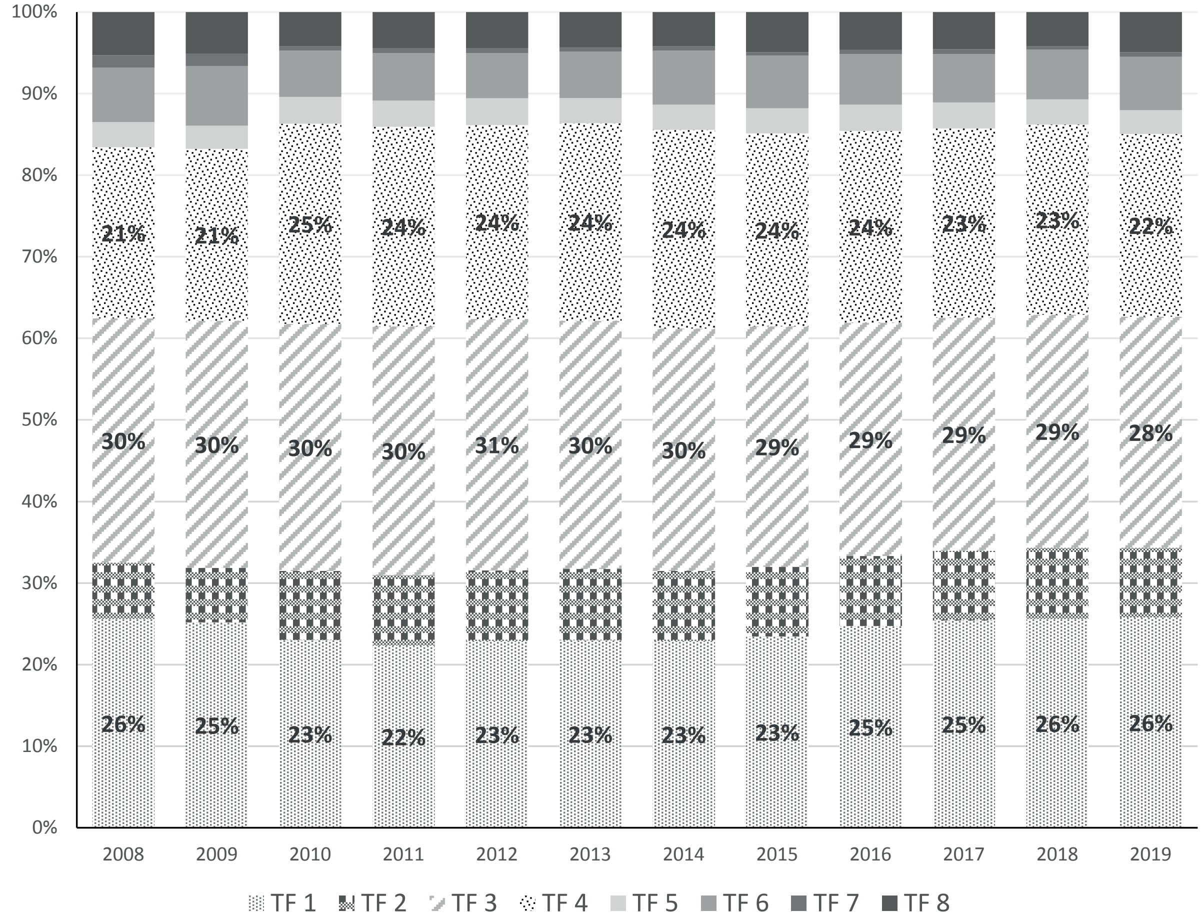

Figure 8. Evolution of the Type-of-Farming (TF) categories over the 2008-2019 period within the Italian FADN balanced sample (% is indicated only for FT >10%,). Legend: TF1 = Field crops; TF2 = Horticulture; TF3 = Permanent crops; TF4 = Grazing livestock; TF5 = Granivores; TF6 = Mixed crops; TF7 = Mixed livestock; TF8 = Mixed crops&livestock.

tifunctional 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).

5. THE CO-EVOLUTION

This section derives from the analysis above some stylised facts about nature and extent of the co-evolution of CAP support and farm behaviour. By co-evolution here we mean that the dynamics of the CAP and the change of farmers' behaviour concur (so they appear to be correlated) in such a way that it is very difficult, if not unfeasible in practice, to distinguish which is the cause and which is the effect. Therefore, with the term co-evolution we do not want to necessarily mean policy neutrality (or ineffectiveness) in promoting farm practice changes. It may be definitely the case that some agricultural practices are triggered by the change in the CAP support. However, empirically assessing this causal linkage, may be very challenging.

We want to motivate this conclusion more in detail by separately considering the three abovementioned major policy objectives (income support, production diversification, environmental goods provisions) to which we associate three respective research questions.

5.1. Farm income and CAP support

Is there any evidence that CAP payments did really protect the farm's net income in both level and variabil-

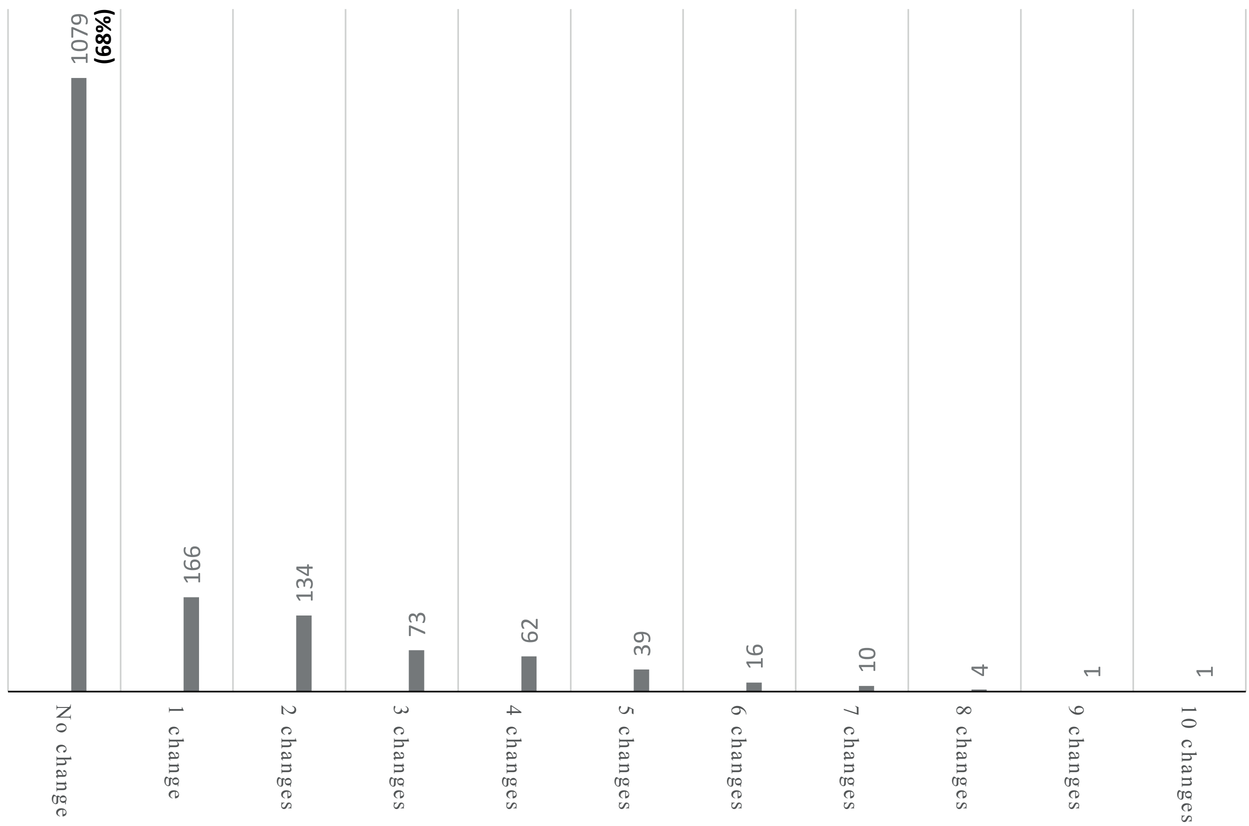

Figure 9. Farms per number of TF changes over the 2008-2019 period within the Italian FADN balanced sample.

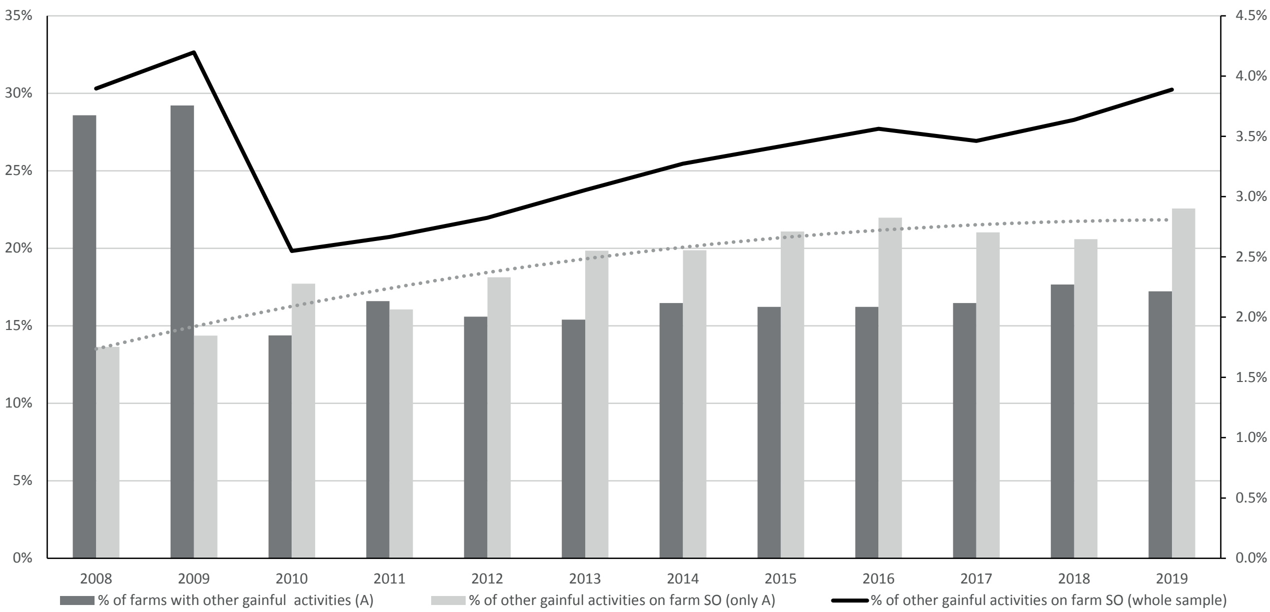

Figure 10. Evolution of the farms and of the incidence on farm Standard Output of other gainful activities within the Italian FADN balanced sample.

ity? An income-protection 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 problems. These problems 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 income problems can be also intended as a large income variability.

In order to assess this question, 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 3 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 11 displays the CAP support and number of farms with a CAP support larger than the net income (included net income<0). Five major facts are worth noticing.

1. 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.[23]

2. The support per unit of FAWU increased by 21% in nominal terms (8% in real terms) from 2008 to 2019, but if the comparison is made between 2009 and 2019, the increase falls to 4% in nominal terms and becomes a decline (-7%) in real terms.[24]

3. The correlation between the CAP support per unit of FAWU and the respective unit net income is significantly positive[25] and it slightly reinforces over time with a maximum of 0.67 in 2018. 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.

4. 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%).

5. The growth of unit CAP support[26] 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 protection policy. On the one hand, CAP support may have really supported the farms' income as its incidence is remarkable. On the other hand, however, support and support growth, though very disperse, go more towards farms that need less, i.e., more profitable farms.[27] 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.

5.2. Production diversification and CAP support

Is there any evidence that the change in CAP payments, either the decoupling of I Pillar payments and the increase of II Pillar payments, induced production diversification? To assess a diversification-inducing effect we need a metric to measure production diversification. Here we firstly 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. 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. For both indexes, more diversified farms are expected to show an higher DI_{it} and, more

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

[24] Due the presence of negative values, In computing this indicator, farms with negative net income are attributed the highest incidence observed in the rest of the sample.

[25] It is worth reminding that, as detailed in section 4.2.1, the calculation of the net farm income includes the CAP support. Therefore, even when the latter shows a limited incidence on the former on average, a slight positive correlation between the two necessarily occurs.

[26] For farms with a zero initial CAP support, the attributed growth rate corresponds to observed maximum finite value.

[27] A similar evidence for the Italian FADN farms is obtained by Ciliberti *et al.* (2022).

Table 3. 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%	1,207%	408%	270%	805%	628%	810%	363%	953%	11,234%	732%	266%
Coefficient of Variation	9.9	41.6	7.6	6.7	18.9	19.3	34.4	7.3	20.3	220.3	11.1	6.7
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	9,868%	16,679%	8,601%	3,553%	21,479%	17,270%	6,455%	9,591%	27,578%	2,388%	23,517%	3,902%
B) CAP support/FAWU (€)												
Mean	13,660	15,954	14,701	14,041	14,789	16,774	16,627	16,239	14,330	15,240	14,561	16,534
Standard deviation	33,102	45,784	40,671	32,212	34,684	53,774	61,150	43,461	36,434	42,160	37,633	39,940
Coefficient of Variation	2.4	2.9	2.8	2.3	2.3	3.2	3.7	2.7	2.5	2.8	2.6	2.4
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	556	800	1,096	1,244	1,470	1,330	1,350	1,164	1,043	1,175	1,386	1,754
2nd Quartile (Median)	4,038	4,802	4,519	4,525	5,165	5,369	5,238	5,303	4,414	4,893	4,954	5,592
3rd Quartile	12,498	14,468	13,835	13,489	15,083	14,765	15,201	16,545	14,457	13,841	14,328	16,522
Max	647,037	973,039	781,053	533,976	597,378	1,233,624	1,413,233	1,053,225	883,780	828,248	1,005,035	886,387
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.

importantly, an increased production diversification within the sample is expressed by an higher average DI_{it}.[28]

Figure 12 shows the evolution of the average Shannon and Simpson diversity indexes within the adopted field of investigation. 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%. As usual, these average values may hide a major heterogeneity within the sample as can be better appreciated by looking at the descriptive statistics reported in Table 4. In both cases, the dispersion (as indicated by the CV) and the asymmetry (as indicated by the median-mean ratio) are limited compared to most variables investigated above. The growth of the lower quartiles is more intense than the higher ones, thus indicating that not only diversification increased, but also that it distributes more uniformly within the sample.

The bottom of Table 4 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.

[28] 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.

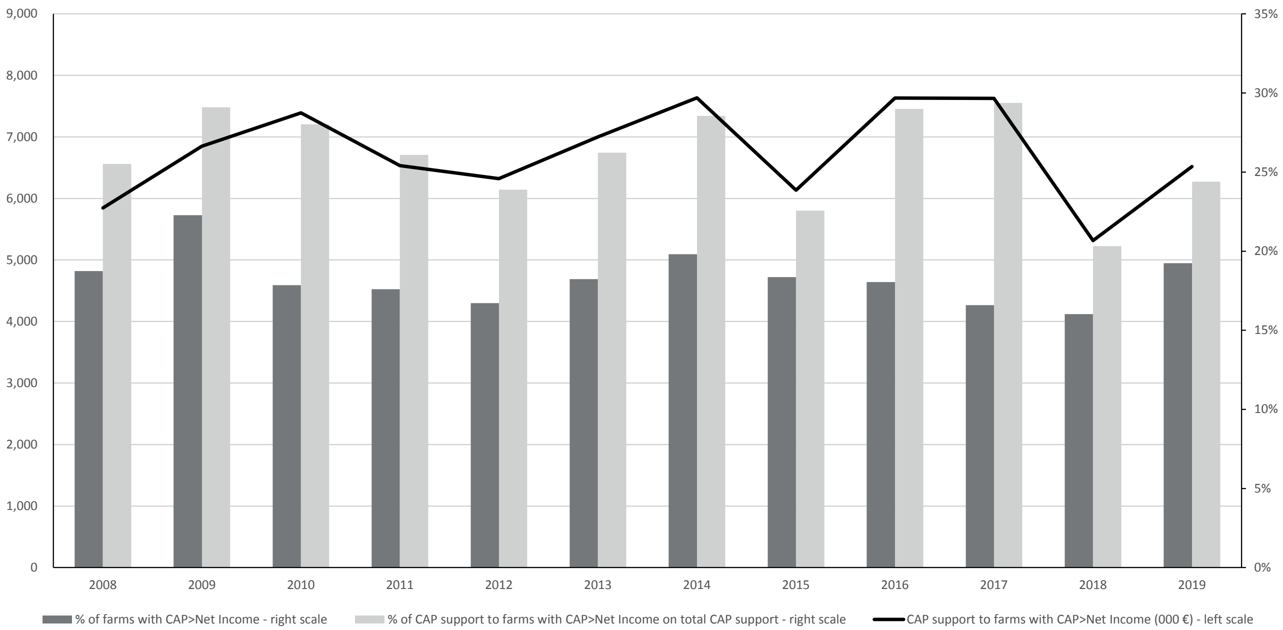

Figure 11. CAP support and number of farms with CAP support > net income (included net income < 0) within the 2008-2019 Italian FADN balanced sample.

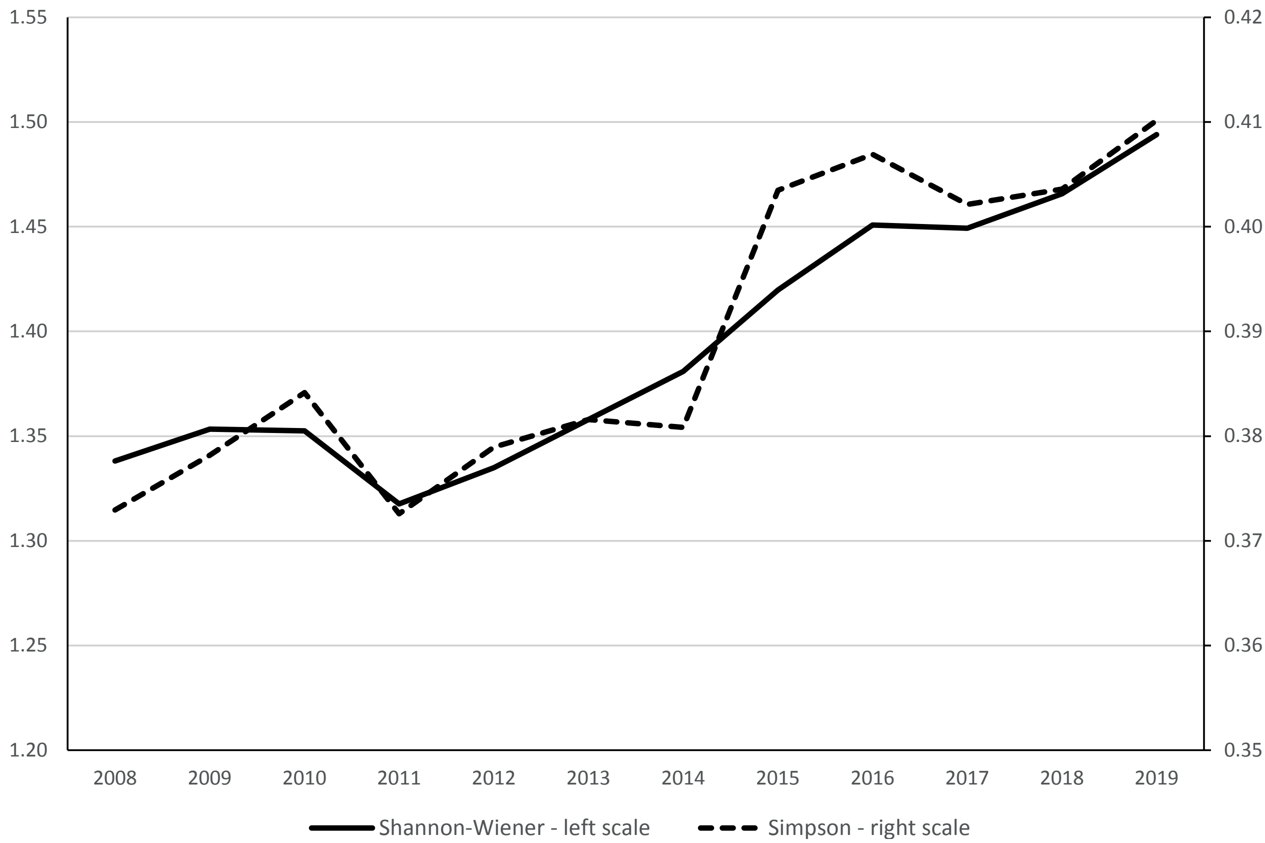

Figure 12. Evolution of the average Shannon and Simpson diversity indexes within the Italian 2008-2019 FADN balanced sample.

Table 4. 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
Coefficient of Variation	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
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
Coefficient of Variation	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.6
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

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 5 reports the correlation coefficients between CAP support (and its different components) per unit of FAWU and four indicators of this "vertical" diversification.[29] 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 5 only weakly support the linkage between the unit CAP support and these diversification indicators. 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 support statisti-

[29] 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.

Table 5. 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

*Statistically significant at 5% confidence level.

cally disappears in the case of product quality certification and multifunctional diversification.

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, the empirical evidence is not enough to interpret the observed linkage as an undisputable cause-effect relationship. It can be again interpreted as a co-evolution between market-driven production choices and the path-dependent CAP support.[30]

[30] 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.

5.3. Environmental goods and CAP support

Did the change in the CAP support and composition (II Pillar in particular) really induce a greater provision of environmental goods? Also an environmental-good-provision effect of the CAP requires an appropriate metric, i.e., appropriate indicators (Janssen *et al.*, 2010).[31]

[31] 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. 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.

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 other 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 13 shows the evolution of the share of farms with organic and environmental certifications. For the sake of comparison, also product quality certifications are reported. All certifications significantly grew over the whole period with +162% for organic farming, +52% for all environmental certifications and +47% for product quality certifications. 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 environmental certifications over time as it was just 34% on the total in 2008 and reached 58% in 2019.

Table 5 presents the correlation coefficients between the two categories of II Pillar 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 relationship between the AEM support and organic farming and, more generally, environmental certifications actually emerges. But, again, this does not imply a treatment effect 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.

6. CAUSAL INFERENCE, CAP ASSESSMENT AND THE CO-EVOLUTION HYPOTHESIS

We can now go back to the original question of the present study, i.e., the actual applicability of the TE logic to CAP assessment. Previous section points to some major features of the co-evolution of CAP support and of farmers' performance. As shown, this co-evolution does not necessarily exclude causation but makes it hardly identifiable. In practice, co-evolution is the consequence of the particular forms in which CAP measures are delivered to farmers and these latter progressively take decisions combining voluntary participation to these measures with production choices. These forms eventually enter in conflict with the prerequisites of a TE logic. Without entering into technical details, it must be reminded that 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 was not treated (and the other way round) (Perraillon *et al.*, 2022). But empirical identification and estimation of the TE within this conceptual framework requires an appropriate quasi-experimental design[32] and imposes its conditions.[33]

In particular, six specific sources of conflict between these conditions and the abovementioned forms of co-evolution deserve detailed discussion. Not only they may be all encountered in CAP assessment exercises; more importantly, they may occur simultaneously. Let's discuss them from the more general (and problematic) to the more technical (and manageable) ones.

6.1. Voluntary and universalistic treatments

As discussed at the beginning of this paper, and as shown repeatedly in the empirical analysis, CAP meas-

[32] 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.

[33] In particular, three assumptions are critical: 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. 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 treatment status on another individual's potential outcome. If these conditions are satisfied, observational data can be regarded as generated by a "natural experiment".

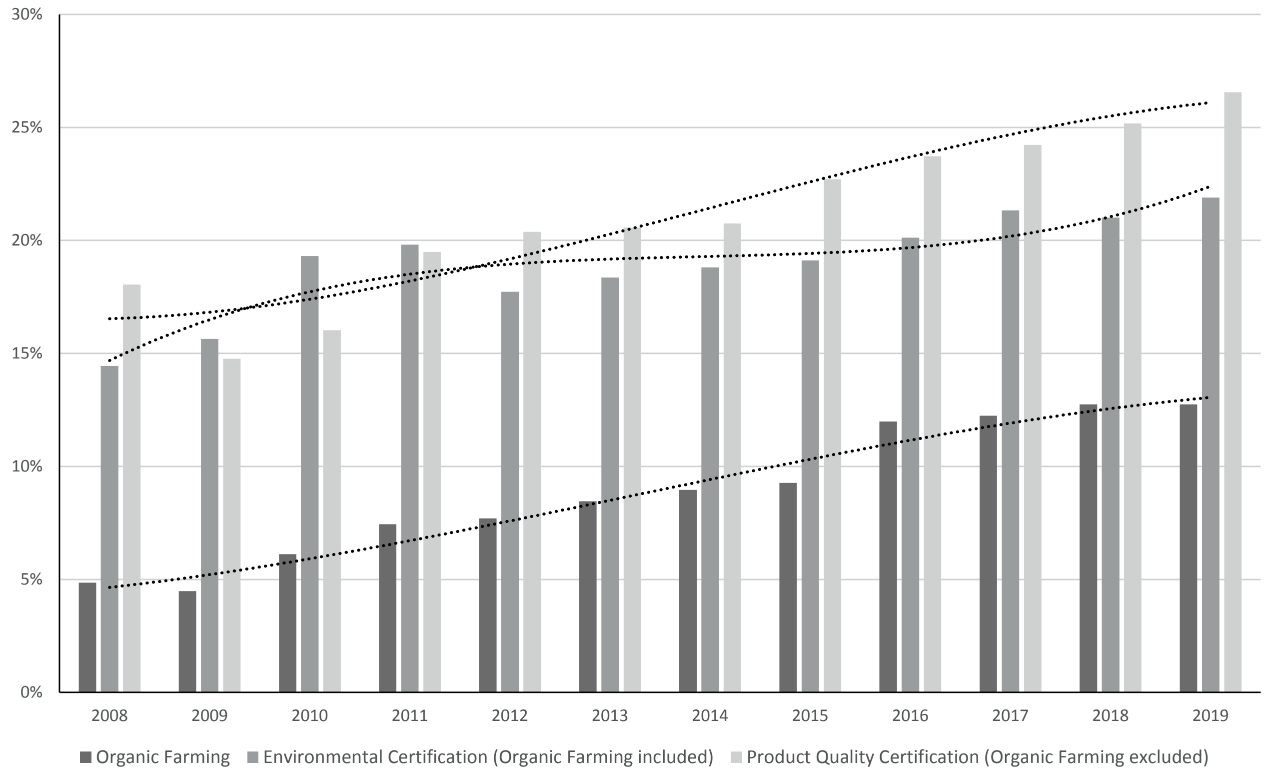

Figure 13. Evolution of the share of farms with certifications within the Italian 2008-2019 FADN balanced sample.

ures 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. This makes the application of the TE logic to CAP assessment seriously questionable. Any possible way out of this problem relies more on a proper design of the quasi-experimental setting rather than on alternative or adapted TE estimation approaches. In practice, however, available datasets (like the FADN) might make these alternative settings unfeasible.

6.2. Outcome variable

The search of an appropriate quasi-experimental setting encounters another major issue. It has to do with the ambiguity about the outcome variable to be considered. The empirical analysis here performed clearly illustrate the point. On the one hand, for many CAP measures a policy target variable is simply neither explicit nor univocal. In such case, the present investigation had to identify, more or less arbitrarily, a suitable metric for the policy assessment. 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. As shown, 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 the TE logic to CAP assessment. Also in this case, the solution does not necessarily depend on some 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.[34]

[34] 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).

6.3. Heterogeneity

Coexistence of the voluntaristic and universalistic nature of the CAP aims to cover very diverse farming conditions. As repeatedly emerged in sections 4 and 5, farms under investigation (treated or not) are characterized by vast heterogeneity. This has to do with 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*). Literature in the field has proposed several solutions (Abadie, 2021) that have also widely adopted in CAP assessment (Esposti, 2017a,b).

But farm heterogeneity is challenging also for another more fundamental, and often disregarded, reason: the TE itself may be strongly heterogeneous. In such case, although the average TE (ATE) is correctly identified and consistently estimated, it simply remains uninformative. Under strong TE heterogeneity, estimating the group or the individual TE is needed for policy assessment and learning (Esposti, 2022). Recently proposed Machine Learning (ML) approaches seems interesting in this respect (Bertoni *et al.* 2021; 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).

6.4. Multivalued treatments

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

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 Propensity Score Matching (PSM) of the binary case (Generalised Propensity Score, GPS, estimation) (Esposti, 2017a). However, it provides consistent estimates only whenever the treatment assignment can be considered exogenous once all confounders have been taken into account. 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.

6.5. Multiple treatments

Almost all CI studies concentrate on single treatments. As shown, however, the main feature of the CAP and its co-evolution with the farmers' choices is that it delivers multiple treatments to farms. Identifying and consistently estimating the TE of any single treatment with the conventional approaches is possible only under the assumption of treatment independence. But the empirical evidence clarifies that this assumption is quite unrealistic as interdependence is likely to occur both in terms of treatment assignment and in terms of outcome variable. In particular, within the CAP both interdependencies may evidently occur 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).

6.6. 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 (the so-called *parallel trend assumption*) that excludes that time behaves as an additional confounder.[35] But what really

[35] See Arkhangelsky *et al.* (2021), Chan and Kwok (2022), Cho *et al.* (2022), for recent developments in this field.

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). This issue can become even more problematic in the agricultural context as the timing of the farms' response can be itself heterogenous across units depending on their structural characteristics: even under the same treatment timing, some farms can respond immediately others may take some years.

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 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).

However, as shown in sections 4 and 5, CAP magnifies these issues and these methodological solutions may be insufficient or unfeasible. 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, possibly melded with periods without the treatment.

7. SOME CONCLUDING REMARKS

Assessing the farm-level impact of CAP measures and reforms with a TE 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. The present paper contributes to this discussion not by proposing an empirical application of methods based on this logic, but presenting an empirical evidence that poses doubts and conditions on their actual applicability.

Provided that the target of the policy to be investigated is clearly identified (in fact, it is often not clear at all) (Matthews, 2021), empirically assessing whether and to what extent this policy has been successful requires specific pre-conditions. Firstly, we need appropriate datasets. FADN surely is very helpful in this respect, but some of its limitations may reduce the application of these evaluation methodologies. Secondly, and more importantly, we need to investigate the co-evolution of the policy instruments and of the potentially treated units, that is, farmers' behaviour. Investigating co-evolution means finding enough support to the existence of a possible cause-effect relationships and to the feasibility of its investigation. In the meaning here given to the term, co-evolution implies that a correlation occurs but this does not necessarily imply causation as it may be the consequence of interdependence between the two processes making an unidirectional cause-effect relationship unidentifiable.

On the basis of the empirical investigation here presented and the observed co-evolution, we can conclude that the CAP has really moved in the right direction, that is, consistently with the declared objectives. And the farmers' changed their behaviour and performance, as well. At the same time, however, this does not mean that the policy induced the expected farmers' response. Achieving this conclusion within a TE logic requires conditions that are not always compatible with the CAP features. It does not follow that these approaches are and will be always inappropriate in this specific case. It rather implies that 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 suggests that any consistent application of these approaches requires more attention on setting up appropriate quasi experimental design with the consequent appropriate datasets and theoretical representation of farmers' choices, and on suitable adaptations and refinements of these approaches.

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ANNEX

A1. Evolution of the AEM support

Figure A1 shows how AEM 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.

A2. The Lorentz curve of the farms' CAP support and income

To better illustrate the distributional characteristics of CAP support, and its evolution over time, within the sample, the Lorentz curves of the Pillar I and Pillar II support, respectively, are reported in Figure A2 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 investigation, 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.

Figure A3 presents the analogous Lorentz curves of the farm net income for selected years 2008, 2015 and 2019.[36] 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%.

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

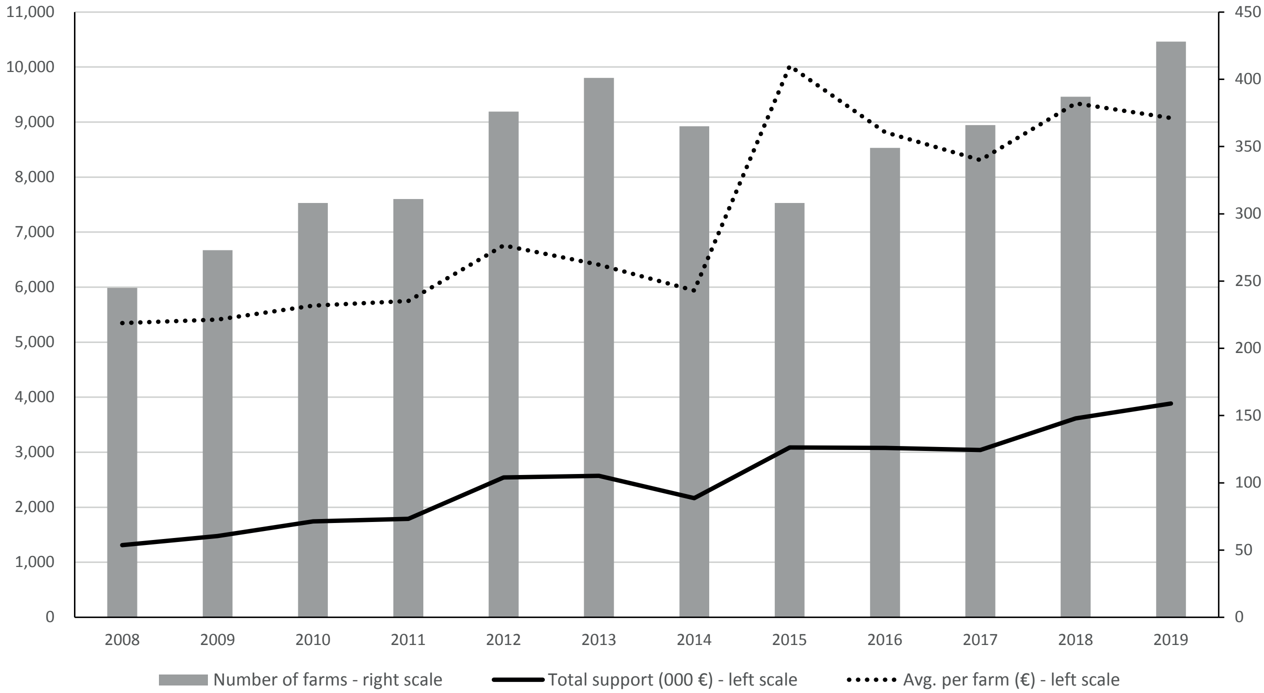

Figure A1. Evolution of the Agro-Environmental Measures (AEM) support within the Italian 2008-2019 FADN balanced sample: number of beneficiaries, total support and average support per beneficiary.

A3. Factors' intensification

To better investigate the nature of factors' intensification, Table A2 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 CV) and asymmetry (as expressed by the median/mean ratio) emerges within the field of investigation. 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 A2. 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%.

A4. TF switches

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 A3).[37] As could be

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

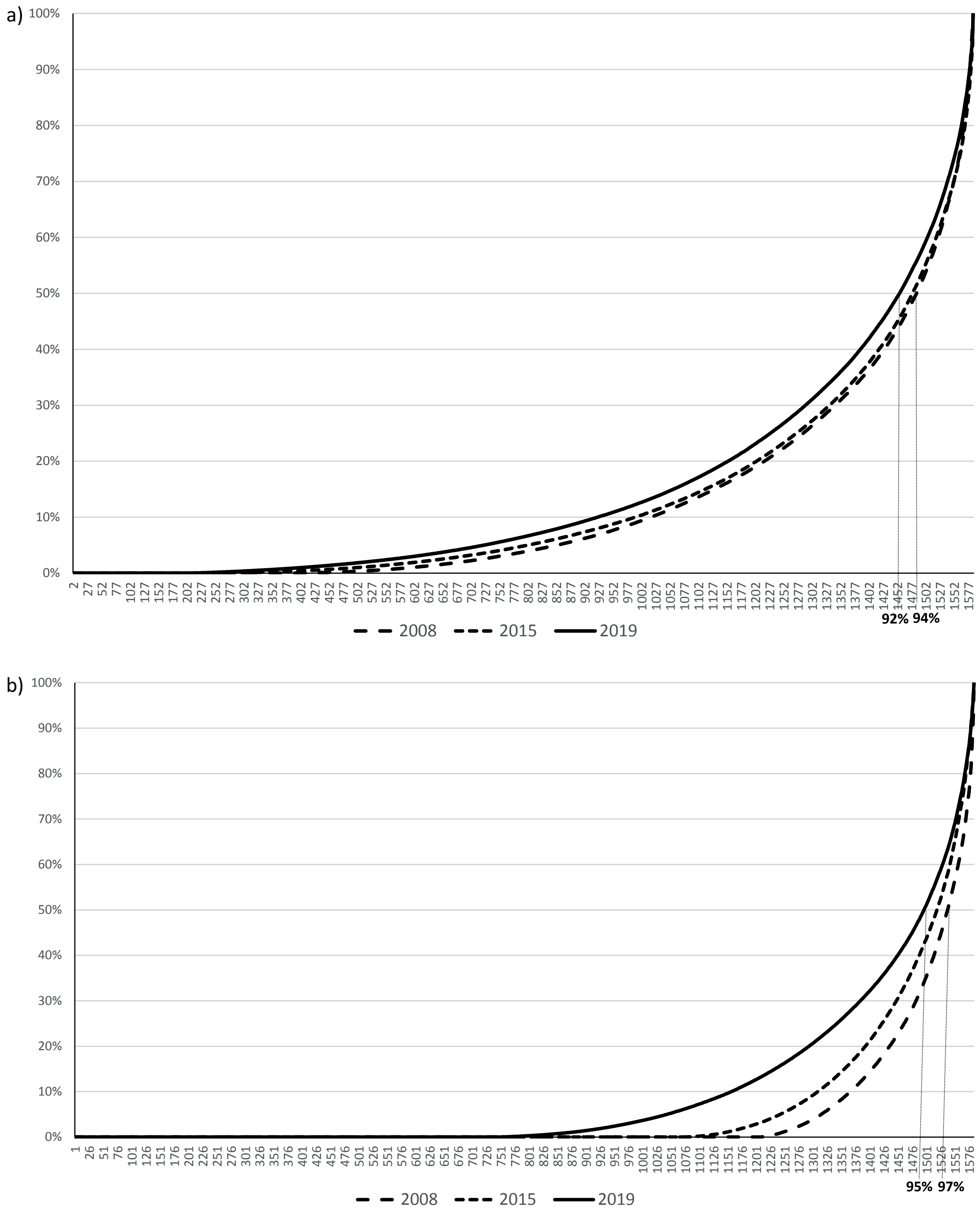

Figure A2 – Lorentz curves of the Pillar I (a) and Pillar II (b) support within the Italian 2008-2019 FADN balanced sample: years 2008, 2015, 2019.

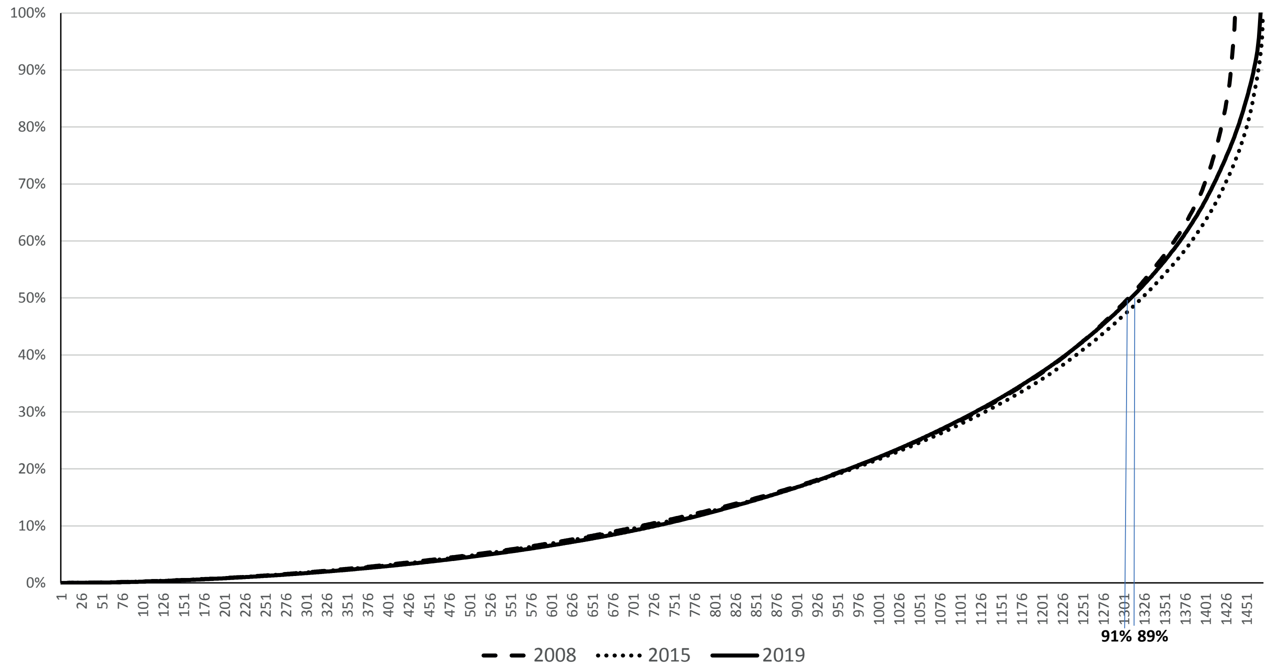

Figure A3. Lorentz curve of the (positive) farm net income within the Italian 2008-2019 FADN balanced sample: years 2008, 2015, 2019.

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.

Table A1. Representativeness of the balanced FADN sample. Comparison of the Italian 2008-2019 FADN balanced panel (year 2010) with the Italian 2010 agricultural Census: distribution by Types of Farming (TF) and Economic Size (ES) classes (SO=Standard Output).

	FADN balanced sample	2010 Census (Total)	2010 Census (SO>8000 €)
TF classes:			
TF 1	23%	24%	23%
TF 2	8%	2%	6%
TF 3	30%	55%	43%
TF 4	25%	8%	16%
TF 5	3%	1%	1%
TF 6	6%	7%	7%
TF 7	1%	0%	1%
TF 8	4%	2%	4%
Not Classified	0%	1%	0%
Total	100%	100%	100%
ES classes:			
Small (SO <25,000 €)	30%	18%	49%
Medium-Small (SO=25,000-50,000 €)	19%	8%	21%
Medium (SO=50,000-100,000 €)	22%	5%	15%
Medium-Large (SO=100,000-250,000 €)	20%	4%	10%
Large (SO>250,000 €)	9%	2%	5%
Total	100%	37%	100%

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

Table A2.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
Family AWU/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
Coefficient of Variation	0.43	0.46	0.39	0.42	0.43	0.42	0.42	0.43	0.41	0.43	0.40	0.45
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
Coefficient of Variation	1.44	1.39	1.36	1.36	1.40	1.38	1.39	1.72	1.29	1.28	1.28	1.24
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

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
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
Coefficient of Variation	1.03	0.93	0.98	0.89	0.86	0.86	0.86	1.95	0.91	0.94	0.95	0.97
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	1,341	1,010	2,010	812	798	926	846	8,560	1,488	1,123	1,488	1,488
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
Coefficient of Variation	2.97	3.32	3.13	4.03	2.98	3.65	3.25	3.87	3.95	3.81	3.21	3.54
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	1,032	992	1,782	580	881	860	1,042	1,125	1,291	604	723
Environment-using Costs/AWU (€)												
Mean	5,498	5,432	5,501	5,920	6,197	6,033	6,223	6,908	6,419	6,602	6,398	6,488
Standard deviation	8,373	7,237	8,036	7,993	8,199	7,813	8,101	19,089	9,226	11,042	9,776	9,830
Coefficient of Variation	1.52	1.33	1.46	1.35	1.32	1.30	1.30	2.76	1.44	1.67	1.53	1.52
Min	0	0	0	0	0	0	0	0	0	0	0	0
1st Quartile	1,452	1,444	1,543	1,737	1,856	1,827	1,938	1,873	1,669	1,688	1,670	1,705
2nd Quartile (Median)	3,068	3,184	3,199	3,484	3,598	3,634	3,743	3,678	3,602	3,608	3,691	3,764
3rd Quartile	5,940	6,072	5,957	6,428	6,838	6,635	6,914	6,960	7,002	6,927	7,031	7,018
Max	102,031	64,425	84,848	75,441	92,735	73,174	82,336	671,360	119,471	189,599	154,697	132,348
Net Income/Family AWU (€)												
Mean	44,928	50,549	43,592	45,238	45,209	45,561	43,007	45,313	43,174	45,413	45,861	45,113
Standard deviation	103,713	141,432	107,183	124,906	102,187	115,314	126,977	104,157	107,065	95,329	99,178	97,087
Coefficient of Variation	2.31	2.80	2.46	2.76	2.26	2.53	2.95	2.30	2.48	2.10	2.16	2.15
Min	-456,321	-166,321	-82,087	-80,300	-64,492	-181,104	-182,261	-162,664	-170,206	-229,603	-69,855	-208,142
1st Quartile	5,919	4,881	6,080	6,016	7,051	6,647	5,871	7,063	6,116	7,134	6,955	5,817
2nd Quartile (Median)	18,756	16,773	18,025	17,781	19,567	18,784	16,593	19,057	17,168	18,894	19,262	17,367
3rd Quartile	45,051	45,133	43,189	43,864	45,927	46,124	43,316	46,335	46,287	49,011	48,762	48,544
Max	1,454,834	3,459,005	1,944,858	2,197,699	1,246,851	2,693,079	3,166,903	2,041,645	1,986,362	1,609,615	2,085,363	1,821,656
Net Income/AWU (€)												
Mean	33,991	34,658	33,194	33,845	31,891	31,971	29,003	29,232	31,445	30,749	32,729	29,628
Standard deviation	78,467	96,969	81,619	93,450	72,083	80,916	85,630	67,193	77,978	64,547	70,778	63,762
Coefficient of Variation	2.31	2.80	2.46	2.76	2.26	2.53	2.95	2.30	2.48	2.10	2.16	2.15
Min	-345,243	-114,033	-62,508	-60,077	-45,493	-127,082	-122,912	-104,936	-123,965	-155,465	-49,852	-136,698
1st Quartile	4,479	3,346	4,630	4,501	4,974	4,664	3,959	4,556	4,455	4,831	4,963	3,820
2nd Quartile (Median)	14,190	11,500	13,726	13,303	13,803	13,181	11,190	12,294	12,503	12,793	13,746	11,406
3rd Quartile	34,085	30,944	32,888	32,817	32,397	32,365	29,211	29,891	33,712	33,185	34,799	31,881
Max	1,100,695	2,371,566	1,480,981	1,644,227	879,534	1,889,753	2,135,670	1,317,088	1,446,709	1,089,877	1,488,212	1,196,382

Table A3. Source-Destination matrix for TF category within the Italian 2008-2019 FADN balanced sample (in grey >10 elements).

Destination	Source								
	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.