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Participation in biodiversity schemes and environmental performance: overall farm-level impact and spillover effects on non-enrolled land

Franziska Zimmert[†,*], Pierrick Jan[†], Petyo Bonev[†,‡]
[†]*Agroscope, Ettenhausen, Switzerland;* [‡]*University of St. Gallen, Switzerland*

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Abstract

We evaluate how the share of farmland enrolled in agri-environmental schemes affects the biodiversity friendliness of management practices both on the overall farmland as well as on the enrolled and non-enrolled plots separately. To this end, we prepare a unique dataset for Switzerland that links farm-level accountancy data to plot-level data on management practices and their impact on organismal biodiversity. Our estimates allow us to calculate bounds for potential spillovers on non-enrolled farmland. We find that these are positive but small in magnitude. The effect on the overall farmland is also positive but again rather small.

Keywords: agri-environmental schemes, biodiversity, direct payments, spillover effect, Switzerland

JEL classification: Q24, Q57, Q58

1. Introduction

To ease the pressure on biodiversity and the environment in general caused by agricultural activities, governments across the world have implemented various agri-environmental policies (Wuepper et al., 2024). One major policy instrument is the so-called action-based agri-environmental scheme (AES). This policy instrument typically grants direct payments to farmers for managing their land according to prespecified environmental requirements, such as the reduced use of fertilisers and pesticides (Batáry et al., 2015). A plot

*Corresponding author: E-mail: franziska.zimmert@agroscope.admin.ch

of farmland enrolled in these action-based AES is referred to as an ecological focus area (EFA).[1] In Europe, cross-compliance rules for receiving direct payments include a requirement for a minimum share of farmland to be managed as EFA per farm. In Switzerland, this share amounts to 3.5 per cent for the farmland used for special crops (wine, vegetables and fruits) and 7 per cent for the remaining farmland (Ordinance on Direct Payments, DZV, 2013). In the European Union, depending on the option chosen by the member state, 3–7 per cent of the arable land must be devoted to non-productive features and areas, including land lying fallow (European Commission, 2023).

Although action-oriented schemes are widespread in European agriculture (Mack et al., 2020; Bartkowski et al., 2021), they have been criticised because their eligibility criteria are independent of actual environmental performance (Burton and Schwarz, 2013; Reed et al., 2014). Empirical evaluations have produced heterogeneous estimates of the effectiveness of such policies, both within and across countries. For example, Stetter et al. (2022) evaluated a German state-level (Bavarian) action-based nature conservation programme and found small effects that varied in magnitude and were sometimes even adverse. Tsakiridis et al. (2022) analysed an Irish action-based payment scheme and found no significant relationship with habitat quantity and quality. In the Swiss context, Meier et al. (2021) carried out a plot-level analysis and concluded that the action-based payments scheme is effective in promoting biodiversity. However, in an earlier study, Herzog et al. (2005) found that a large share of the land enrolled as EFA in Switzerland did not benefit from the programme. Other earlier plot-level studies of different European schemes (the Netherlands, Switzerland and Austria) also found mixed effects (Kleijn et al., 2004; Knop et al., 2006; Roth et al., 2008; Wrbka et al., 2008).

We highlight two reasons that limit our understanding of these mixed results. On the one hand, since data on the actual environmental performance of a plot or a more aggregated level are expensive to collect, there is an implicit tension between the causal statistical framework on the one hand and the quality of the environmental indicators on the other. Several AES evaluation studies rely on actual biodiversity measures, such as the occurrence of specific plant species (Herzog et al., 2005; Kleijn et al., 2004; Knop et al., 2006; Roth et al., 2008; Wrbka et al., 2008; Meier et al., 2022; Meier et al., 2024). However, obtaining flora or fauna observational data is a process that is typically associated with a high cost, so that in most cases, these studies have to rely on a low number of observations. This limitation has forced many studies to focus on correlations and/or on other descriptive statistics, such as mean comparisons between enrolled and non-enrolled plots. However, such comparisons may lead to erroneous conclusions because farmers are typically more likely to enrol land that already satisfies the criteria (and is thus of high environmental quality), which induces a bias (see, e.g. Kleijn and Sutherland, 2003; Gailhard and Bojnec, 2015; Meier et al., 2024). Studies that account for this potentially endogenous selection in their empirical strategy are rare

1 We use the word ‘farmland’ to describe the utilised agricultural area.

(e.g. Kleijn et al., 2001; Kleijn and Zuijlen, 2004; Kleijn et al., 2006). These studies typically found small effects of the studied programmes on biodiversity. In contrast, studies with a causal strategy commonly employ very indirect measures of biodiversity, such as crop diversity, area enrolled in biodiversity conservation programmes or monetary measures of pesticide use intensity (see Bertoni et al., 2020; Chabé-Ferret and Subervie, 2013; Pufahl and Weiss, 2009; Wuepper and Huber, 2022; Stetter et al., 2022).[2] These proxy variables can be considered so-called means-based environmental performance indicators, i.e. as indicators located at the beginning of the environmental cause–effect chain (Repar et al., 2017; Payraudeau and Werf, 2005). Indicators of this type are easy to measure. However, they do not allow a direct assessment of the environmental outcomes and may be—depending on the study context—weakly related to them (Repar et al., 2017; Payraudeau and Werf, 2005). For a more reliable environmental impact assessment, preference should be given to so-called effect-based indicators, which are located at the end of environmental impact pathways (Repar et al., 2017). The assessment of these indicators is more challenging and costly as it requires very comprehensive data collection and complex impact-assessment models. However, these indicators are of higher relevance, as they are tightly related to environmental outcomes (Repar et al., 2017). Thus, our study represents one of very few studies that use an effect-based performance indicator.

A second limitation of the existing literature is that there are either studies at the EFA-plot scale relying on actual outcome variables or studies at the whole-farm level relying on rather coarse proxies. No study has measured the actual outcome in each field of a farm, which makes it impossible to study the impact of AES on the environmental performance of the entire farmland disentangled into EFA versus non-EFA impacts. Specifically, while action-based schemes define a set of minimum management requirements for the portion of land that is to be enrolled in the biodiversity scheme, no additional incentives are provided for the plots that are not enrolled. However, when devoting a given share of agricultural land to the production of environmental services, both the foregone productivity of that land as well as the freed resources may create an adverse incentive for the farmer to intensify agricultural management on the non-EFA. In the case of a livestock farm, for instance, this may occur if the farm is unable to fulfil its annual feed requirements for its livestock operations as a consequence of enrolling a portion of its farmland in an AES for biodiversity conservation. Depending on the magnitude of the spillover, the total effect of participating in a biodiversity scheme can also be neutral or even negative.

The main objective of our paper is to evaluate the Swiss AES for biodiversity conservation, with a particular focus on the two aforementioned problems: first, the trade-off between a causal statistical framework and the quality of the environmental outcomes, and second, the disregard of possible effects on the non-enrolled land. To this end, we construct a unique dataset

2 To our knowledge, only Tsakiridis et al. (2022) use the Field Boundary Evaluation and Grading System (Collier and Feehan, 2003) to evaluate three randomly selected field boundaries such as hedgerows as an approximation for environmental performance on the farm level.

that links farm participation in biodiversity programmes in Switzerland to environmental performance on land managed as both EFA and non-EFA. To construct this dataset, we merge data provided by the Swiss Farm Accountancy Data Network (SFADN; Renner et al., 2019) with data from the Swiss Agri-Environmental Data Network (SAEDN; Gilgen et al., 2023). The former provides detailed information on the structure and economic performance for a sample of the Swiss farms population. The latter dataset includes plot-specific information on a variety of environmental indicators and management practices for a sample of the Swiss farms population. This information includes, among other data, the plot area and whether a given plot is enrolled as EFA.

Our main outcome variable is a so-called biodiversity score, which is an index that measures the biodiversity impact of the mix of management activities employed by farms on each plot (Jeanneret et al., 2014). This index is based on expert knowledge and almost 1,000 scientific articles and validated for use for grasslands, arable crops and semi-natural habitats (SNHs) in Switzerland and neighbouring countries. It relies on much more detailed and accurate information than the indirect proxies for biodiversity used in the literature. It has been shown to be highly correlated with actual biodiversity at the plot level (e.g. with a correlation of about 0.6 and 0.4 with the abundance of plant species and grasshoppers, respectively, found in the field). Thus, it can be considered a valid effect-based biodiversity performance indicator.

Our rich dataset allows us to compute several policy-relevant parameters. First, using farm-level information and a variety of empirical strategies, we compute the farm-level effect of enrolling land as EFA on the overall (i.e. farm-level) biodiversity score of the farm. Since farms are often considered as atomic units at whose level decisions are made, this is a relevant policy parameter. Moreover, most datasets in the literature are at the farm level; consequently, calculating the effects at the farm level renders our results comparable and compatible with those of other studies. Second, we use plot-level information to compute a further parameter that complements the aggregate results at farm level. Specifically, we compute the effect of enrolling land as EFA *separately* on the land that remains outside the EFA scheme. This is the spillover effect discussed earlier.

Our findings are twofold. First, we find that increasing the share of EFA has a positive impact on the biodiversity performance of the farm as a whole. However, our effect estimates are of a very small magnitude. To be specific, our models predict that a ten-percentage-point increase in the share of EFA leads to an increase of 0.3 in the farm's biodiversity score, which corresponds to roughly 2.7 per cent of the average biodiversity score in our dataset. To put this into perspective, note that the average share of EFA is 14 per cent in 2009 and increases to about 18 per cent in 2020. Studying the heterogeneity of the estimates across groups, we find that larger farms show higher effects, although these benefits are also very small in magnitude. Combining our findings with the results of Wuepper and Huber (2022) shows that an increase in action-based payments by 10 per cent leads to an increase in a farm's biodiversity score by roughly 1.6 per cent.

Second, our results also suggest that participating in the biodiversity scheme yields positive but very small benefits for the non-EFA. Specifically, our most optimistic estimates predict that, on average, enrolling additional land as EFA increases the biodiversity score of non-enrolled land by roughly 2.3 per cent of its average. Our most pessimistic results point out that a negative spillover cannot be excluded, although the magnitude of the negative spillover does not exceed 2 per cent of the average biodiversity score. To the best of our knowledge, this is the first paper to study potential spillovers to non-enrolled land in the context of biodiversity payments.

The paper proceeds as follows. Section 2 describes the institutional background and the data; then, the empirical strategy is described in Section 3. Section 4 presents a description of the results. The final section discusses the results and concludes.

2. Institutional setup and data

In the following, we briefly explain the institutional setup, describe the data sources and provide summary statistics.

2.1. Institutional setup

In its current form, the Swiss agricultural policy for biodiversity conservation consists of two main instruments.

First, there are cross-compliance requirements called Proof of Ecological Performance. One requirement is that farmers manage a certain share of their farmland as an EFA. Depending on the biotope (grassland, arable land, permanent cropland or woody elements), EFA management requirements may include restrictions on pesticides and insecticides, guidelines on the earliest and latest dates of harvest and so forth (FOAG, 2021b). Only farms that satisfy the Proof of Ecological Performance qualify to receive any kind of direct payment.

The second instrument, which closely relates to the first one, consists of direct payments that explicitly target the preservation and promotion of biodiversity and that are paid per hectare of EFA (see, e.g. Huber et al., 2023). The two main categories, which are cumulative, are the so-called action-based and result-based payments.[3] Action-based payments are *plot-specific* payments granted to a farm whenever the respective plot is managed as EFA. These payments were first introduced in 1999 with the aim of incentivising the voluntary implementation of biodiversity-friendly techniques by compensating farmers for their (potentially) forgone income (Wuepper and Huber, 2022). In 2017, the total agricultural area qualifying for action-based biodiversity payments corresponded to a share of 18 per cent (FOAG, 2019). The majority is managed on grassland (about three quarters), followed by permanent cropland and woody elements (Figure 1a). A small portion of EFAs is on arable land. Enrolment

3 Another category consists of payments for agglomeration bonus schemes aiming to improve the connectivity of EFAs at the regional landscape level.

Fig. 1. Distribution of EFAs by payment scheme in 2017. (a) Area share enrolled in an action-based biodiversity scheme. (b) Area share enrolled in an action-based scheme also qualifying for result-based payments across EFA categories. (c) Area share enrolled in a result-based biodiversity scheme. *Source*: Authors' illustrations using data from FOAG (2019). *Notes*: The data are based on a statistical public report that informs about the state of biodiversity schemes for the population of Swiss farms. The EFA categories presented here can differ from those used in the SAEDN. Vine area with natural diversity only receives result-based payments. The share for this category is therefore 100 per cent in Figure 1b.

is inversely correlated with how favourable the natural production conditions are: while only 14.7 per cent of the total usable area on the plains is declared as EFA, the EFA share of the total usable area in the highest mountain zone (the so-called mountain zone IV) amounts to 45.1 per cent (FOAG, 2021a). The result-based payments, on the other hand, are granted to plots that achieve a pre-defined minimum of ecological quality. This minimum is achieved if a certain level of so-called indicator plant species are found to reside on the plot and if there exist certain structural elements (Elmiger et al., 2023; Mack et al., 2020).[4] In addition, only some EFA categories qualify for result-based payments. They are provided cumulatively, that is, they are only paid if the farmland is managed under action-based requirements. Of all EFAs on grassland, 41 per cent are also eligible for result-based payments, while this number is the highest for litter meadows (Figure 1b).[5] Similar numbers can be observed for traditional orchard trees, hedges and field and riparian shrubs. Regarding the distribution of EFAs that are eligible for result-based payments, the large majority belongs to grassland categories, and only less than one quarter to permanent cropland and woody elements (Figure 1c).

After the new direct payment system was introduced in 2014 (Mann and Lanz, 2013), farmers received more action and result-based payments per hectare of agricultural land for almost all EFA categories. Thereafter, result-based payments increased gradually, while action-based payments were cut over the years. Accordingly, in 2020, per-hectare results-based payments were higher than per-hectare action-based payments for all eligible EFA categories. At the beginning of our observation period in 2009, the opposite was true. This change in incentives allowed the share of plots qualifying for result-based payments to increase (FOAG, 2019).

2.2. Data sources

We use two datasets from two related data sources. The first is the SFADN, which is part of the agricultural monitoring system under the authority of the Swiss Legislature. Its main objective is to monitor agricultural income. Organised in a similar way to other European FADNs, the network collects annual data from a subset of all Swiss farms through a survey (Renner et al., 2019). The data comprise a comprehensive set of economic and structural farm variables, such as market income, direct payments and farm size. They also encompass information on farmer characteristics, such as age and education.

The second data source is the SAEDN, which collects very detailed farm management data and processes them to calculate a rich set of farm-level agri-environmental indicators (Gilgen et al., 2023). An important feature of the data provided by the SAEDN is that some variables are at the plot level. This allows us to distinguish between plots managed as EFA and the remaining plots (non-EFAs) and to obtain their plot-specific environmental indicators.

4 See 'Ordinance on direct payments to agriculture' (Direktzahlungsverordnung, DZV; SR 910.13).

5 Vine area with natural diversity is an exception, as this category only receives result-based payments. The share for this category is therefore 100 per cent.

For the purposes of this paper, we merge the datasets provided by two networks for those farms that provide data to both SFADN and SAEDN. Thus, our dataset represents an unbalanced panel of 410 farms spanning the period from 2009 to 2020 (in detail, we observe about 120 to 270 farms each year). In total, our dataset contains 2,341 observations. It covers all production types according to Meier (2000), such as dairy farming, with the exception of farms with a strong focus on special crops.[6]

2.3. Descriptive statistics

In this subsection, we describe the three categories of variables used in this paper: outcome, treatment and control variables. In addition, we provide descriptive statistics for each of the three categories.

2.3.1 Outcome variables

Our main outcome variables are from the SAEDN and based on an index that measures the level of biodiversity. This index was developed in Jeanneret et al. (2014) and allows us to measure the impact of management techniques on the organismal biodiversity of 11 indicator species groups (ISGs), such as amphibians (Amphibia), small mammals (Mammalia), snails (Gastropoda), grasshoppers (Orthoptera) and others (see Jan et al., 2024: for a short explanation). This index, referred to as the biodiversity score, aggregates the impacts of a comprehensive list of management techniques for a given crop or SNH on the organismal biodiversity of 11 ISGs into a single score. The higher the score, the better the environmental performance on a given plot of land. Importantly, the score is validated at the plot level relying on biodiversity data collected in the field. For the purposes of our study, we aggregate the plot-specific outcome data into three types of farm-level measurements: biodiversity score at the overall farm level, for the EFAs and for the non-EFAs. The first aggregates the plot-specific biodiversity scores across the entire farmland, the second across farmland managed as EFA and the third across the remaining portion (i.e. non-EFA farmland). Table 1 displays descriptive characteristics of the three outcome variables. On average, the farm-level biodiversity score is 10.68, with a standard deviation of roughly 2. The average biodiversity score for the EFAs is almost twice as high, while the average score for the non-EFAs is slightly lower than the farm-level average. Furthermore, Figure 2 shows that all three biodiversity scores remain largely constant across years, even if we can observe a slight decline in the average biodiversity score for the EFAs.

2.3.2 Treatment variable

The SAEDN dataset also contains the treatment variable. Specifically, for each plot of a given farm, we observe whether it is enrolled in a biodiversity scheme. This allows us to aggregate the area of all plots managed as EFA of

6 For more information about the data sources and the merged dataset, please refer to Jan et al. (2024).

Table 1. Summary statistics of outcome variables

Variable	Mean	Std. dev.	Min	Max
Outcomes:				
Biodiversity score (total)	10.68	1.98	5.60	17.83
Biodiversity score (EFAs)	17.12	2.12	6.70	27.40
Biodiversity score (non-EFAs)	9.65	1.92	4.83	16.09
Treatment:				
Overall farmland's share of EFAs in %	15.10	9.76	0.89	85.35

Notes: The dataset is unbalanced panel data from 410 farms for the years 2009–2020 ($N = 2,341$).
Source: Authors' calculations based on SAEDN and SFADN 2009–2020.

any given farm. While EFAs on arable land can only be enrolled in an action-based scheme, grassland EFA categories and some structural elements also qualify for result-based payments (see Jan et al., 2024: for details). Since we cannot distinguish between the two payment types in our data, we assume that the enrolled plots fulfil at least the requirements for the action-based scheme.

The overall farmland's share of EFA is calculated as the total EFA divided by the overall farmland. Thus, our treatment variable can take values in the interval $[0,1]$. Practically though, because of the cross-compliance requirements, the observed share is never less than 0.07.[7] In our sample, we have information on 64,889 plots (including SNHs). The average farm has an area of about 4.3 hectares managed as EFA (18,238 plots receive biodiversity payments), corresponding to a share of 15.1 per cent (Table 1). Additionally, we observe that the average share of EFAs increased across years from about 14 per cent in 2009 to about 18 per cent in 2020 (see the orange line in Figure 2).

Table 2 shows summary statistics for each EFA category in our sample. Grassland is the most important habitat where EFAs are implemented, both in terms of size and occurrence. In particular, extensively used meadows represent about one half of the total size and the total number of EFAs. Arable land contributes little to the total size of EFAs. This is also largely true for permanent crops, woody elements and other categories, with the exception of orchard trees, which account for more than 10 per cent of the total size (the area for trees is budgeted at 100 m^2).

2.3.3 Control variables

Table 3 shows descriptive statistics for three types of control variables considered in this study. The first type of variables are economic indicators of the farm, such as the share of employees in the total farm labor force, shares of different farming activities in terms of their monetary importance, but also information on the amount of direct payments received, which allows us to

7 A farm is allowed to collaborate with one or more other farms to fulfil all of the cross-compliance requirements or parts thereof. In this case, the required minimum share of EFAs applies not to each single farm, but to the farm collective. This explains why some farms can show a share of EFAs below 7 per cent.

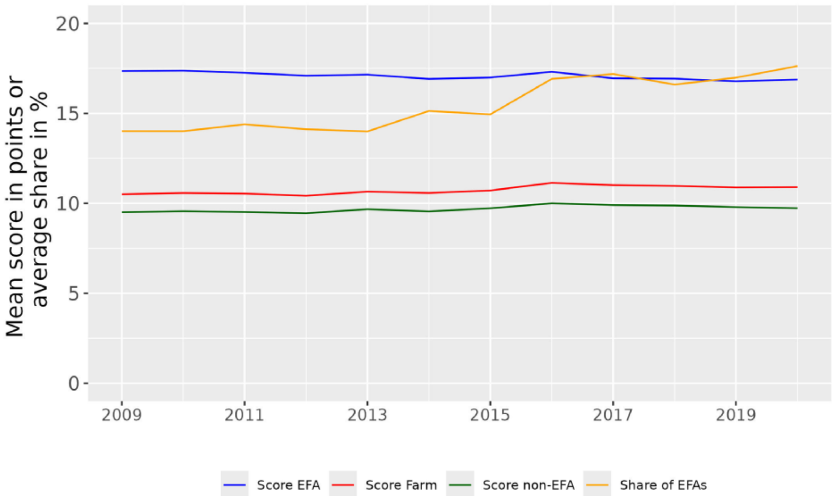

Fig. 2. Development of the mean biodiversity scores and the average share of EFAs (in per cent) over time. *Notes*: Mean values of the biodiversity scores in points and the share of EFAs in per cent over time. Number of farms $n = 410$, time periods $T = 1$–12, number of observations $N = 2{,}341$. *Source*: Authors' illustrations using SAEDN and SFADN 2009–2020.

distinguish between general, ecological and other payments. The second type of variables capture a farmer's individual characteristics, such as age and education. Finally, the third type of variables describes the structure of the farm, such as the total area, the share of land under ownership, the livestock density per total farm area and the location of the farm.[8]

All three types of variables were previously shown to be important predictors of the farmer's decision to enrol in a biodiversity scheme (Mack et al., 2020; Schaub et al., 2023). For example, several articles report that younger farmers participate more in AESs (Hynes and Garvey, 2009; Murphy et al., 2014) or have higher shares of EFAs qualifying both for action- and result-oriented payments (Mack et al., 2020). Furthermore, Mack et al. (2020) provide evidence that farmers with higher education invest more in result-oriented EFAs and less in action-based, because different skills are needed (Batáry et al., 2015). As a further example, several studies have found that farm size plays a crucial role in participating in AES (Lastra-Bravo et al., 2015; Pavlis et al., 2016; Mack et al., 2020). Apart from the size of the agricultural land, we include information on the share of land under ownership as well as the number of plots.

Thus, our controls represent a comprehensive list of enrolment factors (Mack et al., 2020), and we exploit this feature of our data in our empirical strategy below.

8 The location of a farm may be either a valley, hill or mountain region. The mountain region is further divided into mountain zones I to IV, with higher altitude for higher numbers.

Table 2. Summary statistics of plot data (SAEDN)

EFA category	Mean size (ha)	Aggregated size (ha)	Number of plots N_{plots}
Grassland			
Extensively used meadows	0.51	4,825.88	9,384
Extensively used pastures	0.98	1,489.95	1,515
Wooded pastures	2.68	327.30	122
Less intensively used meadows	0.67	1,233.58	1,856
Litter meadows	0.61	172.59	283
Riverside meadows	0.10	1.74	17
Arable land			
Conservation headland	0.56	164.61	295
Rotational fallows	0.80	63.21	79
Arable field margins	0.17	12.11	70
Flower strips for pollinators and other beneficial insects	0.16	7.04	45
Permanent crops, woody elements and others			
Traditional orchard trees	0.68	1,275.75	1,871
Hedges, field and riparian shrubs	0.15	229.43	1,501
Native individual trees and tree alleys	0.10	100.61	1,027
Ruderal areas, rock piles and rock walls	1.74	107.87	62
Unpaved natural path	0.50	37.86	76
Ditches and ponds	0.23	7.89	35
All EFA plots	0.551	10,057.42	18,238

Notes: The statistics are calculated in a pooled dataset (covering the years of observation 2009–2020) for two reasons: first, we cannot identify single plots across years and, second, the cultivation type of a given plot can change. This implies that the plot data are not identical across the years. N_{plots} is the number of plots (including SNHs). In total, we have information on 64,889 plots, of which 18,238 plot habitats receive biodiversity payments.

The area for trees is budgeted at 100 m^2.

Source: Authors' calculations using plot data for combined SFADN and SAEDN farms from 2009 to 2020.

3. Empirical strategy

We are interested in how a rise in the share of EFAs affects the biodiversity score (Jeanneret et al., 2014) measured for a farm's EFAs and non-EFAs as well as for its overall farmland. In the following section, we discuss our empirical strategy (i.e. we define the parameter of interest and show how it is identified and estimated).

3.1. Notation and treatment effects

Let $S_i \in [0, 1]$ represent the share of total land that farm i declares as EFA. Furthermore, let $Y_i(s)$ denote the potential outcome of farm i if the farm received a

Table 3. Summary statistics for control variables

Variable	Mean	Std. dev.
Economic factors		
Share of employees in the total farm labour force	0.239	0.221
Farming form (reference *full-time farming, individual farm*)		
Full-time farming with secondary activity, individual farm	0.320	0.467
Part-time farming, individual farm	0.229	0.420
Farming collective	0.028	0.166
Share of arable crops in the farm's agricultural monetary market output	0.137	0.225
Share of vegetables in the farm's agricultural monetary market output	0.010	0.030
Share of permanent crops in the farm's agricultural monetary market output	0.013	0.040
Share of milk and milk products in the farm's agricultural monetary market output	0.365	0.304
Share of cattle in the farm's agricultural monetary market output	0.266	0.259
Share of granivores in the farm's agricultural monetary market output	0.129	0.236
Share of para-agricultural activities in the farm's total monetary output	0.020	0.061
General direct payments in CHF/agricultural land in hectares	2,030.62	648.62
Ecological direct payments in CHF/agricultural land in hectares	780.27	498.99
Other direct payments in CHF/agricultural land in hectares	130.02	187.59
Market income in CHF/agricultural land in hectares	9,015.72	6,001.25
Farmer's characteristics		
Age of farm operator	45.90	9.66
Education (in shares, reference *no diploma*)		
Currently in training	0.002	0.041
Completed vocational training	0.390	0.488
Completed higher vocational training	0.514	0.500
University (of applied sciences)	0.065	0.246
Farm structure and natural environment		
Farmland in hectares	27.43	14.32
Share of land under ownership	0.675	0.468
Number of plots	27.700	11.900
Livestock density (livestock units per total farm area)	1.320	0.834
Share of arable crops in the farmland	0.262	0.273
Share of special crops in the farmland	0.004	0.013

(continued)

Table 3. (Continued)

Variable	Mean	Std. dev.
Agricultural production zone (in shares, reference *valley zone*)		
Hill zone	0.199	0.400
Mountain zone I	0.147	0.354
Mountain zone II	0.120	0.326
Mountain zone III	0.078	0.268
Mountain zone IV	0.025	0.157
Altitude of production site in metres above sea level	691.61	222.07
Production system (reference *in shares, conventional farming*)		
Organic farming	0.109	0.312
In conversion to organic farming	0.009	0.094

Notes: The dataset comprises unbalanced panel data from 410 farms for the years 2009–2020 ($N = 2,341$). More detailed statistics can be found in Jan et al. (2024).
We use the agricultural production zone, the altitude of the production site and the production system only as controls in the estimation approach using the Frisch–Waugh theorem, since these are variables with almost no temporal variation.
Cattle include cattle breeding and fattening, including dairy cattle culling but excluding milk and dairy products.
Source: Authors' calculations based on SFADN 2009–2020.

treatment $s \in [0,1]$, that is, if the farm declared the share of EFAs to be s. The corresponding measured outcome is denoted as Y_i. For outcome variables, we use the (i) biodiversity score of the EFAs, (ii) of the non-EFAs and (iii) of the overall farmland. Finally, let X_i be a random vector that collects pre-treatment characteristics of the farm. These characteristics are listed in Table 3 in the previous section.

With this notation, we can now define the following average treatment effect (the individual index i is omitted whenever the context allows):

$$\Delta(s,s') = \mathbb{E}[Y(s) - Y(s')], \tag{1}$$

where s and s' are any two different treatment values in $[0,1]$. Intuitively, $\Delta(s,s')$ describes the effect of switching from a share s' to a share s. Depending on which outcome variable is used, we distinguish between the three treatment effects $\Delta^{\text{total}}, \Delta^{\text{nonefa}}$ and Δ^{efa}. The effect Δ^{total} refers to the effect on the farm's overall biodiversity score, Δ^{nonefa} to the effect on the farm's biodiversity score of the non-EFA and Δ^{efa} to the effect on the farm's biodiversity score of the EFA.

3.2. Identification and estimation

3.2.1 Main effects

The main challenge in identifying $\Delta^{\text{total}}, \Delta^{\text{nonefa}}$ and Δ^{efa} is endogenous selection into the treatment. In particular, farmers who are more likely to benefit from declaring a larger share s as EFA would choose a higher value s (see, e.g. Bertoni et al., 2020). To deal with this selection problem, we employ three different complementary panel data regression specifications.

Specification 1

The first specification exploits the rich information on confounders in our dataset that we described in the previous section. Specifically, we assume that the combination of observed farm-specific economic and natural environment indicators, as well as farmers' characteristics, allows us to account for the relevant *time-varying predictors* of the choice variable S_i. This list of variables represents a comprehensive set of characteristics that has been previously used in the literature to model and predict the decision of the farmer to enrol land as EFA (see, e.g. Mack et al., 2020). With this assumption, we estimate the effect of S on the three outcome variables using the fixed-effects panel data model

$$Y_{it} = \theta S_{it} + X_{it}\beta + \alpha_i + \delta_t + \varepsilon_{it}, \quad (2)$$

where θ and β are unknown coefficients, α_i are farm fixed effects and δ_t are time dummies. The time dummies allow us to capture general structural changes over time, such as technological changes and changes in legislation, while the farm fixed effects allow us to capture farm-specific components, such as unobserved management skills. Estimating this model with a fixed effect method (such as a within transformation) yields consistent estimates of the unknown effect θ, provided that ε_{it} is independent of the observed covariates.

The main advantages of this model are its simple interpretability as well as its efficiency if correctly specified. Given the small cross-sectional number of observations in our sample (2,341 observations from 410 farms), efficiency is the major reason to use a parametric model. There are two main disadvantages of Model (2). The first potential disadvantage is that ε_{it} may still contain factors of biodiversity that are correlated with the decision to enrol land as EFA. Specifically, the decision on the size S_{it} is potentially based on a two-sided tradeoff. On the one hand, farmers factor in the lost productivity on a given field due to the stricter environmental requirements. Conditioning on economic variables, or more precisely, on the market income per hectare of farmland, aims to capture this part of the tradeoff. On the other hand, farmers consider the effort made to meet environmental standards on the same plot of land, which determines whether they receive direct payments. A potential pitfall of Model (2) is that the available economic and structural characteristics of the farm only poorly capture the environmental aspect of the tradeoff. Controlling for the environmental component is particularly important when the economic and the environmental outcomes are not perfectly correlated.

Specification 2

To account for this potential pitfall, in a second panel data regression specification, we include past biodiversity scores as additional covariates. By conditioning on past environmental outcomes, we effectively control for the second component of the tradeoff. The reason is that farmers are also likely to base their decisions on past biodiversity scores when considering the environmental aspect of the tradeoff.[9] To estimate this dynamic version of Model (2),

9 More reliable approaches, such as staggered difference-in-differences, cannot be used for several reasons. First, although we observe the biodiversity scores for the EFAs and non-EFAs separately,

we follow Arellano and Bond (1991), using three lags of the respective outcome variable as control variables.[10]

Specification 3

Adjustment to habitat resulting from a change in management activities is likely to take time. However, our data allow a dynamic assessment of the effect only to a restricted extent. The main limitation is as follows. The dataset includes only 12 periods, and within these 12 periods, the treatment variable has a limited within-farm variation. Thus, including lags of the treatment in our models would substantially reduce the precision of our estimates (multicollinearity), and this would be feasible for only a small number of lags.

Despite this limitation, we study the effect of an increasing share of EFA on the biodiversity score by estimating a distributed lag model (e.g. Wooldridge, 2010) that includes different lags of the treatment variable in the same regression equation.[11] Note that we can only include up to two lags, as a higher number of lags leads to multicollinearity.

Finally, we allow the dependence on observed covariates to have an arbitrary functional form and estimate a semi-parametric model. This specification is explained in Appendix A.1 (Specification 1).

3.2.2 Subgroup-specific effects

Furthermore, we estimate how the effects differ between several subgroups ('effect heterogeneity') by interacting the treatment variable with a dummy for the respective subgroup. θ_j with $j = 1, \ldots, 4$ indicates how the effect varies from the reference group.

Firstly, it is possible that large farms implement different extensification strategies compared to small farms (Wuepper et al., 2020). To test this hypothesis, we define a dummy depicting the farmland's distribution (larger than the first or second tercile [19.5 and 29.1 hectares, respectively] with the reference smaller than the first tercile). Furthermore, we interact our treatment variable with an indicator of a farm's production intensity measured as the ratio of market income (in Swiss francs [CHF]) to the farmland (in hectares). Again, we use the intensity distribution and define three subgroups using the terciles. Then, we estimate the following equation:

$$Y_{it} = \theta_0 S_{it} + \theta_1 S_{it} * Area\_q2_{it} + \theta_2 S_{it} * Area\_q3_{it} + \\ \theta_3 S_{it} * Intens\_q2_{it} + \theta_4 S_{it} * Intens\_q3_{it} + X_{it}\beta + \alpha_i + \delta_t + \varepsilon_{it}. \quad (3)$$

we cannot track the plots over time, as the plot identifier changes over time. Thus, we do not know which plots have been converted into EFA in a given year. As a result, the models are specified at the EFA/non-EFA-levels, involving a continuous treatment variable (share of EFA in the UAA), which is not staggered. Second, a large share of all observations (33 per cent) does not change the share of EFAs across years. These observations cannot be meaningfully included in approaches that involve pre–post-treatment comparison, such as (staggered) difference-in-differences and event study approaches.

10 We use the pgmm function of the plm package in R.

11 Specifically, we estimate the following models: $Y_{it} = \theta S_{it} + \gamma_1 S_{it-1} + X_{it}\beta + \alpha_i + \delta_t + \varepsilon_{it}$ and $Y_{it} = \theta S_{it} + \gamma_1 S_{it-1} + \gamma_2 S_{it-2} + X_{it}\beta + \alpha_i + \delta_t + \varepsilon_{it}$.

3.3. Decomposing estimated effects into spillovers and shifting effects

The treatment effects Δ^{nonefa} and Δ^{efa} defined above have limited policy relevance. Specifically, they represent a weighted average of an area-specific (EFA or non-EFA) effect and a land-shifting effect. In what follows, we elaborate on this problem and mathematically derive the policy-relevant parameters.

One major limitation of our plot data is that it is not geo-referenced, and plot identification numbers change over time. Thus, while we observe plot-specific data, such as biodiversity scores and whether plots are EFA or non-EFA at each point in time, we cannot follow the biodiversity score of a plot or its enrolment status over time. Instead, our outcome variables are farm-averages: for each point in time, we measure the biodiversity score for non-EFAs as an average across all plots that are not enrolled as EFA at that point in time (and analogously for the biodiversity score of the EFAs). This limitation leads to a subtle restriction of the interpretation of Δ^{nonefa} and Δ^{efa}. Specifically, each of these two estimates consists of an actual treatment effect and a so-called shifting effect. The latter results from the fact that with an increasing share of EFA, the plots' composition of EFAs and non-EFAs changes. This combination of treatment and shifting effects hampers the usage of Δ^{nonefa} and Δ^{efa} for deriving policy implications.

In the following, we derive a simple framework that shows these relationships mathematically. Using this framework, we accomplish the following: we use the estimates of $\Delta^{\text{total}}, \Delta^{\text{nonefa}}$ and Δ^{efa} to bound the actual spillover effect of an additional enrolment in EFAs on the biodiversity score of the non-EFAs.

Consider first an average farm that has three types of land: Plot 1 is managed as non-EFA, Plot 2 is first managed as non-EFA and then enrolled in the biodiversity scheme, and Plot 3 has been managed as EFA from the beginning (Figure 3a).[12] In the following, we use the potential outcome notation with the enrolment of Plot 2 being the treatment. We denote the biodiversity scores *before* Plot 2 is enrolled as $BD_1(0), BD_2(0)$, and $BD_3(0)$, respectively. The biodiversity scores of the three plots after the enrolment of Plot 2 are $BD_1(1), BD_2(1)$ and $BD_3(1)$. The plot-specific treatment effects are denoted by $\Delta_j, j = 1, 2, 3$, and defined as $\Delta_j := BD_j(1) - BD_j(0)$.

First, note that even if all three treatment effects Δ_1, Δ_2 and Δ_3 are equal to zero, it is possible to observe non-zero Δ^{nonefa} and Δ^{efa}. The reason is that the latter two treatment effects constitute an ex ante–ex post comparison of different plots of land. To understand this, note that ex ante (i.e. before Plot 2 is enrolled), the non-EFAs consist of Plots 1 and 2, as depicted in Figure 3a. The biodiversity score is thus a weighted average of the biodiversity scores of Plots 1 and 2. Ex post, however, the non-EFAs consist only of Plot 1 (Figure 3b). Thus the ex ante–ex post difference in the biodiversity scores of the non-EFAs, which is represented by Δ^{nonefa}, can be non-zero even if $\Delta_i = 0$

12 We call the three types of land 'plots', but our framework generalises to the case of more than three plots.

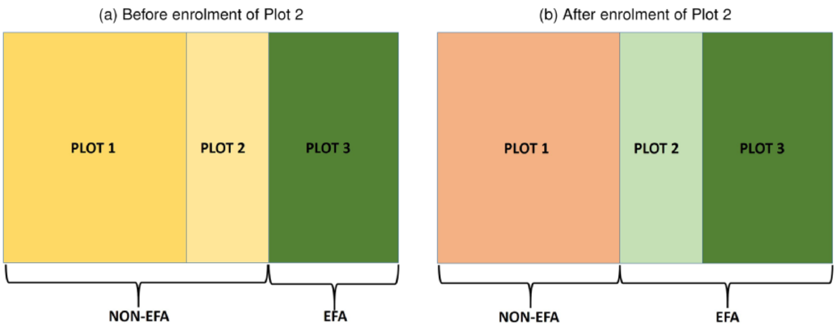

Fig. 3. An average farm with non-EFA and EFA land. (a) Before enrolment of Plot 2. (b) After enrolment of Plot 2.

for all $i = 1, 2, 3$. As an example, if $BD_1(0) < BD_2(0) < BD_3(0)$, which is a very realistic scenario, and if $\Delta_i = 0$, then both Δ^{nonefa} and Δ^{efa} will be negative. This 'shifting'-component, which is a result of deliberate land selection decisions by the farmers, makes it possible for both estimates Δ^{nonefa} and Δ^{efa} to be negative, but the total farm-level treatment effect Δ^{total} is positive. Conversely, these considerations show that Δ^{nonefa} and Δ^{efa} are less policy-relevant because they are a combination of plot-specific treatment effects and changes in scores due to land selection.

Instead, to learn about the actual policy effects, one needs to focus on Δ_1, Δ_2 and Δ_3. These three treatment effects describe how enrolment in a scheme changes the management techniques both on the land that is enrolled as well as on the land that is not enrolled. Δ_1 represents the potential spillover effects of the policy on non-enrolled land and is of particular interest. Note that a direct estimation of Δ_j is not precisely possible because we do not observe when a plot becomes enrolled. Thus, the objective is to identify these three objects from the estimated treatment effects $\Delta^{\text{total}}, \Delta^{\text{efa}}$ and Δ^{nonefa}.

To see how the estimates $\Delta^{\text{total}}, \Delta^{\text{nonefa}}$ and Δ^{efa} and Δ_1, Δ_2 and Δ_3 are related, first note that at any given moment, the total farm-level biodiversity score is a weighted average of the biodiversity scores of the three plots of Lands 1, 2, and 3.[13] Formally, it holds that

$$BD^{\text{total}} = w_1 BD_1 + w_2 BD_2 + w_3 BD_3, \tag{4}$$

where w_1, w_2 and w_3 represent the weights of Plots 1, 2 and 3 on the total surface of the farmland. Relationship (4) implies that the farm-level treatment effect can also be decomposed into three separate plot-specific treatment effects:

$$\Delta^{\text{total}} = w_1 \Delta_1 + w_2 \Delta_2 + w_3 \Delta_3. \tag{5}$$

Next, the estimated treatment effect for the non-EFAs is equal to the difference of the biodiversity scores of the non-EFAs with and without the treatment:

13 Here, we ignore the possibility that the farm can acquire land. In the period of observation, this is not an issue of high relevance: the third quartile of the distribution of the change in agricultural land is less than a hectare.

$\Delta^{\text{nonefa}} = BD_{\text{nonefa}}(1) - BD_{\text{nonefa}}(0)$. Crucially, these two scores are defined according to different plot combinations. $BD_{\text{nonefa}}(1)$ is simply the score of Plot 1, because the treatment is defined here as the enrolment of Plot 2 in the scheme (and so, after the treatment, only Plot 1 is managed as non-EFA). On the other hand, $BD_{\text{nonefa}}(0)$ is the weighted average biodiversity score of Plots 1 and 2. With these considerations, Δ^{nonefa} can be written as

$$\begin{aligned} \Delta^{\text{nonefa}} &= BD_{\text{nonefa}}(1) - BD_{\text{nonefa}}(0) \\ &= \frac{w_1}{w_1 + w_2}\Delta_1 + \frac{w_2}{w_1 + w_2}(BD_1(1) - BD_2(0)) \qquad (6) \\ &= \Delta_1 + \frac{w_2}{w_1 + w_2} SE^{\text{nonefa}}, \qquad (7) \end{aligned}$$

where $SE^{\text{nonefa}} := BD_1(0) - BD_2(0)$.[14] Equation (7) has an intuitive interpretation: the measured effect on the non-EFAs is equal to the treatment effect on Plot 1, Δ_1, and a weighted 'land-shifting' effect, which is equal to the ex ante difference in the biodiversity scores of the non-EFAs (Plots 1 and 2). Under equivalent considerations, it can be shown that the EFA-specific treatment effect Δ^{efa} can be written as

$$\Delta^{\text{efa}} = \frac{w_2}{w_2 + w_3}(BD_2(1) - BD_3(0)) + \frac{w_3}{w_2 + w_3}\Delta_3 \qquad (8)$$

$$\Delta^{\text{efa}} = \frac{w_2}{w_2 + w_3}(\Delta_2 + SE^{\text{efa}}) + \frac{w_3}{w_2 + w_3}\Delta_3, \qquad (9)$$

where $SE^{\text{efa}} = BD_2(0) - BD_3(0)$ is the pre-treatment difference in biodiversity scores between Plots 2 and 3. Thus, the measured effect on the EFAs is equal to the combined effects on Plots 2 and 3 (Δ_2 and Δ_3, respectively) and the shifting effect SE^{efa}.

Since the separate $BD_j(d)$ ($j = 1, 2, 3,\ d = 0, 1$) are unknown, Equations (5), (7) and (9) represent a system of three equations with more than three unknowns. To solve the system, further assumptions are necessary. We explore the identification under a variety of different assumptions. Our basic assumption is a no-impact assumption:

Assumption 1 There is no impact on already enrolled land.
Our first assumption is that enrolling Plot 2 has no impact on the biodiversity score of Plot 3.

Formally, this assumption is equivalent to assuming that $\Delta_3 = 0$. It can be violated when Plots 2 and 3 are upgraded simultaneously due to an overall

14 See the appendix for details.

change in the management strategy. Under Assumption 1, the system of Equations (5), (7) and (9) simplifies to

$$\Delta^{\text{total}} = w_1\Delta_1 + w_2\Delta_2, \tag{10}$$

$$\Delta^{\text{nonefa}} = \Delta_1 + \frac{w_2}{w_1 + w_2} SE^{\text{nonefa}}, \tag{11}$$

$$\Delta^{\text{efa}} = \frac{w_2}{w_2 + w_3}(\Delta_2 + SE^{\text{efa}}). \tag{12}$$

This is a system with three equations and four unknowns $(\Delta_1, \Delta_2, SE^{\text{nonefa}}, SE^{\text{efa}})$; therefore, the system is still underdetermined. In the following, we explore three different assumptions. Each of these three assumptions implies a bound for the effects Δ_1 and Δ_2.

Assumption 2 It holds that $SE^{\text{nonefa}} \leq 0$.

Assumption 3 It holds that $SE^{\text{efa}} \leq 0$.

Assumption 4 It holds that $\Delta_2 \geq 0$.

Assumption 2 states that before the treatment was implemented, the biodiversity score of Plot 2 was not lower than the biodiversity score of Plot 1. Since Plot 2 is the plot eventually enrolled as EFA, this assumption implies that farmers enrol land, which is the least costly to enrol (i.e. for which the management practices hardly need to be adapted; see, e.g. Huber et al., 2021). Moreover, if the biodiversity score is interpreted as the biodiversity friendliness of farm management, the assumption would be equivalent to assuming that farmers select their EFAs based on the potential biodiversity outcome. This is a natural assumption, and it has been frequently regarded by the literature as a potential source of endogeneity when evaluating the effects of policies on biodiversity (e.g. Schaub et al., 2023).

Assumption 3 states that before the treatment was implemented, the biodiversity score of Plot 3 was not lower than the biodiversity score of Plot 2. Since the biodiversity score measures the environmental friendliness of a much wider and more detailed range of management techniques than those considered in the eligibility criteria, this is an implicit rationality assumption. Specifically, a violation of the assumption would imply that the land enrolled is managed in a less biodiversity-friendly manner than the non-enrolled land, which would be irrational.

Assumption 4 has an analogous interpretation. A violation of Assumption 4 would mean that the biodiversity friendliness of the farm management of Plot 2 would decrease when enrolling it as EFA. This would imply that farmers were ex ante eligible to enroll Plot 2 as EFA but did not do so, thus foregoing payments.

The following proposition states the bounds under each of the three assumptions.

Proposition 1. *Under Assumption 2, it holds that*

$$\Delta_1 \geq \max\{\Delta^{\text{nonefa}}, \frac{\Delta^{\text{total}} - (w_2 + w_3)\Delta^{\text{efa}} + w_2(BD_{\text{nonefa}}(0) - BD_3(0))}{w_1}\} \quad (13)$$

$$\textit{and} \qquad \Delta_2 \leq \frac{w_2 + w_3}{w_2}\Delta^{\text{efa}} - (BD_{\text{nonefa}}(0) - BD_3(0)). \quad (14)$$

Under Assumption 3, it holds that

$$\Delta_1 \leq \frac{\Delta^{\text{total}} - (w_2 + w_3)\Delta^{\text{efa}}}{w_1} \quad (15)$$

$$\textit{and} \qquad \Delta_2 \geq \frac{w_2 + w_3}{w_2}\Delta^{\text{efa}}. \quad (16)$$

Under Assumption 4, it holds that

$$\Delta_1 \leq \frac{\Delta^{\text{total}}}{w_1} \quad (17)$$

$$\textit{and (trivially, per assumption)} \qquad \Delta_2 \geq 0. \quad (18)$$

In Section 4, we calculate these bounds based on actual estimates.

4. Results

The following subsection describes our main findings from Model Specifications 1–3 and their interpretation. As we are interested in the effect of an increasing share of EFAs on the biodiversity score of the whole farmland and of its two subcomponents, namely the EFAs and non-EFAs, we present only the respective point estimate and its clustered standard error.[15] Afterwards, in Subsection 4.2, we calibrate the theoretical framework presented in Subsection 3.3 to derive the policy-relevant parameters.

4.1. Estimation results

Our estimates from all three main model specifications show very similar results, as described in detail hereafter.[16]

15 The resulting point estimates of the control variables are included in Appendix A.3.

16 The last sensitivity check, obtained with Specification 4, is displayed in Figure A.1. The coefficients are also very close to our main findings in Figure 4, although the estimate for the biodiversity score of the non-EFAs becomes zero.

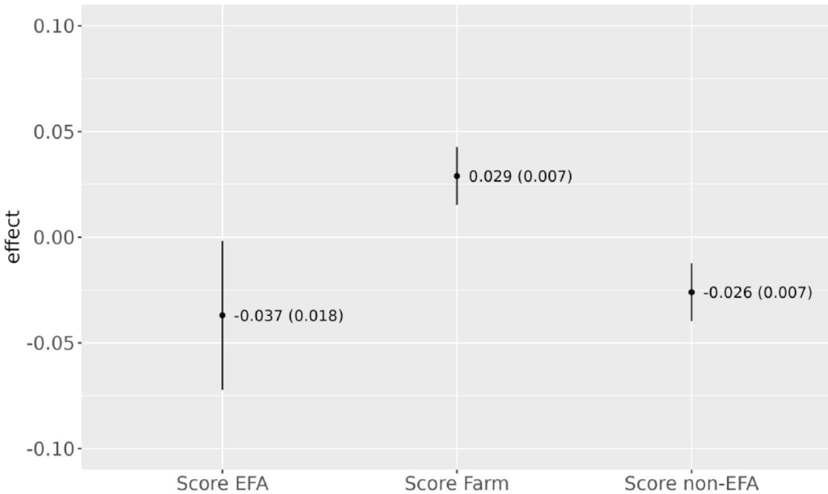

Fig. 4. Main estimation results. *Notes*: Point estimates from linear fixed effects estimation with clustered standard errors (Specification 1). Number of farms $n = 410$, time periods $T = 1–12$, number of observations $N = 2,341$. *Source*: Authors' illustrations using SAEDN and SFADN 2009–2020.

4.1.1 Results from Specification 1

Figure 4 presents the main estimation results of Model 2 for the three outcome variables. It shows that the effect on the biodiversity score measured for the whole farm is significantly positive, for example, a ten-percentage-point higher EFA share results in a score that is higher by 0.3. This change corresponds to an increase of about 2.7 per cent in the average biodiversity score. In contrast, the effects on the biodiversity score measured for both the EFAs and the non-EFAs are negative and amount to about –0.4 and –0.3, respectively, for a ten-percentage-point higher EFA share.

4.1.2 Results from Specification 2

The resulting effects from the first sensitivity test (Specification 2) are depicted in Figure 5. They show that, albeit a bit larger in size for the score of the EFAs and the overall score, the signs of the effects remain consistent with our main findings presented in Figure 4.

4.1.3 Results from Specification 3

The results obtained with this specification for the biodiversity score at the overall farm level, for the EFAs and for the non-EFAs, are displayed in Figure 6. The immediate effect estimates are similar to the estimates in the main results, while further lags are of a smaller magnitude. Nevertheless, overall, these estimates suggest that there is some accumulation of the effects over time; thus, our main results represent a lower bound for the long-term effects of the treatment.

Although these findings—an overall positive effect and negative effects on the score measured for the EFAs and non-EFAs—are surprising at first glance,

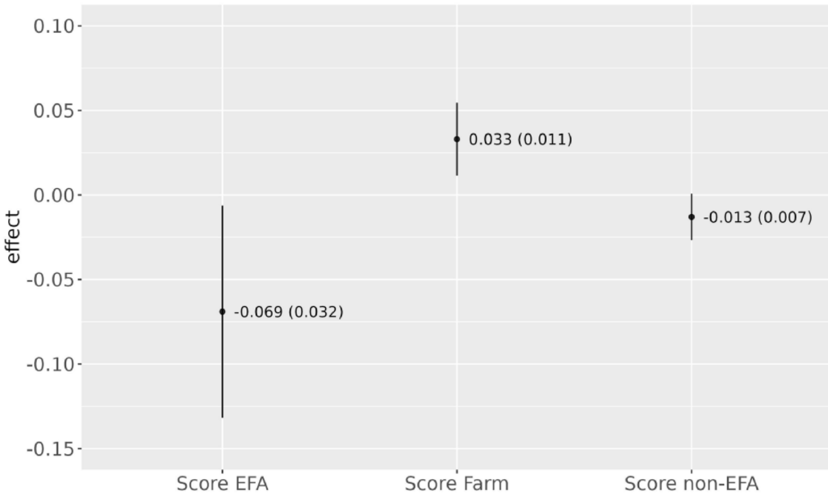

Fig. 5. Estimation results for a dynamic panel data model with three lags. *Notes*: Point estimates from a dynamic panel data model (Specification 2; Arellano and Bond, 1991). Number of farms $n = 410$, time periods $T = 1$–12, number of observations $N = 2{,}341$. Three lags of the respective outcome variable ($y_{i,t-1}, y_{i,t-2}$ and $y_{i,t-3}$) are used as additional control variables and instrumented with $y_{i,t-2}, y_{i,t-3}$ and $y_{i,t-4}$. F-statistics from first-stage regression 7.189, 7.421 and 7.246. *Source*: Authors' illustrations using SAEDN and SFADN 2009–2020.

they can be explained by the example we give regarding the shifting effect described in Subsection 3.3.

4.1.4 Subgroup-specific effects

Figure 7a depicts the regression results of Equation (3) and shows that larger farms perform better regarding the effect on the biodiversity score achieved on the EFAs. This is also reflected by the 0.01 higher effect on the overall score for medium-sized compared to small farms, while the biodiversity score for the non-EFAs is not differently affected between different size classes. A possible explanation for the positive interaction effect of farm size on the biodiversity score relates to the distance between the plot and the farm. Studies on farm growth show that farms often do not grow optimally (Bradfield et al., 2021; Valtiala et al., 2023). Due to the scarcity of land, farmers may expand their farmland with defragmented plots that are far away from the main farm building and more expensive to cultivate. When the operator of a growing farm decides on which plots to enrol, she or he takes not only the foregone market income and the financial compensation through the direct payments into account but also the cost reduction resulting from the plot management extensification. As shown by Huber et al. (2021) for agglomeration bonus schemes in Switzerland, this may lead farmers to first enrol plots that are far away from the farm buildings, which are not necessarily the plots that are managed originally (i.e. before enrolment) in the most biodiversity-friendly

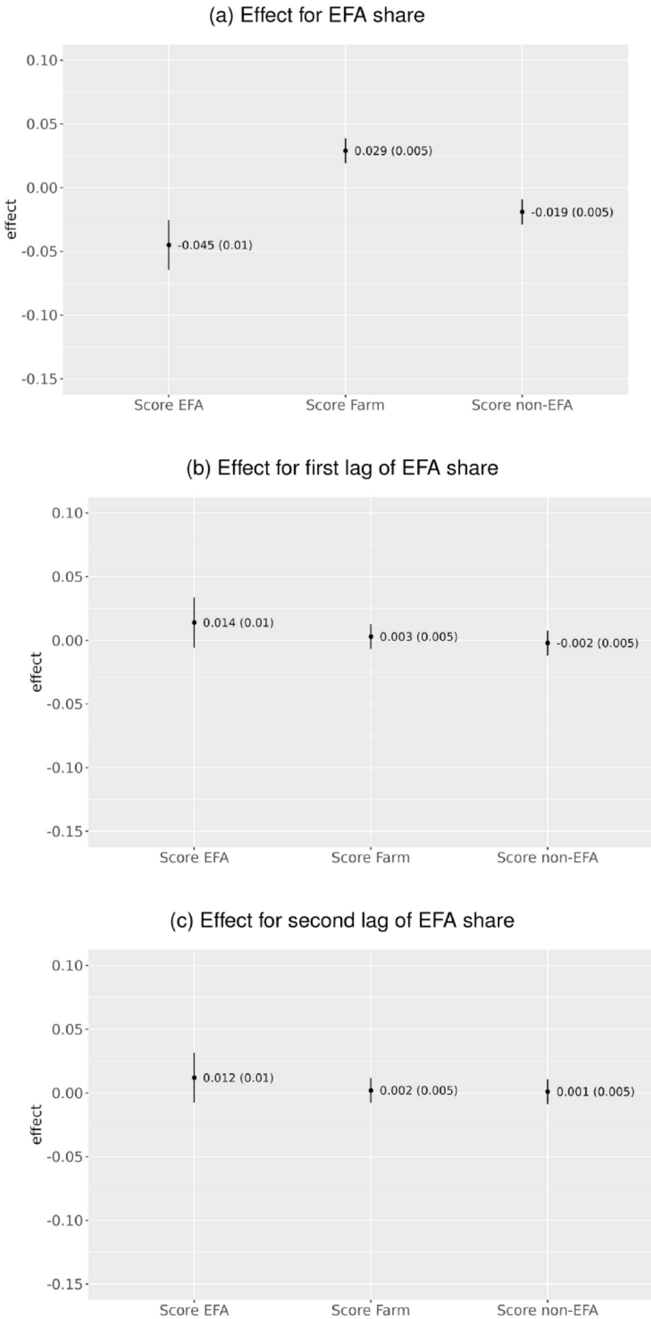

Fig. 6. Estimation results using distributed lags. (a) Effect for EFA share. (b) Effect for first lag of EFA share. (c) Effect for second lag of EFA share. *Notes*: Point estimates from linear fixed effects estimation including the first two lags of the share of EFAs (Specification 3). Number of farms $n = 287$, time periods $T = 1–10$, number of observations $N = 1,362$. *Source*: Authors' illustrations using SAEDN and SFADN 2009–2020.

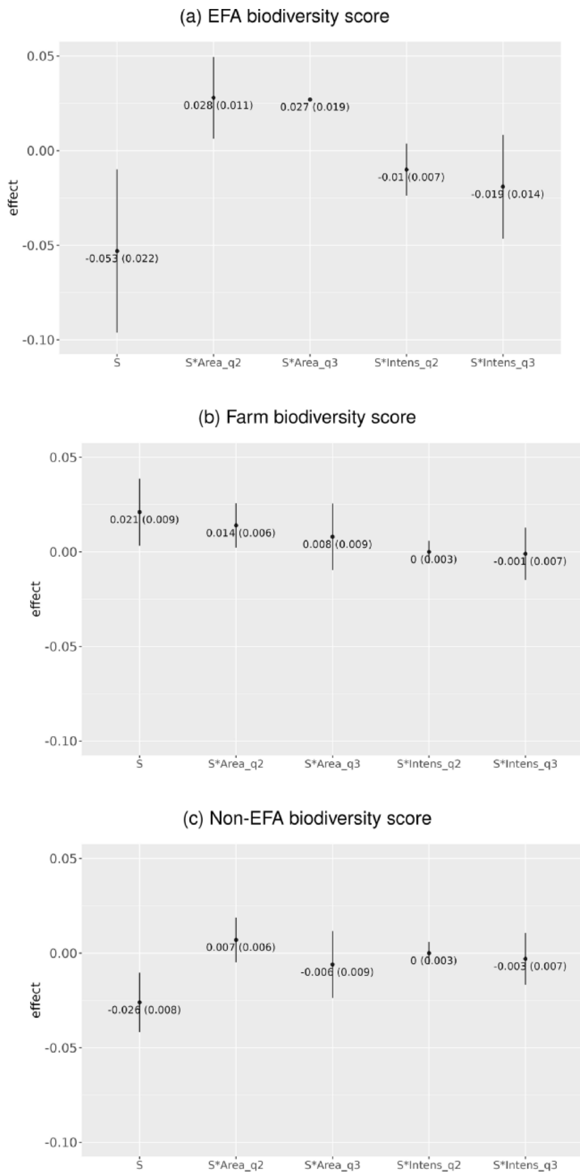

Fig. 7. Subgroup specific effects according to farm size and production intensity. (a) EFA biodiversity score. (b) Farm biodiversity score. (c) Non-EFA biodiversity score. *Notes*: Point estimates from linear fixed effects estimation with clustered standard errors (compare Equation (3)). Number of farms $n = 410$, time periods $T = 1$–12, number of observations $N = 2,341$. $S * Area\_q2$ and $S * Area\_q3$ depict the interaction for the group above the first (19.5 ha) and second terciles (29.1 ha) of the farmland. $S * Intens\_q2$ and $S * Intens\_q3$ depict the interaction for the group above the first (5,706 CHF/ha) and second (9,695 CHF/ha) terciles of production intensity (market income/farmland). The reference is the group with values lower than the first tercile. *Source*: Authors' illustrations using SAEDN and SFADN 2009–2020.

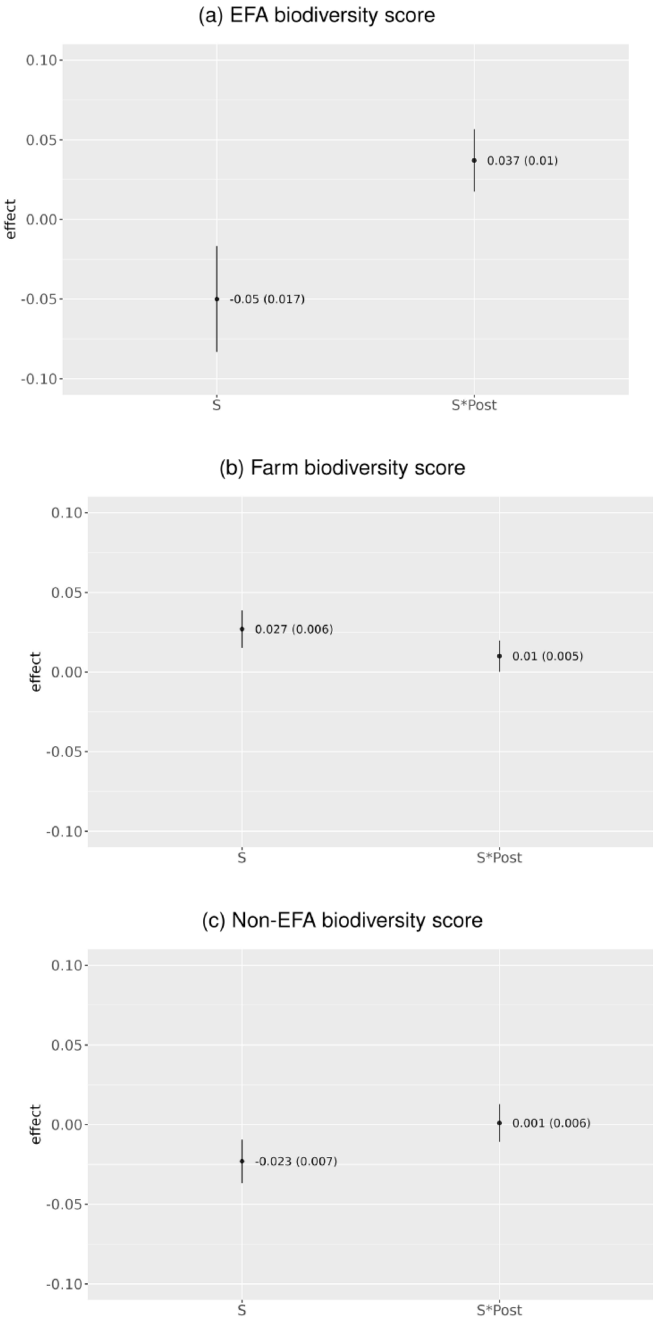

Fig. 8. Estimation results for policy periods. (a) EFA biodiversity score. (b) Farm biodiversity score. (c) Non-EFA biodiversity score. *Notes*: Point estimates from linear fixed effects estimation with clustered standard errors. Number of farms $n = 410$, time periods $T = 1$–12, number of observations $N = 2,341$. The model is fully interacted with the *Post* variable, which is equal to 1 for observations after the new policy regime ($\geq$2014) and 0 otherwise. $S * Post$ gives the effect of interest for the post-reform period. *Source*: Authors' illustrations using SAEDN and SFADN 2009–2020.

way. With an increasing share of EFAs, plots that are managed originally in the most biodiversity-friendly way may be enrolled.

We cannot find meaningful differences between farms with different production intensities for any of the three outcome variables (Figure 7). This finding is very interesting because one could hypothesise that especially farms with high production intensity tend to intensify the use of non-EFAs to compensate for the foregone market income. Hence, the financial incentives seem to be high enough to compensate for this even for farms showing the highest levels of intensity.

We also estimate the effects of interest in two different policy periods to learn more about the implementation of action- and result-based schemes. Figure 8 shows that the policy change in 2014, which is described in Subsection 2.1, implies a 0.037-point higher effect on the score measured for the EFAs. This finding indicates that as the share of EFAs increased after the policy change was implemented, farmers were more likely to transform land into plots qualifying for result-based payments, which show, on average, better environmental performance compared to action-based schemes (Saint-Cyr et al., 2023; Meier et al., 2021). While there is no difference in the effect on the score for the non-EFAs between the two policy periods, the overall biodiversity score is also higher in the post-policy period.

4.2. Calibrating the bounds

Now, we calculate the bounds of the spillover effect Δ_1 presented in Proposition 1. Since our data do not allow us to directly trace out $BD_{\text{nonefa}}(0), BD_{\text{efa}}(0), w_1, w_2$ and w_3, we calibrate the model using three alternative approaches.

Calibration 1 A 'back-of-the-envelope' approach
In the first approach, we use descriptive estimates of the above quantities. We divide this procedure into two steps.

Step 1. Consider first the weights w_1, w_2 and w_3. The weight w_3 is taken to be the share of EFAs at the beginning of our period of observation (2009) and is equal to 14 per cent. It follows that $w_1 + w_2 = 86$ per cent. The weight w_2 is calculated as the difference between shares of EFAs in 2020 (the end of the period of observation) and 2009 and is equal to four percentage points.[17] Similarly, $BD_{\text{nonefa}}(0)$ and $BD_{\text{efa}}(0)$ are taken to be the average biodiversity scores of the non-EFAs and EFAs in 2009, respectively, and are equal to 9.5 and 17.3.

Step 2. The estimates for $\Delta^{\text{total}}, \Delta^{\text{efa}}$ and Δ^{nonefa} are calculated as the differences in biodiversity scores between 2009 and 2020. For example, Δ^{efa} is calculated as the difference between the average biodiversity score of the EFAs

17 One drawback with this calculation of w_2 is that the sample of farms changes its composition over time. To account for this problem, we calculate farm differences over time in each of the two subsequent periods and then calculate the average of these differences. Similar calculations are conducted for the biodiversity scores. This alternative approach does not change the bounds qualitatively. The results are therefore omitted and obtainable from the authors upon request.

in 2020 minus the average biodiversity score of the EFAs in 2009. An analogous approach is applied to the other two parameters. With this approach, it holds that $\Delta^{\text{total}} = 0.39$, $\Delta^{\text{efa}} = -0.47$, and $\Delta^{\text{nonefa}} = 0.23$.

With these preliminaries, Proposition 1 translates into the following bounds (three alternative bounds under three alternative assumptions):

$$\Delta_1 \geq 0.23 \quad \text{and} \quad \Delta_2 \leq 5.6 \quad \text{under Assumption 2,} \tag{19}$$

$$\Delta_1 \leq 0.56 \quad \text{and} \quad \Delta_2 \geq -2.1 \quad \text{under Assumption 3,} \tag{20}$$

$$\Delta_1 \leq 0.48 \quad \text{and} \quad \Delta_2 \geq 0 \quad \text{under Assumption 4.} \tag{21}$$

One important implication of Result (19) is that there is a positive (albeit small in magnitude) effect of enrolling land as EFA on plots that are not enrolled in an AES. Specifically, this result precludes the type of negative spillovers discussed earlier and is thus an encouraging result.

On the contrary, the bounds obtained for the effect Δ_2 on land that is actually enrolled are very wide and include 0; therefore, they provide fewer insights.

Calibration 2 An approach based on counterfactual estimates
In this approach, we keep the way that weights are calculated in Step 1 in the above approach but use predictions from our estimation models to calculate all other quantities. Specifically, we take our main estimates from Figure 4 as estimates for $\Delta^{\text{total}}, \Delta^{\text{efa}}$ and Δ^{nonefa}.[18] To calculate $BD_{\text{nonefa}}(0)$ and $BD_3(0)$, we take averages of the observed covariates and insert them into the equation $\bar{Y} = \hat{\theta}\tilde{S} + \bar{X}\hat{\beta}$, where the share of EFAs $\tilde{S}$ means that S is set to either 0 or to its average value in 2009 (both approaches yield very similar values), and $\hat{\theta}$ and $\hat{\beta}$ are the estimated coefficients from the main fixed effects model. We do this using the outcomes of the biodiversity scores for both the EFAs and non-EFAs. With these preliminaries, Proposition 1 translates into the following bounds:

$$\Delta_1 \geq -0.19 \quad \text{and} \quad \Delta_2 \leq 7.2 \quad \text{under Assumption 2,} \tag{22}$$

$$\Delta_1 \leq 0.17 \quad \text{and} \quad \Delta_2 \geq -0.66 \quad \text{under Assumption 3,} \tag{23}$$

$$\Delta_1 \leq 0.04 \quad \text{and} \quad \Delta_2 \geq 0 \quad \text{under Assumption 4.} \tag{24}$$

18 However, since we use causal estimates, we need to relate them to the average change in the share of EFA in the sample. In particular, the effects must be adjusted to reflect a 4 per cent change in w_2, while, due to the units of the variable S, the estimated coefficient reflects an effect driven by a 1 per cent increase in the share of EFAs. Therefore, the regression estimates are multiplied by 4.

Calibration 3 A mixed approach
Finally, we also calculate the bounds using a mixed approach. Specifically, we keep Step 1 from Calibration 1 and use our main estimates for Δ^{total}, Δ^{efa}, and Δ^{nonefa} as in Calibration 2. With these preliminaries, Proposition 1 translates into the following bounds:

$$\Delta_1 \geq -0.19 \quad \text{and} \quad \Delta_2 \leq 7.1 \quad \text{under Assumption 2,} \tag{25}$$

$$\Delta_1 \leq 0.17 \quad \text{and} \quad \Delta_2 \geq -0.66 \quad \text{under Assumption 3,} \tag{26}$$

$$\Delta_1 \leq 0.04 \quad \text{and} \quad \Delta_2 \geq 0 \quad \text{under Assumption 4,.} \tag{27}$$

The results obtained using the last two approaches are qualitatively similar to the results obtained with the first approach. In particular, they imply that if there is a negative spillover effect on the non-enrolled land, this spillover is of a very small magnitude at worst. The bounds on the effect Δ_2 are non-informative as they are very wide.

Based on the above results, several conclusions can be drawn. First, the back-of-the-envelope approach yields the most optimistic bounds on the spillover effects. This is an intuitive result, since the approach calculates treatment effects based on an ex ante–ex post comparison, ignoring possible endogenous selection into EFA. This leads to an overestimation of the effect Δ^{total} and subsequently to an overestimation of the spillover effect Δ_1. The other two approaches deliver smaller lower bounds and smaller upper bounds. Overall, however, all three approaches predict a spillover effect that is of a small magnitude. Even under the most optimistic scenario, our bounds imply that the average spillover effect for the period of observation amounts to an increase of roughly 2.3 per cent of the average baseline biodiversity score for the non-EFAs. Our most pessimistic results indicate that a negative spillover cannot be excluded, although the magnitude of the negative spillover does not exceed 2 per cent of the average biodiversity score. These results are in line with the small overall effect on the farm-level biodiversity score Δ^{total}.

4.3. Interpretation of results

In this subsection, we summarise our results and discuss possible mechanisms. First, our main finding is that an increasing share of EFA leads to a modest improvement in biodiversity. This result is in line with existing studies (Tsakiridis et al., 2022; Stetter et al., 2022; Wuepper and Huber, 2022). Our results also suggest that the full effect is not immediate but takes time to realise. Importantly, our results can be combined with the results of Wuepper and Huber (2022) to quantify the elasticity of biodiversity with respect to the size of the payment incentives. Specifically, combining our effect on the biodiversity score of the overall farmland of 0.029 with the results of Wuepper and Huber (2022) demonstrates that an increase in action-based payments by

10 per cent leads to an increase in the farm's biodiversity score by roughly 1.6 per cent. As we will discuss later, whether this elasticity qualifies action-based payments as cost (in)effective remains an open question.

Second, we find that enrolling land in an EFA scheme has a small but positive spillover effect on non-enrolled land. This is a novel finding. There are three major possible explanations for this result: a management explanation, a learning explanation and a pure environmental spillover. The overall spillover effect may be due to one or a combination of these factors. Regarding the first channel, the positive spillover could be due to a change in the overall management strategy. In particular, it is plausible to assume that farms embed the enrolment decision into a broader strategy of farm management. Enrolling land in EFA modifies the opportunity cost of land and is thus expected to affect a farmer's production decisions (Chakir and Thomas, 2022) and off-farm labour allocation at the farm household level (El Benni and Schmid, 2022). For example, the decision to enrol may cause the farm to shift its overall management to a more extensive one, with a reduction in on-farm labour allocation and an increase in off-farm labour participation. This explanation is supported by Jan et al. (2024), who showed that farms with more extensive management tend to have a larger share of land enrolled in the action-based EFA scheme. Thus, there is a 'management spillover', with non-EFAs benefitting from enrolment through the adjustment of overall management. A second explanation for the positive spillover is learning effects. Specifically, when farmers enrol land in the biodiversity scheme, they improve their knowledge of biodiversity-friendly land management. Thus, a 'learning spillover' arises as farmers apply these newly learned techniques to non-enrolled land. The importance of learning in the context of AESs has received much attention in the literature (Ducos et al., 2009; Hynes and Garvey, 2009; Ruto and Garrod, 2009). This phenomenon has also been emphasised by knowledge transfer experts (Cullen et al., 2018). Finally, a third potential explanation for the positive spillover effect is pure 'environmental spillover'. Specifically, enhanced species richness on the EFAs of a farm may support biodiversity on non-enrolled land (Albrecht et al., 2007; Larsen et al., 2024). Here, a major role for this channel is played by the connectedness of plots, with the spillover decreasing proportionally to the distance between EFAs and non-EFAs.

5. Discussion of results and conclusion

This study explores the effect of enrolment in biodiversity schemes in Switzerland on the environmental performance of farms. To this end, we construct a unique dataset that allows us to study the effect on the environmental performance of the whole farm as well as that of enrolled and non-enrolled land separately. Importantly, the biodiversity score that we use as an outcome measure (Jeanneret et al., 2014) constitutes an effect-based environmental performance indicator showing a higher correlation with the environmental outcome compared to means-based indicators (Repar et al., 2017), which are mostly used in evaluation studies (Bertoni et al., 2020; Chabé-Ferret and Subervie, 2013; Pufahl and Weiss, 2009; Wuepper and Huber, 2022).

Our data allow us to gain unique insights into how farm management adjusts to land enrolment in EFA and what the environmental effects of these adjustments are. Our findings are threefold. First, the share of EFAs has a positive impact on the overall environmental performance of the farm, and this effect likely builds up over time. Second, we find that with an increasing share of EFAs, the biodiversity score decreases for both non-EFAs and EFAs. We also show that the estimated negative effects on the biodiversity score for the EFAs and non-EFAs consist of a true causal effect and a negative shifting effect, with the latter representing changes in the two scores due to different compositions of land. This can, in turn, have two channels. First, as the share of EFAs increases, farmers are more likely to implement categories of EFAs that in principle have a lower biodiversity score (e.g. arable field margins instead of flower strips). Second, with an increasing share of EFAs, farmers enrol fewer plots qualifying for result-based payments, which are found to be more effective compared to action-based measures (Saint-Cyr et al., 2023; Meier et al., 2021). We then develop a methodology that isolates the true effects (up to a bound) from these compound effects. Third, using this 'effect isolation', we find that enrolling additional land as EFA has a small but positive effect on the environmental performance of the farm on the non-enrolled land. We suggest three possible channels for this positive spillover effect: management spillovers, learning spillovers and environmental outcome spillovers. All three suggested mechanisms are supported by existing empirical studies, and the overall spillover effect may be a combination of these.

One major question that is not addressed in this article is the cost-benefit of the AES. Addressing this question would require a monetary valuation of the increase in local biodiversity resulting from land enrolment into EFA. Such an assessment is beyond the scope of the present paper and is of major interest for future research. Although we cannot draw any conclusions on the cost-benefit of the investigated AES at the present stage, we can estimate the relative change in biodiversity induced by a change in the payment rate. Combining our effect with the results of Wuepper and Huber (2022) shows that an increase in action-based payments by 10 per cent leads to an increase in the farm's biodiversity score by roughly 1.6 per cent. These findings are in line with other studies evaluating action-based payment schemes in Ireland (Tsakiridis et al., 2022) or in the southeast of Germany (Stetter et al., 2022). As the plot data used in our analysis is uninformative about whether the plot is also enrolled in a scheme for result-based payments, our treatment variable describes the extent of participation in at least an action-based payment scheme. As the biggest portion of the share of EFAs is made up of grassland, which also qualifies for result-based payments (Figure 1), we could have expected better effects on the biodiversity score. Nonetheless, our results indicate that the increasing adoption of result-based biodiversity schemes in the post-reform period may have implied biodiversity-friendlier management practices on the EFAs. This is a topic that provides scope for future research, since result-based biodiversity schemes have several advantages for farm management (Elmiger et al., 2023).

Other countries, such as the United States or Australia, choose other market-based mechanisms to promote biodiversity (Hanley et al., 2022; Iftekhar et al., 2012; Cramton et al., 2021). At conservation auctions, farmers offer the auctioneer (typically a government authority) certain management practices on a defined area for a certain price. Since the best offer—in terms of price relative to conservation efforts—wins, this mechanism has a competitive character that is not yet established in many European AESs and that has the potential to increase cost-effectiveness compared to uniform payments (Iftekhar et al., 2012). Conservation auctions have steadily gained importance in the literature, even though much of the research to date has been conducted in laboratory experiments (Hanley et al., 2022). Future research could therefore focus more on the evaluation of field experiments and existing auction schemes in order to shed more light on how such schemes can be implemented.

Authors' contributions

FZ, PJ and PB conceived the research and designed the study. FZ and PJ prepared the data. FZ and PB conducted the statistical analysis. FZ, PJ and PB interpreted the results and wrote the article (original draft preparation, review and editing).

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Supplementary data

Supplementary data are available at *ERAE* online.

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