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Sites side by side: Can an agglomeration bonus with an adjacency rule connect agri-environmental sites?

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ABSTRACT

Many species need to cross landscapes for dispersal or seasonal migration. In view of the biodiversity crisis and increasing landscape fragmentation, incentives are needed to foster landscape connectivity and improve spatial coordination of protected sites across privately owned land. A large body of theoretical work and lab studies proposes that an agglomeration bonus could incentivize farmers to enroll adjacent fields to enhance landscape connectivity. This study empirically investigates a network bonus scheme in Switzerland with a dataset covering 322 program areas. In some program areas, farmers can receive the network bonus only if they are compliant with an adjacency rule of 100 m between sites, a policy that corresponds to an agglomeration bonus. In other areas, this rule does not apply, i.e. farmers can apply for the same bonus but irrespective of the location of their field vis-à-vis others. We empirically compare the impact of this policy with a double robust estimation. Counter to the expectations from the theoretical literature, our results show no impact of the agglomeration bonus on connectivity.

1. Introduction

Biodiversity covers many different aspects of the wealth of species, genes, and ecosystems on the planet. This biological diversity is declining at an alarming rate (IPBES, 2019). While humans bear a significant part of the responsibility for this decline, mainly through land-use change and exploitation, they will also bear the consequences of a depleted nature (Díaz et al., 2019; Jaureguiberry et al., 2022). Many of the various contributions we receive from healthy ecosystems (referred to as Nature's Contribution to People), such as pollination and dispersal of seeds as well as the formation of soil, might be impaired in the future (Díaz et al., 2019). Intensive agriculture is one of the land-use changes that threatens biodiversity (Maxwell et al., 2016). Policy instruments to oppose this trend are available and in place (Karousakis, 2018). However, their success is mixed at best (Díaz et al., 2019).

Where land is used intensively through farming, agri-environmental schemes (AES) have been proposed to lower the pressure on local species. Similar to the more general payments for ecosystem (or environmental) services, AES operate through a voluntary incentive mechanism, and compensate the landowners for the opportunity cost of less intensive land uses (Batáry et al., 2015).

However, often agri-environmental payments ignore the need for biodiversity conservation on a landscape scale (Kuhfuss et al., 2022). For instance, although the effect of fragmentation on biodiversity is not yet entirely clear (Fahrig, 2019), a lack of connectivity of protected areas puts pressure on biodiversity (Ward et al., 2020). Many species depend on small and linear patches as well as scattered trees to cross (man-altered) landscapes for dispersal or migration (Tiang et al., 2021). Fostering landscape connectivity and enabling spatial coordination across privately owned land is thus vital. Agglomeration bonuses (AB) have been proposed as a promising policy instrument that could enhance connectivity. An AB is granted additionally to agri-environmental payments if adjacency to other sites is warranted, resulting in connected habitats (Parkhurst et al., 2002).

The AB was first introduced by Smith and Shogren (2001) and further developed by Parkhurst et al. (2002) with a lab experiment. In the last 20 years of AB research, theoretical discussions (Bamière et al., 2013; Bell et al., 2016) and lab experiments (e.g. Banerjee et al., 2012) dominated the literature. Nguyen et al. (2022) conducted a systematic review of spatial co-ordination incentives and found that only 10% of the studies are empirical. The empirical studies find positive effects of AB on participation in the scheme, spatial coordination and environmental effectiveness (Krämer and Wätzold, 2018; Huber et al., 2021; Nguyen et al., 2022). The same holds for theoretical studies, whereas

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experimental studies find only mixed effects.

Apart from a general lack of empirical studies on the AB, especially the effectiveness for creating a more closely knit network of conservation sites on a landscape scale has not yet been evaluated empirically. In this paper, we aim to fill this gap by empirically investigating an adjacency rule, which specifies a maximum distance between two sites to be eligible for receiving an AB, regardless of who owns the land. We hypothesize that an adjacency rule enhances a network of extensively managed sites. Further, we hypothesize that an adjacency rule will induce farmers to create a network of enrolled sites across neighboring farms. This can be measured by the share of adjacent sites across farms to all connections, i.e. conservation fields belonging to different farms situated at less than the threshold distance to one another.

We analyze these hypotheses by exploring a dataset with enrolled sites that are georeferenced and owner-related (anonymized) and that include areas with and without an adjacency rule. This dataset allows us to compute network characteristics, which we associate with presence or absence of the adjacency rule while controlling for confounding variables. We use a matching approach to select comparable areas and then use this subsample for an estimation of the effect of the adjacency rule (double robust estimation).

The remainder of the paper is organized as follows. In section 2, we outline the policy under investigation. In section 3 we discuss the applied method and in section 4 the data used. Section 5 presents the results and section 6 discusses the findings.

2. Policy background and case study

In Switzerland, farmers can select from a menu of AES including payments for action- and output-oriented 'biodiversity promotion sites'. In 2001, a network bonus payment was introduced as an addition to the payments for biodiversity promotion sites. The ambition was to foster the creation of sites that are spatially allocated and managed so as to enable the development and distribution of plants and animals on a landscape scale (Federal Office for Agriculture, 2015). Many different land uses are eligible as biodiversity promotion sites including meadows and pastures as well as cropland and permanent crops and groves. For this analysis, we focus on meadows and pastures (see Table 1).

Our case study area spans 220 municipalities in the canton of Bern, one of the largest cantons of Switzerland, characterized by a moderate climate zone. The first farmers received the network bonus payment in 2004. By the year 2020, in the whole canton 9′019 out of the 9′440 farmers had sites enrolled for receiving a network bonus. Enrollment is possible each year and the contract ends with the respective contract period. Our data is from the third contract period which has a duration of eight years.

The goal of enabling the development and distribution of plants and animals on a landscape scale requires different measures, given the existing landscape characteristics. This led to spatially varying prerequisites for receiving the bonus, i.e. to a division into different intervention areas, which were introduced at the same time as the network bonus itself. In this analysis, we compare the resulting network of biodiversity promotion sites in two types of intervention areas: the 'networking areas', which are cleared agricultural areas in need of further connectivity elements, and the 'preservation areas' with structurally rich landscapes (ANF, 2017).

Table 1
Number of sites per land use type and per area.

Land use	Preservation area $N = 3'022$ (100%)	Networking area $N = 4'938$ (100%)
Extensively used pastures (<0.3 ha)	307 (10%)	257 (5%)
Extensively used meadows (<0.3 ha)	2′557 (84%)	4′503 (90%)
Less intensively used meadows (<0.3 ha)	188 (6%)	236 (5%)

In the networking areas, an adjacency rule applies to meadows and pastures smaller than 0.3 ha. This rule states that two eligible sites need to be situated <100 m apart from each other, or from the edge of a forest or water body in order to receive a network bonus (ANF, 2016). This specification corresponds to an agglomeration bonus, where a bonus is paid if an adjacent site is enrolled. This aggregation of small areas through an agglomeration bonus reflects a sigmoid ecological benefit function, where a certain size of protected area is required to achieve ecological benefits (Drechsler, 2020; Wu and Boggess, 1999). In the preservation areas, no such adjacency rule is in place which means that farmers receive the bonus irrespective of a site's distance to other sites. In addition to the adjacency rule, other management requirements must be met in order to receive a network bonus. These are the same in both networking and preservation areas.

Interestingly, in the networking areas, farmers can comply with the adjacency rule also when the minimum distance is met with a site belonging to another farmer. This means that a farmer who would not receive a bonus for enrolling only one isolated site of his land can receive the bonus if he cooperates with a neighboring farmer who also registers a site within 100 m distance. In this case, both farmers will receive the bonus.

The base payment as well as the network bonus are the same in both conservation and networking areas. The farmers receive 1′000 CHF per ha annually for meadows and 500 CHF for pasture sites as a network bonus on top of the payments for the biodiversity promotion sites. The payment is triggered by one connection between sites, but does not increase with additional connections. The base payment is 700 CHF for extensively used pastures, between 1′100 CHF and 1′920 CHF for extensively used meadows (depending on the agricultural zone), and 1′200 CHF for less intensively used meadows. Most of the sites in this analysis are extensively used meadows (see Table 1). It is important to note that while the farmer can decide whether he enrolls a site in the network bonus scheme, he cannot decide whether he wants a bonus with or without an adjacency rule.

We include five districts of the Canton of Bern in the analysis, which we chose according to their share of network bonus sites enrolled in a networking area. If >40% of sites were enrolled in a networking area, we included the district in the analysis. This resulted in a dataset covering five districts (Bern-Mittelland, Biel, Emmental, Oberaargau, Seeland) with a total of 220 municipalities.

3. Method

3.1. Connectivity of sites

In the AB literature, spatial connectivity has mainly been measured via its immediate neighborhood. For lab experiments, mainly raster landscapes were used and connectivity was measured via the Moore Neighborhood, defining that all eight neighbors of a cell should be connected to their center (Drechsler and Wätzold, 2009). However, in this application, we work with georeferenced sites (polygons) and not a raster data landscape.

Based on the theoretical literature, an AB should incentivize the creation of a network of connected biodiversity promotion sites (Parkhurst et al., 2002). Measuring and operationalizing the connectivity of sites is difficult, more so if it is not species-specific. The ecological literature distinguishes between structural and functional connectivity. While the first form denotes a physical connection (Euclidean distance), the second takes into account that areas are traversable to different degrees by different species (the optimal route for traversing a landscape is then the route with the lowest costs). This dualism can also be observed in choosing how to represent the landscape structure in ecological-economic modeling (Drechsler et al., 2022). How to measure connectivity on a landscape scale has been discussed widely and resulted in many different approaches (Keeley et al., 2021). One approach to measure connectivity is using graph-based metrics (Urban and Keitt, 2001; Calabrese and Fagan, 2004; Urban et al., 2009; Keeley et al., 2021). In their most basic form, they distinguish between habitat and non-habitat in a landscape. Habitat patches are represented by the nodes of the graph, whereas the connection of patches is described by their edges (Urban and Keitt, 2001). Whether two nodes are connected can be defined via a threshold distance.

Choosing a metric to measure connectivity depends mainly on the underlying research question. Here, we are interested in the number of created connections between sites. In this study, we are not per se interested in the actual movement of animals (functional connectivity), therefore we can rely on a metric that only takes connectedness (structural connectivity) into account. We do not include information on patch area, such as surface or quality. Using a topological measure (which ignores patch area and which is sometimes also called "spatial pattern index") is therefore sufficient in this specific application, and building a graph in its simplest version is appropriate.

In our analysis, we build an unweighted and undirected graph and define a distance threshold of 100 m (in Euclidean space). The distance is calculated from one polygon border to all other polygon borders. For distances less than or equal to 100 m an edge is realized. The threshold of 100 m is predefined by the policy.

To compare the connectivity of the sites between preservation and networking areas, we calculated the connectance of the graphs for the two areas in each municipality. The connectance is a metric for the ratio of realized edges to the total of all possible edges (Rayfield et al., 2011). The higher the connectance of sites, the better their connectivity.

However, not only should an AB incentivize better-connected sites, it should also in particular encourage connectivity of sites across privately owned land (Parkhurst et al., 2002). We, therefore, compared how many of the realized edges (100 m connections) between sites are shared by neighbors, e.g. whether both nodes of an edge belong to the same farmer or not. We call this neighbor connectivity, which is our second dependent variable.

3.2. Econometric framework

With the econometric procedure, we aim to estimate the effect of the adjacency rule on connectance and neighbor connectivity, without any biases through other differences between networking and preservation areas apart from treatment status. We will test the following hypotheses:

H1a: The adjacency rule (treatment) has a significant positive effect on connectance.

H1b: The adjacency rule (treatment) has a significant positive effect on neighbor connectivity.

We followed Ho et al. (2007) and preprocessed the dataset by applying a matching strategy. As Ho et al. (2007) argue, this step improves the estimation procedure, as matching is a non-parametric strategy and thus reduces dependency on modeling choices in the following regression analysis. This makes our result double robust (Stuart, 2010).

Schleicher et al. (2020) discuss the usefulness and application of matching methods for conservation interventions. We followed their proposed three steps: first, specifying the treated and control units, second choosing the matching method and covariates, and third performing the matching and the evaluation.

We merged the networking areas (polygons) into one area per municipality and did the same for the control areas. Our unit of analysis is thus the networking area (=treatment area) and/or the preservation area (=control area) of each municipality. If a municipality has both networking and preservation areas, there is a control and a treatment observation for that municipality in the dataset. If a municipality however has only treatment areas, there is only one observation for this municipality in the dataset (accordingly for the control). Merging the different polygons into a larger area is reasonable and necessary, as sites can be connected across polygon borders. We however did not include connections across municipality borders.

We perform the matching on the treatment model, e.g. the binary treatment variable as the dependent variable. We used the MatchIt package in R (Ho et al., 2011). The goal of the matching process is to identify a balanced subsample of the data set. We chose a matching technique that allows the estimation of the average treatment effect, as we are interested in the effect of the adjacency rule on connectance for all areas and not just for the treated areas.

We applied a profile matching approach, which is a subcategory of cardinality matching (Cohn and Zubizarreta, 2021). The matching identifies the subset of covariates where the balance is lower than a predefined threshold. With profile matching, the full dataset can be used as a template distribution for the control and treatment group and thus the average treatment effect can be estimated with the resulting sample. The included variables are described in the section "Control variables".

We used the matched sample and the associated weights from the matching to estimate the outcome model, where the dependent variables are connectance and neighbor connectivity:

$$\mathrm{Log}(\mathrm{Connectance}) = \alpha + \beta AB + \gamma_i C_i + \varepsilon \tag{1}$$

$$\text{Neighbor Connectivity} = \alpha + \beta AB + \gamma_i C_i + \varepsilon \tag{2}$$

We included all variables that were already used for the matching (C). We observed many zero values and thus applied a Tobit regression. For model 1, we included only a lower limit, for model 2 we included an upper limit as well (at 1 as 100% is by construction the highest possible value). We included the same covariates for both models and report different specifications for each model. We estimated the full model (models 1.1 and 2.1), then made some robustness checks by excluding problematic variables due to multicollinearity (models 1.2, 2.2 and 2.4) and further omitted observations with outliers in certain control variables (models 1.3, 2.3 and 2.4). Statistical analysis was carried out using R 4.1.1 (R Core Team, 2021), the main packages used were tidyverse (Wickham et al., 2019), sfnetworks (van der Meer et al., 2023), landscapemetrics (Hesselbarth et al., 2019), matchit (Ho et al., 2011) (the solver of the optimization problem was Gurobi Optimization, 2023) and AER (Kleiber and Zeileis, 2008). The full reproducible code is available on GitHub. We did not choose a two-step approach (such as Heckman treatment effect model) as we claim that we have modeled the selection into treatment sufficiently with operationalizing "cleared agricultural areas" with several variables (see 4.1 Control variables) and included them in the treatment and outcome model.

3.3. Identification challenges and considerations

We are interested in evaluating whether an agglomeration bonus with an adjacency rule can improve the connectance and the neighbor connectivity of agri-environmental sites. As we outlined in the policy background section, farmers in the conservation area do not have to comply with the adjacency rule and still get the network bonus. This gives rise to two potential causes for effects on connectance and neighbor connectivity. One cause is the adjacency rule which we hypothesize will result in higher connectance and neighbor connectivity in the networking areas. The second potential cause is that the higher unconditional payment in the conservation areas may lead to a higher enrollment rate among farmers which in turn might result in a higher connectivity simply as a "by-product" due to an increase in the probability that two sites lie in proximity to each other.

However, the latter appears unlikely because the number of enrolled sites per farm is not significantly different between the conservation and networking areas (preservation area: 3′003 sites / 1′542 farms = 1.95 sites per farm, networking area: 4′975 sites / 2′744 farms = 1.81 sites per farm, Wilcoxon rank sum test p-value: 0.28). We further compared the number of enrolled sites per farm for meadows and pastures larger than 0.3 ha between treatment and control areas. These sites are, apart from their size, the same as the sites in our analysis. However, these sites do not need to comply with the adjacency rule (neither in control nor treatment areas). If the higher unconditional payment in the conservation areas results in a higher enrollment rate, this effect would likely be reflected in the enrollment rates of sites larger than 0.3 ha. However, we find that the number of enrolled sites larger than 0.3 ha per farm between treatment and control area are not significantly different (Wilcoxon rank sum test *p*-value: 0.73).

We thus assume that the variation in the variables of interest, connectance and neighbor connectivity, may be impacted by the adjacency rule but not by the difference in the unconditional payment. However, it is important to note that our interpretation of the results rests on this assumption, for which we have presented strong indications but lack indisputable proof.

4. Control variables and data

4.1. Control variables

To estimate an unbiased effect, controlling for selection into treatment is crucial, e.g. identifying and including the characteristics of an area that determine whether it was assigned as a networking or a preservation area. Networking areas were characterized as cleared agricultural areas in need of further connectivity elements, in contrast to preservation areas, which have more natural connectivity elements.

Each municipality decided independently which area to designate as a networking area or as a preservation area. Unfortunately, we have no documentation of their decision processes or a clear-cut definition or operationalization of cleared agricultural areas.

To control for this bias of selection into treatment, we account for differences in the structure of the landscape. Helfenstein et al. (2016) summarize that structures in an agricultural landscape can be crop diversity, proportion of semi-natural habitats and others. In order to measure landscape complexity, they propose among others the number of field trees. Guntern et al. (2020) discuss landscape structures for the agricultural landscape in Switzerland. They mention highly diverse structures such as hedgerows and other woody plants, forest edge and fringe vegetation, ruderal areas, cairns and dry stone walls, watercourses, wet sites as well as pits and banks, etc. as structuring elements in the rural areas.

Given the availability of data, we operationalize structural landscapes with the number of individual trees and the percentage rate of forest coverage (which we extracted from a topographic landscape map for each polygon of control and treatment area and averaged it for each municipality, see Appendix A for data sources). Additionally, we used a land cover classification map of Switzerland and used it to compute Shannon's diversity index (SHDI) to account for the degree of diversity of land coverage classes (applied in R with the package "landscapemetrics" by Hesselbarth et al., 2019). The SHDI is calculated as $\mathrm{SHDI} = \sum_{n=1}^{m}(\mathrm{Pi}^{*}\ln\mathrm{Pi})$, where $\mathrm{P_i}$ = proportion of class i. It equals 0 if there is only one class in a defined area. The database consists of 72 land cover and land use classes in settlement, agricultural, wooded and unproductive areas (see Appendix B for an overview of the different categories).

We included these variables as a proxy for a more structural landscape and thus claim that fewer trees, a lower share of forest area and a lower diversity of the landscape are characteristics of cleared landscapes and have been considered when control and treatment areas were assigned.

For the outcome mechanism, we included further variables that might be correlated with the treatment and the connectivity of sites. Determinants of the uptake of AES have been widely discussed in the literature. Based on the literature, we have chosen several characteristics that should not be significantly different for the control and treatment group.

For example, farm size has been shown repeatedly to influence AES uptake positively (Mack et al., 2020; Cullen et al., 2021; Huber et al., 2021). Lastra-Bravo et al. (2015) and Schaub et al. (2023) found in their meta-analyses mixed results on the direction of the effect and significance on AES adoption. To have a proxy for this variable, we divided the intervention area by the number of farms for each observation. Parcel slope seems to have a positive effect on the proportion of networking areas as well (Huber et al., 2021), often associated with lower opportunity costs as steepness increases. We thus included the average slope of the area. As a further proxy for opportunity costs, we include a variable on the soil suitability in the area. This variable divides agricultural land into five different categories according to their suitability for agricultural cultivation. Additionally, we control for the number of farms in an area, as connectance across privately owned land is generally more difficult to establish. Furthermore, we take the share of pasture sites into account, as the network bonus for pasture is only 500 CHF compared to 1′000 CHF for meadows.

4.2. Data

We used datasets provided by the canton of Bern, the Swiss Federal Statistical Office and the Swiss Federal Office of Topography (see overview in Appendix A). The dataset with the biodiversity promotion sites contains all sites that are enrolled in an AES and that belong to a farmer in the canton of Bern. The sites are georeferenced and additional attributes are provided, such as the farmer owning the area (anonymized), the type of biodiversity promotion site (e.g. meadows) and the intervention area. We cleaned the data and excluded overlapping sites as well as observations that had only one farm (reduced the sample size from 322 to 304). The data set contains all sites that have been registered in 2021, if an area thus was registered in 2009 and removed in 2014, it is not in the data set.

We use data from the year 2021 for variables that control for the outcome mechanism and older data to control for selection into treatment, as the matching should optimally be done with data that has been collected before the treatment took place (Schleicher et al., 2020). However, for the variable "individual trees" and "forest" that are derived from the same dataset, we only have data from the years 2016–2018. Although this data is younger than the introduction of the network bonus in 2004, it originates from the beginning of the third round of contracts in 2017. Table 2 shows summary statistics for the dependent and independent variables (prior to the matching). Additional statistics on the topology of the network can be found in the Appendix. For the dependent variables, we run a Wilcoxon test for the connectance and a *t*-test for the neighboring connectivity between control and treatment. Both were insignificant (p-value >0.05).

5. Results

The target matching procedure reduced the dataset from 304 observations to a weighted subset of 116 (88 treatment, 28 controls). We set an imbalance tolerance of 0.1, which reduced the standardized mean difference accordingly. Only the variable "farms" already had a standardized mean difference SMD below 0.1 before the matching. Imbalance decreased for the slope from 1.14 to 0.09 (92%), for farm size from 0.99 to 0.09 (91%), for the SHDI from 0.92 to 0.08 (91%), for individual trees from 0.88 to 0.05 (95%), for forest from 0.69 to 0.09 (87%), for soil suitability from 0.61 to 0.04 (94%) and for pasture from 0.56 to 0.07 (87%). The corresponding love plot and the density plots can be found in the Appendix.

With the matched dataset, we estimated three model specifications for connectance, respective four specifications for neighbor connectivity (see Table 3). As the variable connectance was right-skewed, we took the natural logarithm following Cameron and Trivedi (2022) in order to get a normally distributed dependent variable and normally distributed error terms of the Tobit regression.

Model 1.1 contains all covariates used in the matching process. We checked for multicollinearity with the variance inflation factor (VIF) and

Table 2
Summary statistics. The unit of observation is the treatment/control area per municipality. The data set consists of 304 observations, comprising 207 unique municipalities as 97 have both control and treatment area. 117 observations are preservation areas, and 187 observations are networking areas.

Variables	Description	Unit	N(%) for binary variables	Mean (SD)	Min	Max	Year
Dependent variables							
Connectance	Ratio of realized connections to the total of all possible connections	percentage		0.08 (0.13)	0	1	2021
Neighbor Connectivity	Ratio of shared connections to overall connections	percentage		0.42 (0.32)	0	1	2021
Independent variables							
Agglomeration Bonus	Binary, 0 for control and 1 for treatment		187 (62%)				2021
Farms	Number of farms	absolute		14 (16)	2	108	2021
Farm size	Surface area divided by the number of farms	hectares		10.88 (8.10)	0.01	58.77	2021
Individual trees	Number of individual trees (per ha)	trees/ha		3.00 (2.53)	0	19.18	2016–2018
Forest	The percentage covered with forest	percentage		0.03 (0.06)	0	0.51	2016–2018
Pastures	Share of extensively used pastures to other sites	percentage		0.06 (0.10)	0	0.50	2021
Shannon's diversity index (SHDI)	Degree of the diversity of land coverage	absolute		0.87 (0.34)	0	1.93	1992–1997
Slope	Steepness	degrees		7.11 (5.10)	0.22	23.36	2000/ 2001
Soil suitability	Mean of suitability for agricultural cultivation			2.60 (1.04)	1	5	2000
N = 304							

Table 3
Results from the Tobit regression models; the variable connectance is in logs.

Dependent variable	Connectance (in logs)			Neighbor Connectivity			
	Model 1.1	**Model 1.2**	**Model 1.3**	**Model 2.1**	**Model 2.2**	**Model 2.3**	**Model 2.4**
(Intercept)	−261.97 (166.91)	−251.25 (174.58)	−260.61 (172.41)	51.89 (54.93)	51.82 (52.04)	56.83 (52.68)	50.86 (51.52)
Agglomeration Bonus	−11.13 (55.39)	−8.99 (58.91)	−14.67 (62.10)	−1.45 (18.62)	−1.45 (18.62)	−6.28 (19.41)	−2.01 (17.84)
Forest	335.36 (515.22)	74.89 (481.18)	−422.63 (928.42)	−77.40 (332.06)	−77.08 (329.91)	−279.67 (396.93)	
SHDI	65.85 (128.37)	23.09 (120.69)	28.77 (130.00)	2.28 (44.94)	2.36 (43.42)	8.36 (44.14)	13.94 (42.60)
Individual trees	−12.37 (21.44)	−19.33 (21.72)	−21.90 (35.53)	−6.43 (8.79)	−6.42 (8.52)	−9.68 (9.88)	−9.30 (9.74)
Slope	−17.75 (12.78)			0.03 (4.09)			
Farms *(reciprocal value)*	−154.83 (300.35)	−35.87 (295.92)	2.57 (300.60)				
Farm size	−2.70 (4.29)	−2.51 (4.61)	−1.00 (5.64)	0.13 (1.55)	0.13 (1.57)	0.53 (1.75)	0.05 (1.38)
Pastures	−34.73 (531.94)	−154.17 (531.38)	−37.72 (484.76)	−60.64 (151.53)	−60.55 (154.38)	−73.96 (158.76)	−82.37 (147.27)
Soil suitability	26.59 (45.74)	−7.49 (34.47)	−8.12 (33.27)	−2.35 (14.53)	−2.30 (10.17)	−2.95 (10.46)	−3.07 (10.40)
Farms				0.64 (0.69)	0.64 (0.64)	0.94 (0.63)	0.72 (0.57)
Log(scale)	4.92 *** (0.20)	4.97 *** (0.18)	4.96 *** (0.19)	3.77 *** (0.22)	3.77 *** (0.22)	−0.99 *** (0.18)	3.74 *** (0.22)
BIC	681.60	682.35	663.84	466.32	461.57	446.72	443.25
N	116	116	110	116	116	110	110
Left-censored	16	16	14	31	31	28	28
Uncensored	100	100	96	75	75	72	72
Right-censored	0	0	0	10	10	10	10

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.

found high values for soil suitability (5.2) and slope (7.1). We thus additionally estimated the model without the variable slope. In models 1.3 and 2.3, we furthermore excluded strong outliers for the variables farms, individual trees, pastures and forest, which reduced the sample size from 116 to 110. For neighbor connectivity we additionally estimated a fourth model without the variable "forest" as the VIF increased after removing the outliers. Robustness checks can be found in Appendices G and H.

We do not observe any statistically significant effect of the adjacency rule on the connectance of sites (see models 1.1.-1.3). Furthermore, the sign of the effect is negative, which would rather imply that in the preservation (control) areas, more sites are situated at a distance of <100 m from each other compared to the networking (treatment) areas. Similarly, there is no significant effect of the adjacency rule on the connectivity across neighboring borders (see models2.1–2.4). The positive sign for the number of farms, indicating an increase in the connections across farmers, align with our expectations. For the connectance, as we have a log-linear model, the coefficient shows the change of the dependent variable in percentages on the latent variable connectance (14.67/100 (note that we multiplied the dependent variable for better readability of the effects)*100). A change in the dependent variable of 14.67% for the mean of connectance (after matching without outliers) results in a change from 6.7 to 5.8 (for the median from 3.49 to 2.99). As it is a Tobit estimation, this is the effect on the latent variable and to get the effect on the original variable, we need an adjustment factor. As we followed Cameron and Trivedi (2022) for the transformation of the variable, we also used the adjustment factor they provide with the formula for estimating the censored mean: $\Phi((\gamma - \mu - \sigma^2)/\sigma)$. This yields an effect of 14.65 which is similar to what we estimated. To check this result, we additionally estimated the censored mean,[1] holding all variables except for the treatment variable constant at the mean, and get an expected value of 0.10 for the control and 0.09 for the treatment (original variable, before any transformation such as taking the logarithm or scaling). The difference is 0.0145, which is a change of 14.08% and thus close to what we estimated. This effect size is thus neither very small nor very pronounced. We claim that given this effect size and the non-significance of the estimation, we did not find any evidence of an effect.

For the neighbor connectivity, model 2.4 estimates an effect of −2.01 (note that we scaled the dependent variable by 100). Ceteris paribus, neighbor connectivity in areas with an AB is thus around 2.01 points lower. As also this model is a Tobit estimation, we need an adjustment factor to get the effect for the original variable, which must also take into account the upper limit: $\Phi((b - \mu)/\sigma) - \Phi((a - \mu)/\sigma)$. With this factor considered, we get an estimate of −1.5. As the mean of neighbor connectivity is 39, we argue that the effect size is small.

6. Discussion and conclusion

To improve the landscape-scale management of biodiversity promotion areas, offering an AB to farmers has been proposed. This additional monetary incentive should improve connectivity, especially across privately owned land. However, empirical assessments testing if and how connectivity is improved are rare (Nguyen et al., 2022). This paper contributes to this discourse by examining an AB with an adjacency rule in Switzerland.

We tested the hypothesis, that an AB with an adjacency rule enhances connectivity, compared to other areas where a network bonus payment is not conditional on realizing a certain distance to other sites (H1a). Our results suggest that the conditionality of an AB on a distance rule does not foster connectivity. We furthermore tested, if the rule might encourage coordination across farmers, such that we could observe more connected sites across farm borders in areas with an adjacency rule. However, also this hypothesis (H1b) could not be verified.

Our findings thus do not confirm results from previous work on AB, where for participation and spatial coordination positive results were found in theoretical and empirical studies (Nguyen et al., 2022). However, a direct comparison is difficult, as our study is, to our knowledge, the first in testing the connectivity of AB sites empirically.

One possible reason for the absence of an effect might be the non-differentiation of the bonus across areas, as a higher conservation effort (complying with the adjacency rule) and the resulting restricted selection of sites (patch restriction, see Drechsler et al., 2010) is not remunerated with a higher bonus. Krämer and Wätzold (2018) found that farmers do take costs and benefits into consideration when enrolling sites, which would support this reasoning. The same holds for the neighboring connectivity. Farmers might feel that the bonus for the sites does not compensate them sufficiently for the time and effort of coordination.

Villamayor-Tomas et al. (2021) conducted a choice experiment with farmers in the Swiss cantons of Zurich and Aargau to assess whether farmers would like to participate in a tree-planting program that requires coordinated implementation. They found that farmers that already have trees on their land preferred to participate on their own over coordinating with their neighbors. Generally, farmers seemed to be more hesitant to participate in programs where trees have to be planted in a coordinated way with other farmers (effect not stat. significant) and a majority of farmers reported that they consider coordinating with their neighbor as rather complicated. These results align with our findings that farmers would rather prefer not to coordinate with their neighbors.

Furthermore, especially for the neighbor connectivity, there might be a problem with the knowledge transfer to the farmers. The management requirements of network bonus sites are rather complicated and difficult to communicate. Many farmers might not know about the possibility of coordination with their neighbors.

It might also be due to our research design, that no effect could be identified. Although we did control for the selection into treatment mechanisms as well as other factors that might influence the connectance of sites, we might still have neglected inherent differences between the treatment and control areas. It might be more difficult to place meadows and pasture sites in proximity to each other in treatment areas than in control areas due to variables we cannot catch in our analysis.

A similar problem might be that many determinants for the enrollment of sites occur on the farm level and these influential characteristics could not be included in the analysis as aggregating them on a municipality level would be meaningless. Examples are the educational level of the farmers (Huber et al., 2021), their age (Cullen et al., 2021) and their experience with AES (Lastra-Bravo et al., 2015). Likewise, we have not incorporated variables for the beliefs of farmers which have been shown to be relevant for the enrollment decision (Gabel et al., 2018).

At this point, it is important to note that even if we could have identified an impact on connectance, this would not have guaranteed an ecological effect. Connectance and other simple forms of representing landscape connectivity have been criticized for their oversimplification and for their limitations in representing changes in nodes and edges in an ecologically meaningful way, mostly due to the exclusion of patch area (Pascual-Hortal and Saura, 2006; Ferrari et al., 2007). This criticism resulted in the construction of functional spatial graphs with many more elaborated metrics that satisfy further ecological requirements (Pascual-Hortal and Saura, 2006; Dale and Fortin, 2010; Keeley et al., 2021). For our research question of estimating the effect of the adjacency rule, the simpler approach was sensible, but may not be the best choice when measuring functional connectivity. In that respect, we would like to point out that the results are specific to the selected metric. Testing and comparing alternative metrics, such as the ratio of edges to nodes or estimating the deviation from the expected connectance of randomly distributed sites to the observed connectance, is an interesting question for future research.

Although we could not identify implementing an AB with an adjacency rule as a promising policy option to enhance connected sites, fostering connectivity should not be neglected in biodiversity policies, as additional ecological benefits can be achieved on a landscape level (Kuhfuss et al., 2022). Furthermore, these networking sites with their specific management requirements could very well have a positive ecological effect on biodiversity. We just could not identify an effect on our measures of connectivity. It thus remains unclear, how a policy design to improve connectance and neighboring connectivity should be designed.

CRediT authorship contribution statement

Mara-Magdalena Häusler: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Astrid Zabel:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial

[1] $E(y|x) = exp(\mu + \sigma^2/2)\{1 - \Phi((\gamma - \mu - \sigma^2)/\sigma)\}$

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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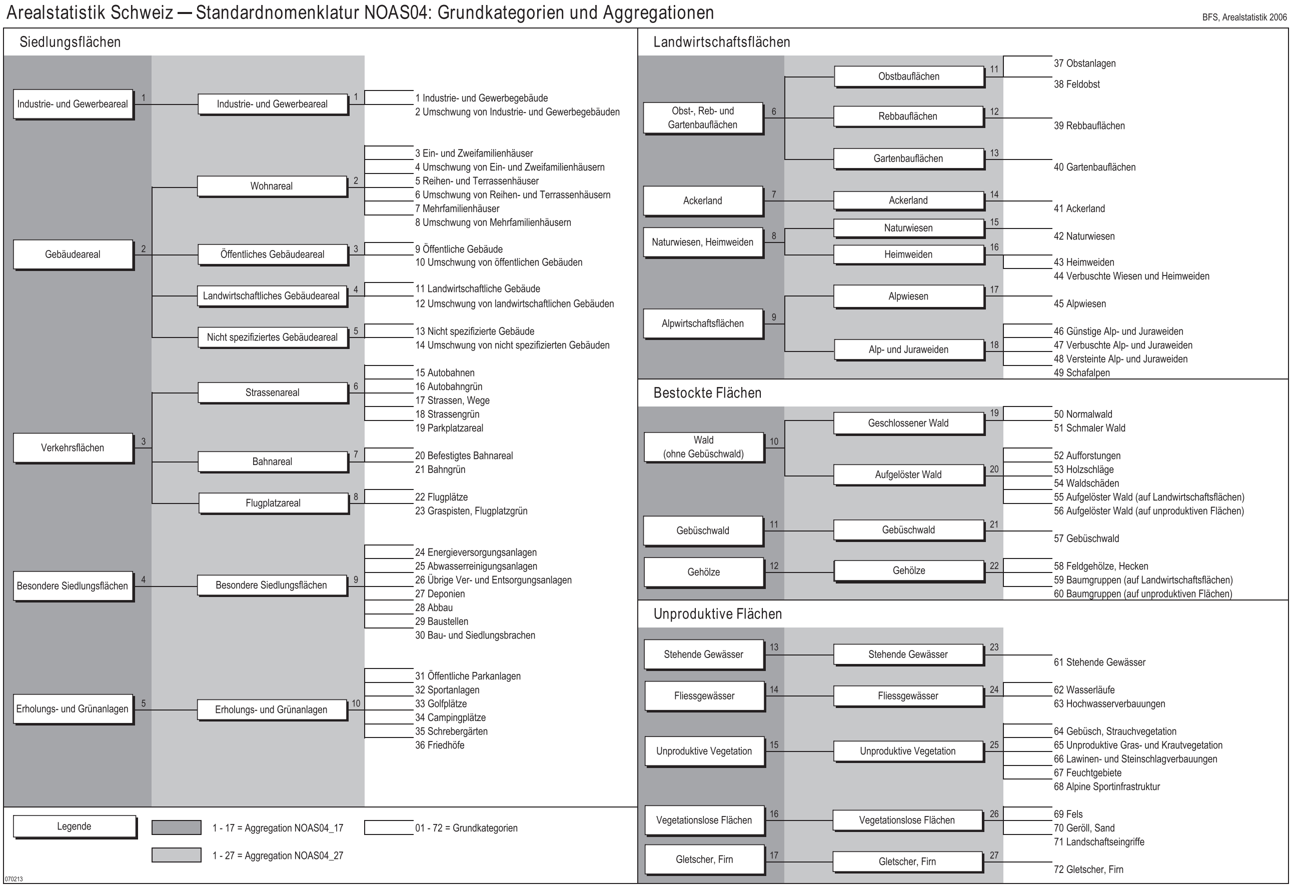
Appendix

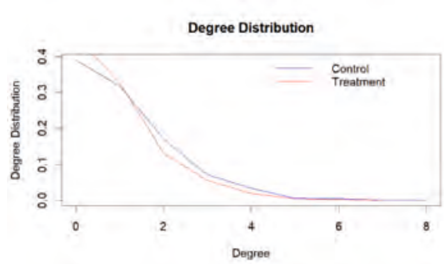
A: Data Availability Statement

Variables	Description	Source
Connectance, Neighbor Connectivity, Pastures, Number of farms, Farm size	Biodiversity promotion areas; georeferenced sites with further attributes	Office for Agriculture and Nature Canton Bern Amt für Landwirtschaft und Natur Kanton Bern, ADZ, GELAN ICT, Zollikofen Data are available on request
Individual trees, Forest area		Federal Office of Topography Swisstopo Topographic landscape model, version 2.0 Available online: swissTLM3D - swisstopo (admin.ch) Files: Ind. trees: swissTLM3D_TLM_EINZELBAUM_GEBUESCH_WEST.shp Forest area: swissTLM3D_TLM_BODENBEDECKUNG_WEST.shp
Shannon's Diversity Index	Land cover classification map of Switzerland	Federal Statistical Office Swiss Land Use Statistics Available online: Arealstatistik Schweiz | Bundesamt für Statistik (admin.ch) File: ag-b-00.03-37-area-csv.csv
Slope		Federal Office of Topography swisstopo Digital height model DHM25 Available online: DHM25 - swisstopo (admin.ch) File: dhm25_grid_raster
Soil Suitability		Federal Statistical Office Swiss Soil Suitability Map Available online: Swiss Soil Suitability Map | Federal Statistical Office (admin.ch) File: Bodeneignungskarte_LV95.shp
Area		Office for Agriculture and Nature Canton Bern Amt für Landwirtschaft und Natur Kanton Bern, ADZ, GELAN ICT, Zollikofen Vernetzungsprojekte nach ÖQV Available online: Vernetzungsprojekte nach ÖQV (be.ch)
	Municipality borders	Office for Geoinformation Bern Amt für Geoinformation des Kantons Bern Politische Grenzen Available online: Politische Grenzen (be.ch) File: GRENZ5_G5.shp
	List of Bernese municipalities and districts	Federal Statistical Office Amtliches Gemeindeverzeichnis der Schweiz Available online: Amtliches Gemeindeverzeichnis der Schweiz | Publikation | Bundesamt für Statistik (admin.ch)

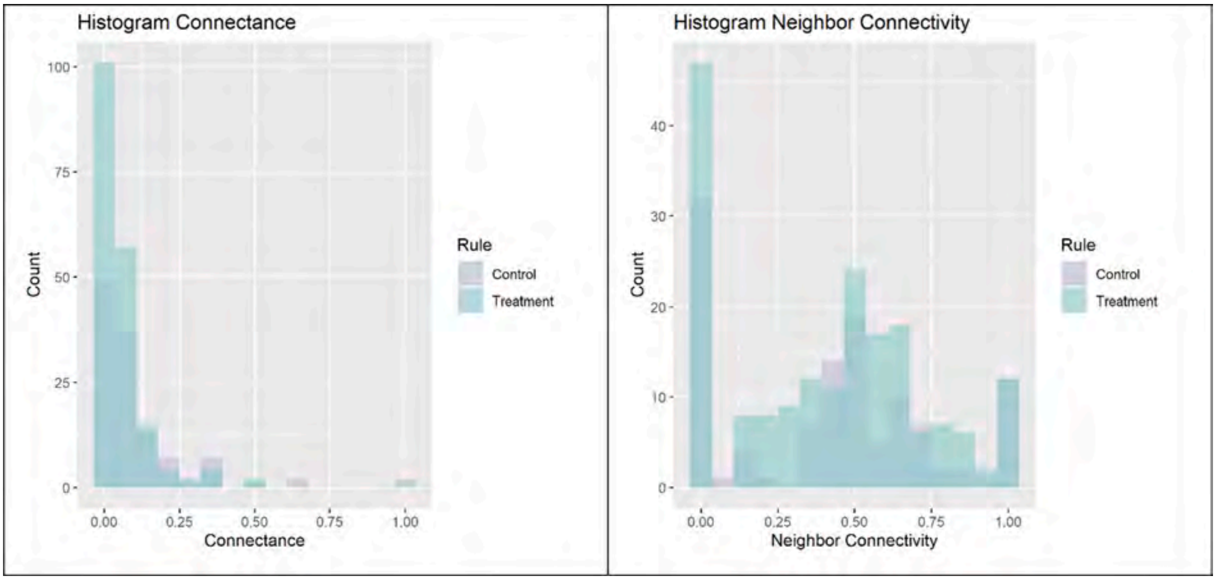
B: Swiss Land Use Statistics



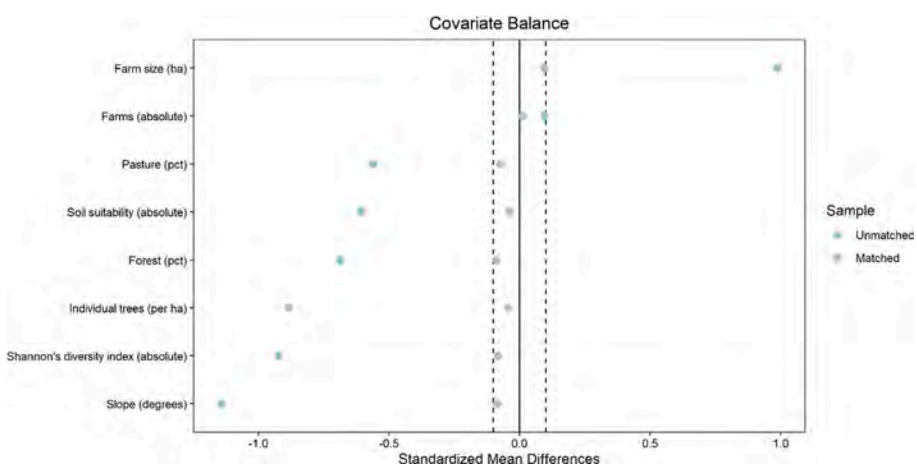
C: Topology of the Network

	Preservation area (Control)	*Networking area (Treatment)*
Nodes	*2984*	*4917*
Edges	*1642*	*2192*
Distribution of number of edges per node	 *Degree: Number of edges per node*	

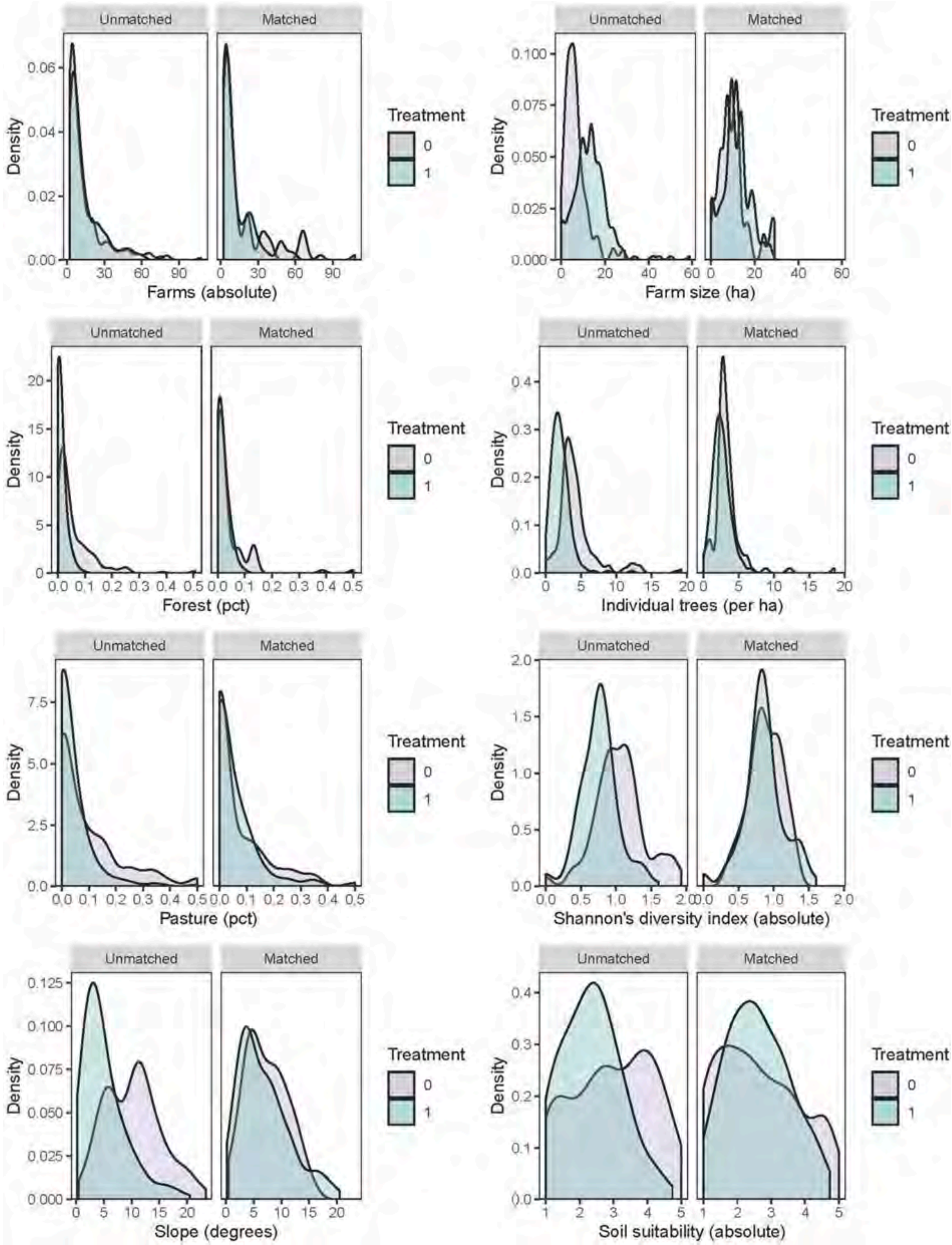
D: Histograms Dependent Variables



E: Loveplot



F: Density Plots Before and After Matching



G: Robustness Check I

	Model 1 Connectance (not in logs)	Model 2 Log(Connectance) Farms not inverted
(Intercept)	6.65	−349.27 *
	(9.17)	(154.90)
Agglomeration Bonus	0.59	−5.84
	(3.45)	(51.58)
Forest	15.87	407.16
	(32.99)	(468.35)
SHDI	2.61	79.00
	(7.20)	(120.74)
Individual trees	−0.71	−14.37
	(1.31)	(19.94)
Slope	−0.84	−8.33
	(0.65)	(13.32)
Farms *(reciprocal value)*	6.50	
	(16.43)	
Farm size	−0.11	−0.41
	(0.23)	(4.45)
Pastures	4.05	−44.35
	(33.76)	(561.44)
Soil suitability	1.54	24.74
	(2.38)	(45.95)
Farms		−2.51
		(1.62)
Log(scale)	2.03 ***	4.88 ***
	(0.45)	(0.23)
BIC	401.23	679.69
N	116	116
Left-censored	16	16
Uncensored	100	100
Right-censored	0	0
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1		

Additional estimations of the model: Model 1 is with the dependent variable in levels instead of logs (please note that this leads to non-normal residuals and thus inaccurate estimations). Although the effect is positive, it is almost 0 (not significant) and would lead to the same conclusion that there is no effect of the AB with an adjacency rule. Model 2 shows the estimation with the variable farms and not its reciprocal values.

H: Robustness Check II

As a robustness check, we additionally estimated the effect of the policy on connectance as well as neighbor connectivity with a difference-in-differences (DID) approach.

Farmers can decide for each site whether to enroll it as a biodiversity promotion area (BPA) only or to add a network bonus on top. This allows us to check whether the difference between the connectance of BPA-sites and network-bonus-sites differs between control and treatment areas, which is essentially a difference-in-differences (DID) approach.

We thus calculated the connectance and neighbor connectivity of sites without a network bonus (BPA), took the control variables from the initial analysis and added a network bonus dummy additionally to the treatment dummy. The interaction term of the network bonus and the treatment dummy then results in the effect of the AB (the effect of the interaction term is for sites that are in a treatment area and get a network bonus).

The assumption for using this approach is that connectance is affected by the network bonus in both areas (the first difference, the "leap" from BPA to a network bonus) and by the treatment (the area). The method relies on the parallel trend assumption, which in this case means that the "leap" of the dependent variable from BPA to the network bonus would be the same if it had the same treatment status. Furthermore, the classical DID approach assumes that there are no time-variant place specific unobservables. For our application, this implies that we need to assume that nothing that is unobserved and affects the dependent variables is different from BPA to the sites with a network bonus in only one of the two areas.

We cannot test whether these assumptions hold true in our case. Furthermore, we would like to emphasize that while the farmer can decide whether he enrolls a site as an AES only or adds a network bonus, he cannot decide whether his land is in an area with or without an adjacency rule (of course, a farmer can choose to relocate or buy land where there is a preservation area but we assume that the incentive is not high enough and other factors are more important than avoiding the adjacency rule to motivate farmers to relocate their farming activities). This adds another layer of self-selection.

Due to all these shortcomings, we would like to point out that this additional approach is only a robustness check of the results of our main analysis. If we would find a significant positive effect of the AB (interaction AB:NB), this would question our results of the main analysis. If we do not, we see this as an additional, but rightfully contestable, support for our findings.

The model output shows no significant effect of the interaction term (interaction AB:NB) on the two dependent variables. There is a slightly positive effect of the interaction effect on neighbor connectivity in the matched dataset but it is not significant.

The network bonus by itself has a positive effect on the two connectivity measures. This is very likely due to the fact that there are substantially more sites with a network bonus than without (with: 8086, without: 3198).

Model output:

	Unmatched				**Matched**			
	Connectance		**NC**		**Connectance**		**NC**	
	Tobit Model 1	**Linear Model 2**	**Tobit Model 3**	**Linear Model 4**	**Tobit Model 5**	**Linear Model 6**	**Tobit Model 7**	**Linear Model 8**
(Intercept)	−315.92 ***	−307.20 ***	34.79 ***	34.79 ***	−330.66.	−311.03 ***	39.80	39.80 *
	(57.99)	(43.53)	(8.07)	(8.07)	(192.26)	(79.40)	(29.90)	(17.23)
Agglomeration Bonus (Area)	−54.29.	−47.39 *	−6.23	−6.23	−33.14	−26.77	−10.28	−10.28
	(32.39)	(23.88)	(5.00)	(5.00)	(89.87)	(38.03)	(13.82)	(6.92)
Network Bonus	87.37 **	56.24 **	20.39 ***	20.39 ***	80.53	50.75	13.39.	13.39.
	(28.40)	(21.43)	(4.12)	(4.12)	(51.53)	(39.20)	(7.40)	(7.40)
Interaction AB:NB	**−13.61**	**−11.75**	**−0.10**	**−0.10**	**−12.27**	**−10.37**	**6.47**	**6.47**
	(34.37)	**(25.90)**	**(5.36)**	**(5.36)**	**(105.78)**	**(44.86)**	**(18.14)**	**(9.09)**
Farm size	−1.11	−1.07	−0.29	−0.29	−4.54	−4.16 **	−0.04	−0.04
	(1.28)	(1.01)	(0.19)	(0.19)	(4.34)	(1.48)	(0.87)	(0.35)
Farms *(reciprocal value)*	−108.45	6.88			−92.63	−2.24		
	(84.63)	(60.12)			(306.43)	(115.50)		
Farms			0.32 ***	0.32 ***			0.01	0.01
			(0.08)	(0.08)			(0.33)	(0.14)
Forest	153.49	120.29	0.70	0.70	370.49	265.49	31.60	31.60
	(144.16)	(111.32)	(29.44)	(29.44)	(471.59)	(161.64)	(160.43)	(56.16)
Pastures	−144.88	−104.56	−27.73.	−27.73.	−84.38	−64.38	−37.77	−37.77.
	(117.82)	(84.35)	(15.99)	(15.99)	(428.43)	(141.20)	(58.42)	(22.53)
SHDI	−21.81	−8.86	−1.42	−1.42	96.55	77.71	7.45	7.45
	(38.04)	(28.08)	(5.17)	(5.17)	(152.92)	(53.44)	(25.16)	(13.54)
Slope	−5.71 *	−5.37 *	−0.62	−0.62	−0.76	−2.42	1.46	1.46
	(2.77)	(2.11)	(0.52)	(0.52)	(12.42)	(4.81)	(2.67)	(1.13)
Soil suitability	4.89	2.56	0.57	0.57	−27.16	−19.39	−6.58	−6.58.
	(12.19)	(9.13)	(1.92)	(1.92)	(43.92)	(18.50)	(7.38)	(3.53)
Individual trees	0.11	0.02	−1.56 **	−1.56 **	−6.06	−4.46	−2.24	−2.24 *
	(5.41)	(4.05)	(0.56)	(0.56)	(21.20)	(5.31)	(2.00)	(0.99)
Log(scale)	5.20 ***		3.42 ***		5.14 ***		3.38 ***	
	(0.04)		(0.03)		(0.13)		(0.13)	
BIC	5718.59	6935.422	5291.01	5291.005	1074.77	2650.552	987.16	2035.905
Log Likelihood	−2818.42		−2604.63		−502.88		−459.08	
Total	538		538		202		202	
Left-censored	132		0		51		0	
Uncensored	406		538		151		202	
Right-censored	0		0		0		0	

Please note: The interaction effect of the Tobit regression with fixed effects corresponds to the sign of the treatment effect, however, the model does not properly estimate its significance (Puhani, 2012). We thus additionally bootstrapped the model and show here the 95% confidence interval for the interaction effect for each Tobit model:

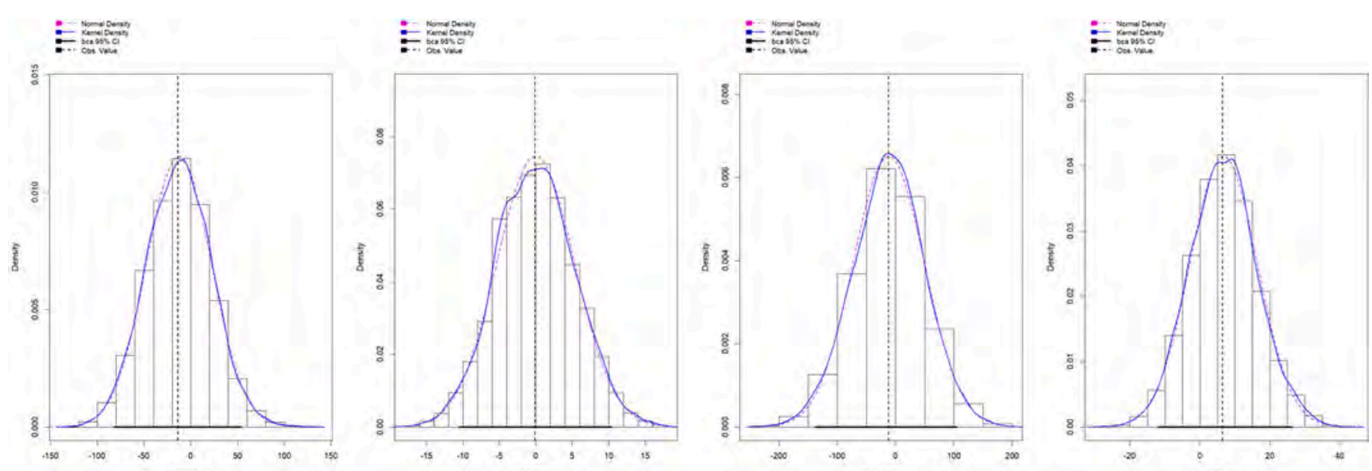


Figure: Interaction effect, bootstrapped with $R = 5000$. None of the effects is significant (the bold line shown is the 95% confidence interval).

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