

A bird's eye view on farm size and biodiversity

Frederik Noack¹, Christian Levers², Johannes Kamp^{3,5}, and Ashley Larsen⁴

¹University of British Columbia

²Vrije Universiteit Amsterdam

³University of Göttingen & Dachverband Deutscher Avifaunisten

⁴University of California, Santa Barbara

February 11, 2021

Abstract

Biodiversity is declining globally, largely due to agriculture. A common claim is that large-scale agroindustrial farming is mainly responsible for this biodiversity decline, while smaller farms are more wildlife friendly. Here we leverage a natural experiment along the former inner German border to estimate the causal impact of farm size on biodiversity. We

For their helpful comments and discussion we thank Amy Ando, Patrick Baylis, Olivier Deschenes, Eyal Frank, Sumeet Gulati, Claire Kremen, Tobias Kuemmerle, Anouch Missirian, and Navin Ramankutty. We further thank the thousands of volunteers that annually survey the large number of CBBC monitoring plots as well as all eBird participants, without whom this project would not be possible. CL gratefully acknowledges support by the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie Grant Agreement No 796451 (FFSize).

combine data on land cover from satellite images with bird diversity data to measure the impact of farm size on bird diversity and to establish the mechanisms through which farm size affects bird diversity. Our results suggest that the increase in farm size at the former border reduces overall bird species richness by 10 % and the richness of common cropland bird species by about 20 % mainly through landscape simplification rather than land use intensification. These results suggest that the negative impact of increasing farm size and land use intensification on biodiversity can be mitigated by maintaining or increasing land use complexity.

1 Introduction

Agriculture is the largest threat to global biodiversity (Tilman et al. 2017). It also provides the incomes for the rural poor and the food for a growing global population. Increasing agricultural productivity and raising rural incomes is therefore important to meet future food demand and to reduce rural poverty. However, raising agricultural production may have devastating consequences for biodiversity (Kehoe et al. 2017; Zabel et al. 2019) but the relationship is not well-understood. Rural incomes, agricultural productivity and farm size are closely related. Increasing farm size provides the economic scale for the adoption of modern technologies and agricultural mechanization (Foster and Rosenzweig 2017). Consequently, larger farms are more mechanized and use less labor per unit of land (Muyanga and Jayne 2019) and farmers of larger farms earn higher incomes (Noack and Larsen 2019). Larger farms also control larger shares of local pest populations and can therefore eradicate pests more effectively (Costello et al. 2017). Unsurprisingly, larger farms are associated with extensive use of agrochemicals such

as pesticides (Meehan et al. 2011; MacDonald et al. 2014; Larsen and Noack 2017). Although increasing farm size is an important component of rural development, its impact on biodiversity is poorly understood. Testing the impact of farm size on biodiversity is complicated by the lack of exogenous variation in farm size and the potentially slow response of biodiversity to any changes in the agricultural landscape. Here we leverage the discontinuous change in farm size along the former inner German border to estimate the casual impact of farm size on biodiversity. The difference in farm size, originating from agricultural collectivization in East Germany during the 1950s, has persisted over the decades, allowing us to study the long-term biodiversity outcomes. To quantify the impact of farm size on biodiversity and to establish the mechanisms that relates farm size to biodiversity, we combine bird diversity data from opportunistic citizen science (eBird) and a systematic bird survey (CBBS) with data on land cover from satellite images in a regression discontinuity approach.

Farm size affects biodiversity through several channels. The increased use of pesticides, fertilizers and other agrochemicals disrupts food webs and displaces less competitive plant and animal species therefore reducing biodiversity (Hautier et al. 2009; Geiger et al. 2010; Hautier et al. 2014). In addition to these direct changes in agricultural practices, larger farms also changes the landscape configuration. First, larger farms are often associated with larger fields (Clough et al. 2020) and therefore with lower amounts of edge habitat such as hedgerows relative to the crop area with demonstrably negative effects on biodiversity (Fahrig et al. 2015; Sirami et al. 2019; Martin et al. 2019a). Second, larger farms may lead to simplified landscapes since land cover is more homogeneous within farms and fields than across different farms and fields. The loss of natural and semi-natural habitat, as well as the heterogeneity thereof, has

important implications for biodiversity and biodiversity-associated ecosystem services. In this study we seek to understand the contributions of these mechanisms to the impact of agriculture on biodiversity.

Farm size and the associated land-use changes are not random but evolve in response to geography and economic incentives. A major challenge for estimating causal relationships between farm size and environmental outcomes is therefore to separate the causal effect of farm size on the environmental outcomes from the underlying, confounding geographical and economic variables. Regression discontinuity (RDD) approaches have been used in similar settings to study the causal impact of policies on environmental outcomes (Almond et al. 2009; Burgess et al. 2018; Englander 2019). Here, we use the discontinuous change in farm size at the former inner German border to isolate the causal impact of farm size from the continuously changing underlying geographical variables such as climate or topography.

This approach relies on the assumption that the discontinuous change in farm size is unrelated to other variables that could affect biodiversity directly. Although there are differences in culture and geography between East and West Germany (Becker et al. 2020), we argue that these differences change smoothly across the former border, since the exact location of the former inner German border was largely determined by the advancement of the allied forces during World War II and historic borders that were abolished more than 100 years prior to the establishment of the former inner German border (Buchholz 1994). This argument is supported by a lack of farm size differences between East and West Germany in the 1950s, just prior to the farm collectivization in the 1960s (Koester and Brooks 1997) and by the smooth change of climate and topographic variables across the former border (see Appendix B). Although

the German reunification in the 1990s placed Eastern and Western German farms in the same institutional setting and market environment, the differences in farm size persisted almost unchanged over the decades. Farms in East Germany are still on average four times larger than farms in West Germany with little signs of convergence. While the percentage of forest and crop cover changes smoothly across the former border, the increased farm size has profound implications for land use. East German farms use only half of the labor, field are twice as large and land cover is significantly less diverse in East Germany than in West Germany. We use these land use legacies of farm collectivization to estimate the causal impact of farm size on biodiversity and to identify the mechanisms that relate farm size and biodiversity.

To measure biodiversity, we use data from the common breeding birds survey (CBBS) as well as data from opportunistic citizen science (eBird). While the CBBS data have the advantage of being from a randomly-stratified sample with standardized sampling procedure, the density of the eBird observations is several times higher than the CBBS observations and allows us to measure changes in bird diversity at the former border with high precision. We combine these data with detailed land cover data in 20×20 m spatial resolution from Preidl

One possible alternative explanation for biodiversity differences across the former border is different mortality rates of birds due to hunting, feral cats and collisions with buildings. However, including the share of areas with buildings as a control in our analysis does not change the result (see Section 4.2). A second alternative explanation is related to agricultural policies. Either lasting effects of former agricultural policies before the German reunification or current differences in agricultural policies could drive the differences in biodiversity. However, Wuepper et al. (2020) shows that there are no significant differences in current agri-environmental policies across the former border. Although we cannot exclude lasting effects of former agricultural policies in East Germany before the reunification, we think that these effects are unlikely to still determine biodiversity outcomes almost 30 years after the reunification.

et al. (2020).

Our main results suggest a strong and negative effect of farm size on bird diversity. Based on our sample of eBird observations in proximity to the former border we find that general bird diversity declines by 20 % at the former border while diversity of common cropland species declines by 34 %. Using the CBBS observations we find a decline of general bird diversity by 10 % and a decline of common cropland species by 17%. These results suggest 1) that the impact of farm size on bird diversity is substantial, 2) that cropland species are more affected by changes in farm size than general bird diversity and that 3) the results based on eBird data are larger than those based on CBBS data. These differences between the eBird and CBBS data are unlikely to stem from species selection bias in the eBird data since the difference remains largely unchanged when we restrict the observations to the same set of common cropland species. However, we find substantial differences in the land cover between eBird and CBBS samples suggesting spatial selection as a potential mechanism to explain the differences in the results.

Adding field size, land use intensity, crop diversity and land cover complexity as controls shows that the negative impact of farm size on bird diversity is almost exclusively driven by landscape simplification. To explore these results further, we then use Germany-wide CBBS observations in a cross-sectional regression. The cross-section results generally confirm the previous results: Landscape complexity has the largest impact on bird diversity followed by cropland extent while all other variables are unable to explain the observed variations in bird diversity.

Our results therefore suggest that the presence of different non-crop habitats is an important

driver of biodiversity in agricultural landscape. The results suggest further that the impact of landscape complexity on biodiversity may even outweigh the impact of land use intensification and cropland extent on biodiversity in the agricultural landscapes of Central Europe. In these landscapes, biodiversity has adapted to agriculture during the long cultivation history while species that depend on large undisturbed habitats have mostly disappeared. The biodiversity in these landscapes therefore depend crucially on the agricultural practices.

The mechanism that relates farm size to biodiversity in our study is landscape simplification. This landscape simplification is the direct consequence of larger farms and larger fields. It is probably also necessary for agricultural mechanization associated with large farms. The relationship between farm size, field size and agricultural mechanization may therefore be fairly general and it has been recorded in different regions including Sub-Saharan Africa (Muyanga and Jayne 2019; Noack and Quaas 2021). Although we rely in our study on the natural experiment in Germany to estimate the impact of farm size on biodiversity, our results may therefore generally apply to farming landscapes with a long cultivation history and biodiversity that has adopted to agriculture.

Agriculture is now the dominant form of land use in large parts of the world. Any changes in agricultural practices may therefore have important implications for global biodiversity conservation. Conserving biodiversity within the agricultural landscape is not only important for achieving global conservation targets but also because of the ecosystem services it provides for agriculture. Local biodiversity enhances and stabilizes agricultural production through ecosystem services including pollination and natural pest control (Larsen and Noack 2017; Binder et al. 2018; Dainese et al. 2019; Martin et al. 2019b; Noack et al. 2019). Despite

these benefits, biodiversity is often neglected in the farmers' decision. Governments therefore implement expensive agri-environmental policies to mitigate the negative impact of agriculture on the environment. The European Union spends several billion Euro every year on agri-environmental policies (Arata and Sckokai 2016; Wätzold et al. 2016) while the Endangered Species Act reduces farmers incomes and land values across the United States (Melstrom 2019). Despite these efforts, the success of these policies is limited (Wätzold et al. 2016). Target agri-environmental policies can reduce the conservation costs and improve the outcomes. Our study contribute to the debate by quantifying the mechanisms that relate farm size to biodiversity outcomes.

Our study contribute to two strands of literature. The first strand concerns the protection of biodiversity on private land. While much of the economics literature within this strand focuses on the Endangered Species Act and other conservation policies (Chabé-Ferret and Subervie 2013; Wätzold et al. 2016; Melstrom 2019; Langpap and Wu 2017) our study contributes to this literature by addressing the question about the consequences of agricultural development for biodiversity conservation. A large literature in ecology and environmental science relates agricultural development to biodiversity outcomes but those studies are either small-scale experiments or large-scale correlations Li et al. (2020) is closely related to the current study which finds a negative effect of neonicotinoid insecticides on bird diversity in the United States using an instrumental variable approach. However, to our knowledge, our paper is the first study that estimate a causal impact of farm size on biodiversity on a larger scale.

See Ando and Langpap (2018) for a recent summary of the economics literature.

See Tschamtker et al. (2012) and Kremen and Merenlender (2018) for summaries of the ecology and environmental science literature.

The second strand of related literature estimates the impact of farm size on agricultural productivity (e.g.(Feder 1985; Assunção and Braido 2007; Barrett et al. 2010; Adamopoulos and Restuccia 2014a; Desiere and Jolliffe 2018; Noack and Larsen 2019)) but this literature largely neglects the environmental consequences of increased farm size. As far as we know only two papers at very different scales relate farm size to environmental outcomes. Using a regression discontinuity approach, Wu et al. (2018) find that small farms lead to more spatial heterogeneity in production and more bare soils. They measure the environmental outcomes (land use diversity and bare soils) from space. In contrast to our study, Batáry et al. (2017) use field level sample data to compare beetles, spiders and plants between small and large fields. Our study bridges the scale of these studies by combining land use data from satellite images with biodiversity data from field surveys.

Agriculture is the dominant land use in many parts of the world. Changes in agricultural practices have therefore potentially devastating consequences for biodiversity. Agriculture also provides the incomes for the majority of the global poor and the food for a growing global population. Reducing poverty and increasing agricultural productivity may require increasing farm sizes (Muyanga and Jayne 2019; Noack and Larsen 2019). Unsurprisingly, farm size and economic development are closely related (Adamopoulos and Restuccia 2014b). Our result suggest that increasing farm sizes reduces biodiversity and can therefore counteract global biodiversity conservation efforts. However, our result also show that these consequences can be mitigated by maintaining the land cover complexity in the agricultural landscape. In practice, this could mean conserving or incentivizing riparian buffers strips, forest patches, hedgerows or other types of non-agricultural vegetation within the agricultural landscape. Our results there-

fore provide new opportunities for targeted interventions to harmonize productive agriculture with safeguarding biodiversity.

In the next two sections we introduce our data (Section 2) and illustrate the impact of farm collectivization on farm size and land use (Section 3). In the main section of our paper we then discuss the regression discontinuity estimation strategy and results on the impact of farm size on biodiversity (Section 4). We support the mechanisms suggested by these results with a cross-sectional analysis of land use to biodiversity (Section 5). Section 6 concludes.

2 Data

To estimate the impact of farm size on biodiversity and to relate our results to credible mechanisms we use data from a range of sources. We use bird diversity from citizen science (eBird) and structured bird surveys (CBBS) as well as land cover from Preidl et al. (2020), land use intensity (EVI) from Radeloff et al. (2019), climatic data from Karger et al. (2017) and elevations maps from USGS (2004). This chapter introduces the data sources in more detail and describes the matching and preprocessing algorithms.

2.1 Bird diversity

eBird: Being one of the world’s largest biodiversity-related citizen science projects, the eBird database contains information on bird distribution, bird abundance, and habitat use (Sullivan et al. 2009). The database is populated by volunteers who enter the time, duration, location, and mode of their bird watching activity, as well as all birds seen and heard during the outing through a standardized checklist. We use the eBird Basic Dataset (EBD) for Germany,

version September 2019, from eBird. We use the auk package (Strimas-Mackey et al. 2018) in R to preprocess the data, following the best practices examples for eBird data (Johnston et al. 2020) regarding data cleaning and filtering. We force the distance traveled to 0 for all stationary checklists and ensure that all non-sightings were set to NA. To reduce the variation in observation effort between checklists, which is often the case for semi-structured data sets as eBird, we restrict checklists to those less than 5 hours long and 5 km in length, and with 10 or fewer observers. Finally, we only use complete observations and restrict the data set to the years between 2015 and 2018 to match them with the land cover data. After this data cleaning process we remain with 54,264 unique bird species and 2,367 bird diversity observations within the 50 km band on both sides of the former inner German border. Panel B in Figure 3 shows the distribution of the bird diversity observations within the 50 km band on both sides of the former inner German border.

To take observer experience into account, we calculate experience as the number of observations entered previously by the same observer into the eBird database.

Matching: The eBird observations in East and West Germany differ in terms of their timing, their observer characteristics and their observation effort. We therefore preprocess the eBird data to make the observations in East and West Germany comparable in terms of their timing, their observer characteristics, their observation effort and the distance to the former border, following the method suggested by Ho et al. (2007). We use nearest neighbor matching with logistic distance as suggested by (Ho et al. 2011). We restrict the sample to observations within 50 km distance to the former border. The matching is based on the distance of the observation to the former border, the duration of the observation, the experience of the observer

as well as the year and the month of the observation. We include duration and experience in logs to account for a declining marginal impact of experience and effort on outcome. We present our results based on the non-matched data set in Appendix E. A

German Common Breeding Bird Survey (CBBS): In the German Common Breeding Bird Monitoring, volunteers map the territories (pairs of breeding birds) of all breeding birds within a quadratic 1×1 km sample areas. The sample areas are surveyed four times in the period from 10 March to 20 June to ensure that all territories are recorded. More than 2,600 quadratic sample areas of 100 ha (1×1 km) are distributed across Germany. Plots were selected randomly-stratified, based on a two-level stratification. The first stratum are Germany's "environmental regions", i.e. spatial units of similar environmental characteristics such as soil, climate and vegetation (Mitschke et al. 2005). The second stratum is land-cover with the classes arable land, rare crops (e.g., grapes and vines), grassland, forest, settlements, and a combined class of rarer land-cover types (Mitschke et al. 2005). Most sample areas were surveyed by the same observer for several years. We include only data between 2015 and 2017 to match them with the land cover data. The data include the number of breeding pairs within each sample area by year and habitat in which they were sighted. This process leaves us with a sample of 117,369 unique bird species and 3,411 bird diversity observations for Germany of which 23,646 bird species and 676 bird diversity observation fall within the 50 km band on both sides of the former inner German border. Panel B in Figure 3 shows the distribution of the bird diversity observations within the 50 km band on both sides of the former inner German border.

Diversity measure: Our main measure of bird diversity is species richness, and we only

report results based on the Simpson or Herfindahl-Hirschman index as a robustness test. In contrast to species richness, the Simpson index also uses the information of relative abundances. Our rationale for choosing bird richness as our main measure is to make the results between CBBS and eBird data directly comparable. CBBS reports abundance of all species while abundance data are often absent in the eBird data.

Figure 1 summarizes all bird diversity observations of our sample within the 50 km band on both sides of the former border. Average species richness is higher in the CBBS data (Figure 1 panel B) than in the eBird data (Figure 1 panel A). While the observation effort is standardized in the CBBS data, it is not in the eBird data.

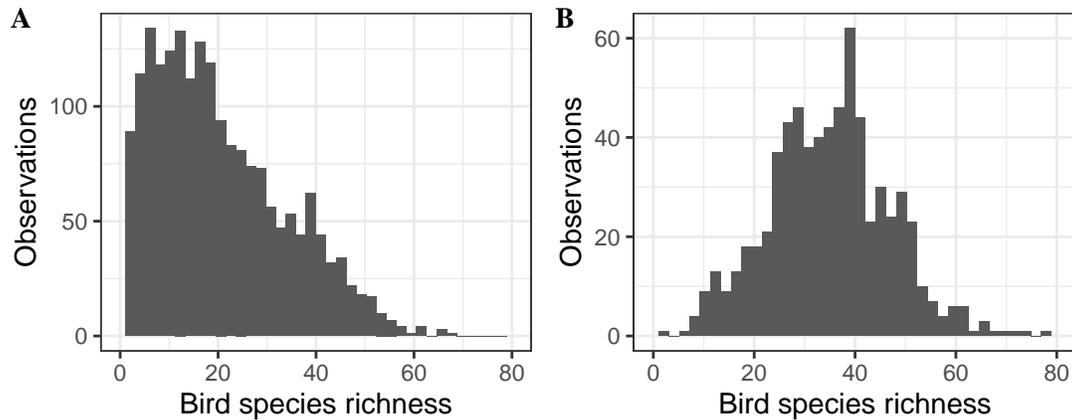


Figure 1: Distribution of bird species richness within a 50 km band of the former inner German border in the eBird data (A) and the CBBS data (B).

Cropland species: We define a set of cropland species using the complete CBBS data set for Germany for the years 2015 to 2017. In a first step we estimate the relationship between crop cover in the sample areas and the number of breeding pairs (territories) for all species

with more than 250 observations in individual regressions:

$$\text{territories}_{ijst} = \alpha_i \text{crop}_{js} + \theta_t + \gamma_s + \varepsilon_{ijst}$$

where territories is the number of territories of species i in sample area j in state s in year t , ‘crop’ is the crop cover in percent in sample area j in the year 2016 and the remaining variables are year fixed effects and an error term. We therefore only use the variation of crop cover and bird abundance within states to estimate the relation between crop cover and species abundance. We cluster standard errors at the site level to account for serial correlations. In a second step, we define species as cropland species if $\alpha_i > 0$ and a p-value below 0.01, i.e. a statistically significant positive relationship between species abundance and crop cover within the sample area. The list of the species is given in Appendix C.

2.2 Land cover

We use the most recent and accurate agricultural cropland cover classification for Germany available (Preidl et al. 2020) to represent habitat and landscape structure. The data layer was generated for the year 2016 using Sentinel-2A satellite imagery (20 x 20 m spatial resolution) and a random forest classifier. It achieved an overall accuracy of 88 % in the following 23 land-cover classes: winter wheat, spelt, winter rye, winter barley, spring wheat, spring barley, spring oat, maize, legumes, rapeseed, leeks, potatoes, sugar beets, strawberries, stone fruits, vines, hops, asparagus, grassland, buildings, water bodies, other vegetation, and forest. To represent bird habitat, we calculate land-cover shares within 1×1 km squares around each eBird bird diversity observation. We chose the 1×1 km area to match the CBBS 1×1 km sample areas. This area represents the immediate habitat of the sighting. In a robustness test

we use 6×6 km squares to represent the wider habitat of the sighting (Mitchell et al. 2001; Semper-Pascual et al. 2018).

We use the *landscapemetrics* package (Hesselbarth et al. 2019) in R to calculate mean patch size and Simpson's Diversity Index (SDI) of land cover for each bird diversity observation using queen contiguity.

Land cover diversity: To measure land cover diversity, we aggregate the original land cover categories to the categories: grassland, cropland, forest, buildings, water, and other land cover. We use the SDI to measure land cover diversity because it is less sensitive to rare class types, equaling 0 when only one patch is present and approaching 1 when the number of classes increases while categories are equally distributed (McGarigal et al. 2012). We measure crop diversity using the SDI with the disaggregated crop land cover categories.

Field size: We approximate field size with the size of crop patches, with patches being contiguous, homogenous land cover units, due to the lack of peer-reviewed, spatially explicit, and high-resolution field size data for Germany, following the argumentation by Weissteiner et al. (2016). We define field size as the mean patch size of crop land cover. Crop land cover includes winter wheat, spelt, winter rye, winter barley, spring wheat, spring barley, spring oat, maize, legumes, rapeseed, leeks, potatoes, sugar beets, strawberries, stone fruits, vines, hops, and asparagus.

To calculate field size for the complete study area, i.e. the area 50 km east and west of the former inner German border, we first convert the categorical land-cover map (Preidl et al. 2020) into binary maps for each crop type class. Second, we convert the resulting raster maps into polygon shapefiles, with separate polygons representing contiguous patches for each crop

type class. Third, we calculate the area of each polygon and its respective centroid, Lastly, we calculate the distance of each centroid to the former inner German border and merge all crop type classes into one data table. To exclude solitary pixels as well as very small or large fields, we trim our data to crop fields larger than 0.36 ha (i.e., nine pixels in any spatially contiguous shape) and smaller than 1,000 ha (i.e., 25,000 pixels in any spatially contiguous shape). We further removed all fields located closer than 1 km from the former inner German border to remove potential trans-border fields, resulting in a final sample size of 666,945 fields.

Summary land cover Figure 2 summarizes the broad land cover categories within the 1×1 km CBBS sampling sample areas and the 1×1 km buffer around the eBird observations. The figure shows that the eBird and CBBS data differ with respect to their surrounding land cover. First, more eBird observations are located in residential areas dominated by buildings (Figure 2, panel A) compared to the CBBS observations (Figure 2, panel B). Second, the relative difference between the land cover in East and West Germany is larger in the eBird observations compared to the CBBS observations except for the “other” land cover category.

2.3 Farm size, land use intensity, climate and topography

Yields and farm size: We use data on crop yields and farm size on district (Kreis) level from the German yield statistics (Erntestatistik) and the agricultural census (Allgemeine Agrarstrukturerhebung) to compare agriculture across the former inner German border in Section 3.

Enhanced vegetation index (EVI): We use the EVI as a proxy for land-use intensity due to its correlation with crop yields (Bolton and Friedl 2013; Burke and Lobell 2017) in combination with land cover shares as controls in our regression specification. EVI is more sensitive

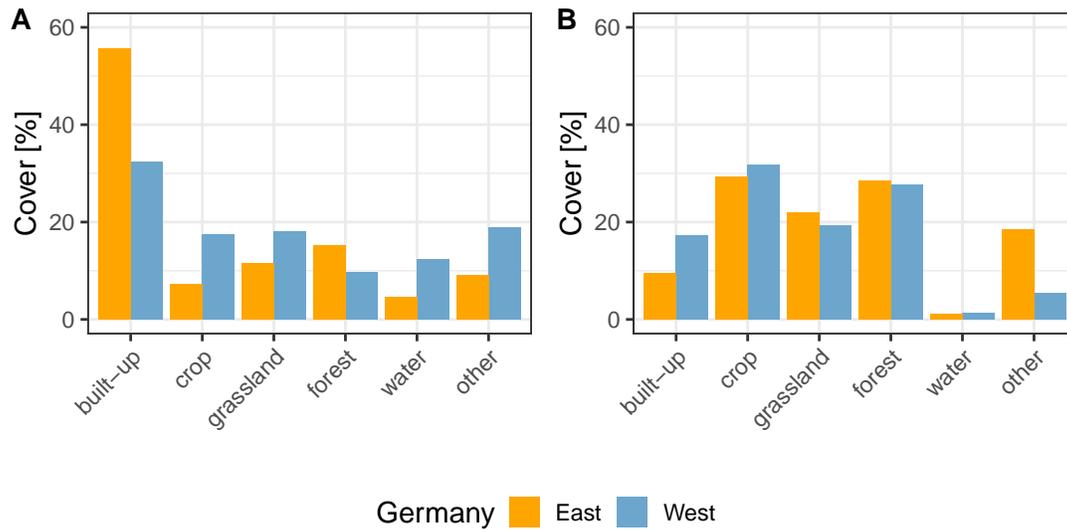


Figure 2: Land cover in the buffers surrounding the eBird (A) and CBBS (B) observations within a 50 km band of the former border.

to changes in areas of high biomass compared to NDVI. Here, we use the cumulative EVI from MODIS 1000-m vegetation productivity data sets for 2003–2014, generated as a Dynamic Habitat Index (Radeloff et al. 2019). Although this is only a rough proxy for land use intensity, it matches our district level yield observations.

Climate and topography: We use CHELSA bioclimatic variables (Karger et al. 2017) to represent climatic conditions for CBBS and eBird observations. We use mean annual temperature (Bio1) and annual precipitation (Bio12), which have shown to influence bird diversity patterns as they determine water availability and energy available for plant growth, and hence shape the available habitat (Karger et al. 2017; Elsen et al. 2020). We further use the GTOPO30 digital elevation model at 1×1 km spatial resolution (USGS 2004) to control for the influence of topography on bird diversity.

3 The land use legacy of farm collectivization

There is a large and discontinuous increase in farm size and field size at the former inner German border as a legacy of agricultural collectivization in East Germany after the Second World War. Farm size in Germany also varies because of other factors including topography and inheritance pattern but this source of variation is dwarfed by the variation of farm size due to farm collectivization. While Southern Germany is largely mountainous or hilly, Northern Germany is largely flat. These topographic differences led to smaller farms in the south and larger farms in the north of Germany. Differences in land inheritance pattern between Northern and Southern Germany magnified these differences. While the land in Southern Germany was divided equally among the heirs ('Realteilung') leading to smaller farms and smaller fields, the farmland in Northern Germany was mainly bequeathed to the oldest heir ('Anerbenrecht') leaving the farm intact. These differences in topography and inheritance pattern led to considerable farm size differences between Southern and Northern Germany. According to the German agricultural census of 2016, average farm size in northern West Germany was 71 hectares while it was only 35 hectares in southern West Germany. However, these differences are small compared to the differences between East and West Germany that resulted largely from the farm collectivization in the formally socialist East Germany. According to the 2016 German Agricultural Census, average farms size in West Germany was 45 hectares while it was 223 hectares in East Germany. Panel A in Figure 3 illustrates these differences in district level farm sizes. The black lines are the former inner German border and the 50 km bands on both sides of the former border.

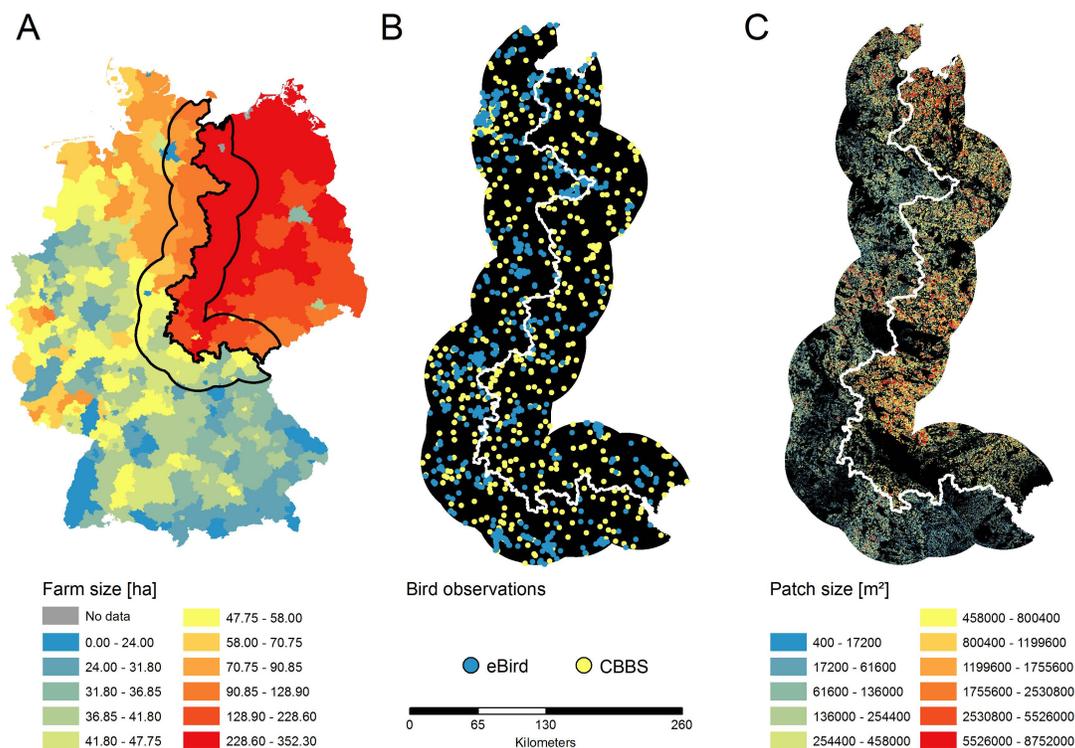


Figure 3: District level farm size distributions in East and West Germany.

These large farm size differences between East and West are not a result of differences in topography or inheritance pattern but largely due to land collectivization. Prior to farm collectivization, farm size was similar between East and West Germany. In 1950, the average farm size was 8.2 hectares in West Germany and 8.8 hectares in East Germany (Koester and Brooks 1997). After 1950, the socialist government in East Germany implemented agrarian reforms that led to large-scale and rapid land expropriation and collectivization. In 1950 almost all farms were private. Only ten years later, in 1960, more than 90 % of the East German farms were collectivized (Koester and Brooks 1997). During this process, private farms were aggregated to large collective farms. While farm size increased from 8 hectare to 18 hectare

between 1950 and 1989 in West Germany, it increased from 8 hectares to 4,538 hectares during the same time period in East Germany. After the reunification of Germany in 1990, farms in East Germany were privatized and operate since then in a very similar political and economic system than farms in West Germany (Wuepper et al. 2020). The process of privatization in East Germany was relatively quick. After the initial phase that transformed the large collective farms to private enterprises, the farm size distribution remained relatively stable over the last two decades. However, farm sizes remained largely different between East and West Germany (Panel B, Figure 4). Panel A of Figure 4 shows the district level farm size distribution in relation to the former inner German border. Districts with relatively small average farms sizes in East Germany are either in urban areas or in the mountainous areas of the South (see panel A in Figure 3).

This change in farm size at the former German border provides a natural experiment to test the impact of farm size on biodiversity. However, the approach relies on the assumption that the location of the former border is not correlated with other variables that could also affect biodiversity. We show regression discontinuity sample areas of geographic variables including climate, elevation, and soil characteristics in the Appendix B. These geographic variables exhibit no discontinuous change at the former border. Only precipitation declines continuously from West to East. We therefore include precipitation as control in our regression.

Agricultural collectivization not only affected farm size but also field size. Figure 5 illustrates the field size differences across the former border based on all fields within a 50 km band of the former border (666,945 observations). It shows that fields in East Germany are, on average, almost twice as large than in West Germany. The difference is also visible in panel C

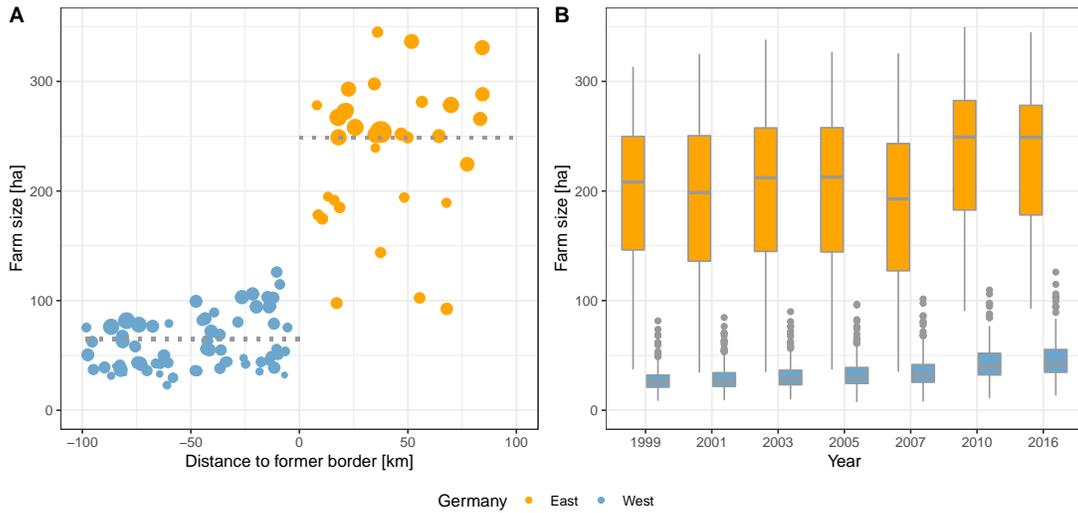


Figure 4: District level farm size distributions in East and West Germany. Panel A shows mean district level farms size relative to the distance of the district centroid to the former inner German border. The size of the points is relative to the district's agricultural area. The dotted lines are the agricultural area weighted means. Panel B shows the district level farm size distribution in East and West Germany over time.

of Figure 3.

Despite the large differences in farm and field size, we find no discontinuous change in land use intensity at the former border when using the EVI index as proxy for land use intensity (Appendix A). This finding is also supported by panel A of Figure 6 which sample areas district level wheat yields against the districts' distance to the former border. The figure suggests that wheat yields are generally higher in West Germany compared to East Germany although the differences are small. In contrast to wheat yields, labor inputs between East and West Germany differ largely. Panel B of Figure 6 suggest that West German farms use on average twice as much labor per unit of land as East German farms. Figure 6 therefore suggests that potential efficiency gains from increased farm size are likely to result from labor saving technologies

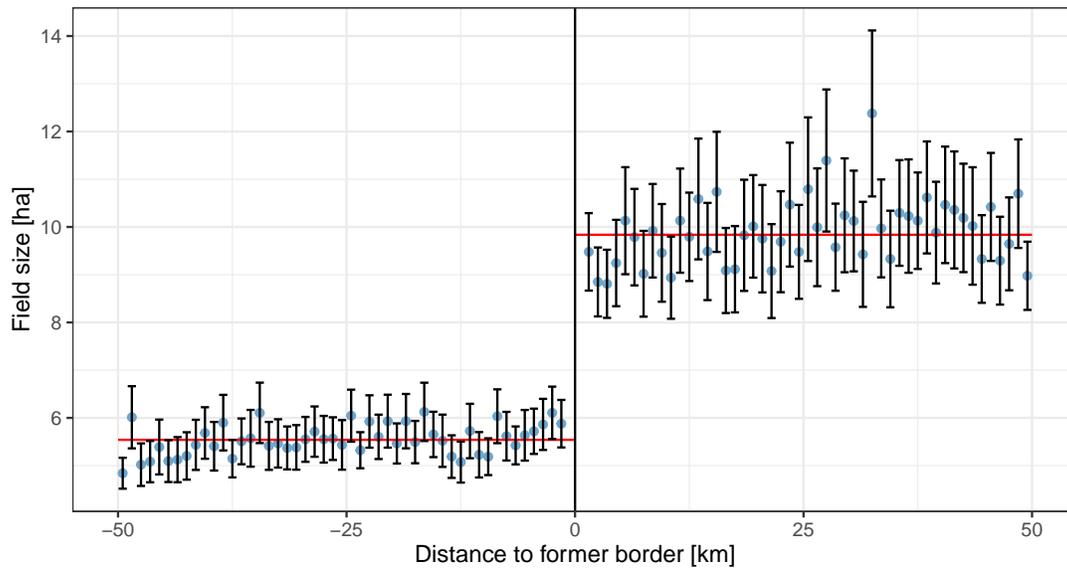


Figure 5: Regression discontinuity sample area of field size (crop patch size). The dots are sample means in 1 km distance bins from the former inner German border. The bars are 95% confidence intervals. The red line shows mean field size for East and West Germany separately. West Germany is to the left of the former border, East Germany is to the right of the former border. The sample consists of all crop patches larger than 3 pixels (0.36 ha) and smaller than 1,000 ha in a 50 km distance band on both sides of the former inner German border.

rather than increased yields.

Another land use implication of the increased farm and field sizes is landscape simplification. Fields and farms are typically managed as relatively homogeneous units. Dividing the same amount of land among fewer farms and fields therefore reduces land cover complexity. Figure 7 illustrates the relationship between crop diversity and distance to the former inner German border for all 1×1 km grid cells with crop cover. It shows a strong reduction of crop diversity at the former border.

Although these land use differences could play an important role in explaining the impact

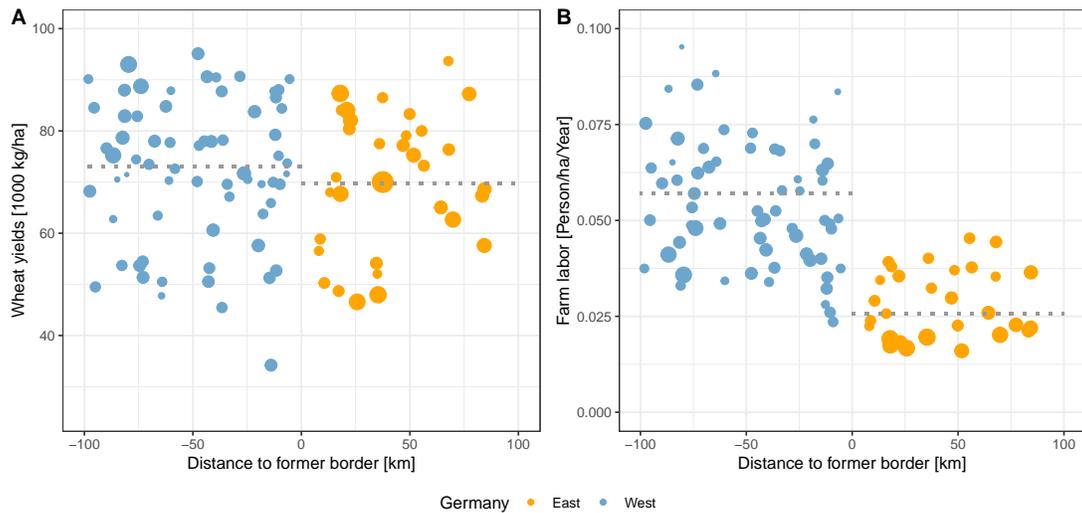


Figure 6: Panel A plots mean district level wheat yields against the district centroid’s distance to the former inner German border. Panel B plots the mean number number of agricultural workers per hectare [ha] of agricultural land against the district centroid’s distance to the former inner German border. The size of the points in both panels is relative to the district’s agricultural area. The dotted lines in both panels are the agricultural area weighted means.

of farm size on biodiversity there are further potentially important mechanisms. These mechanisms include differences in pesticide use, crop diversity or general change in land cover percentage or land cover diversity. We explore some of these mechanisms in the following sections.

4 Farm size and bird diversity

The main aim of the paper is to estimate the causal impact of farm size on bird diversity and to identify plausible mechanisms for this relationship. To do so, we exploit the sharp discontinuity in farm size at the former inner German border in a regression discontinuity design. Figure 8 visualizes the distribution of bird diversity across the former border using the preprocessed

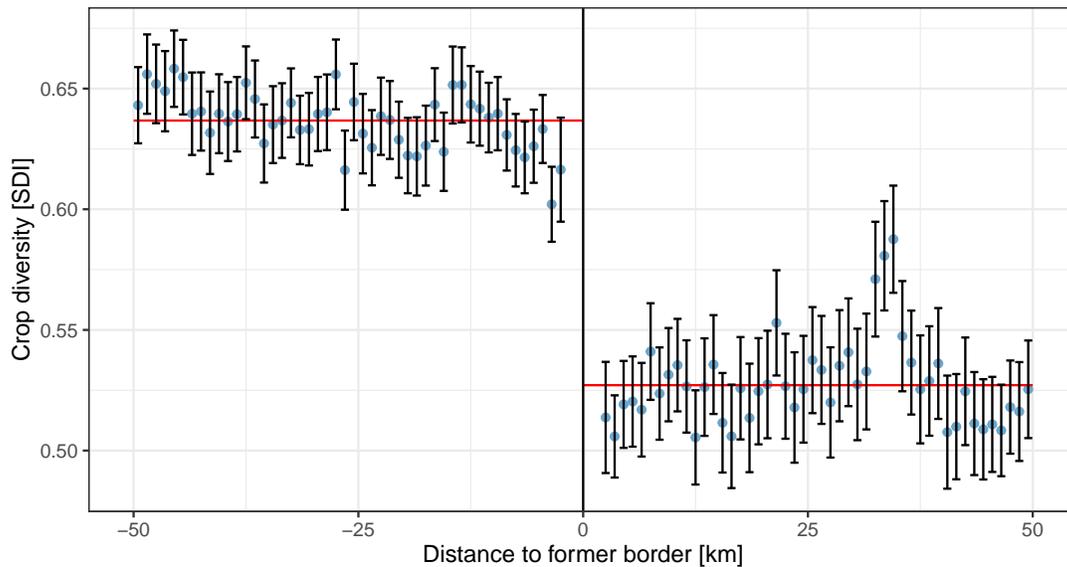


Figure 7: Regression discontinuity plot of crop diversity within 1×1 km grid cells. We use the inverse Simpson index to measure crop diversity. The dots are sample means in 1 km distance bins from the former inner German border. The bars are 95% confidence intervals. The red line shows mean field size for East and West Germany separately. West Germany is to the left of the former border, East Germany is to the right of the former border. The sample consists of all crop patches larger than 3 pixels (0.36 ha) and smaller than 1,000 ha in a 50 km distance band on both sides of the former inner German border.

eBird data. For the figure, we residualize bird diversity to address the variation of observation effort that is common to all citizen science data. Figure 8 suggests that bird diversity generally increases from West to East but also that there is a large and discontinuous jump at the former border.

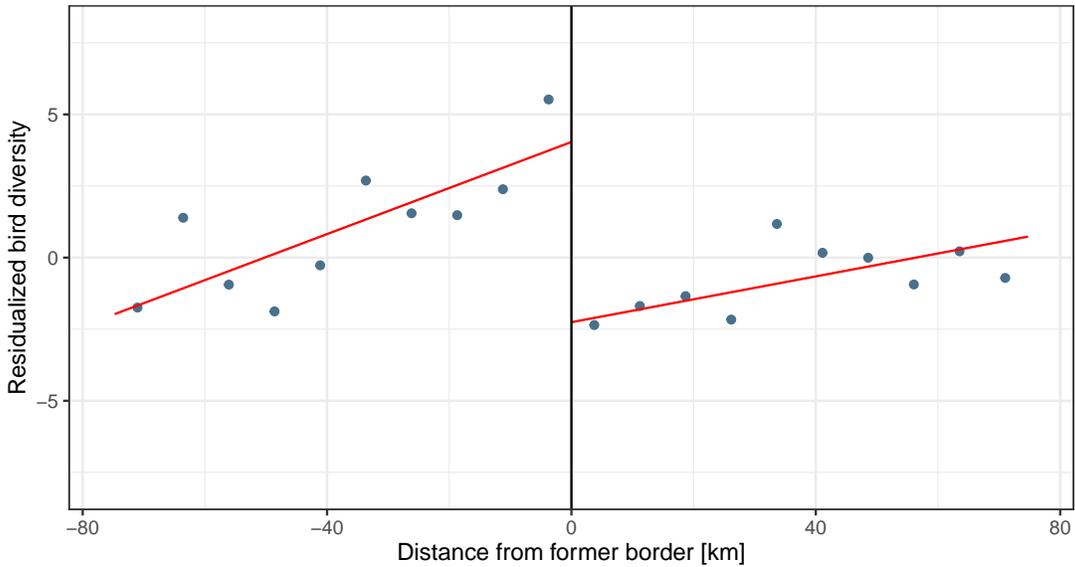


Figure 8: Regression discontinuity plot of residualized bird diversity using eBird data between 2015 and 2018 in a 50 km band on both sides of the former border. The dots are residuals from regressing bird species richness on log observer experience, log duration of the observation, the percentage of broad land cover categories within a 1×1 km buffer around the observation centroid, a border fixed effect as well as month and year fixed effects. The red line is a local linear regression with triangular kernel. West Germany is to the left, East Germany is to the right of the former border.

4.1 Estimation

In this section we formalize the regression discontinuity approach illustrated in Figure 8. We also develop the approach to identifying the mechanisms that relate farm size to bird diversity.

Following Gelman and Imbens (2019) we use local linear regressions with a triangular kernel and optimal bandwidth selection based on the mean squared error criterion. The baseline regression discontinuity equation is

$$y_{it} = f(\text{running}_i) + \beta \text{East}_i + Z_i \eta + \varepsilon_{it} \quad (1)$$

where $f(\text{running}_i)$ is a function of the running variable (local linear), $East_i$ is a dummy for East Germany, Z_i are controls and ε_{it} is the error term. In our baseline specification with the eBird data, the controls include a dummy for the former border i.e. a band of 2.5 km on both sides of the former border, average precipitation levels (see Appendix B), the log observer effort and experience as well as year and quarter fixed effects. We include a dummy for the former border because there is low land-use intensity at the former border as a result of former border security restrictions and conservation measures after the German reunification. We include the experience and duration of the observation in logs to account for concavities in learning and species area relationships.

We then subsequently add additional controls to establish the mechanism through which farm size affects bird diversity. This approach builds on the assumption that the estimated discontinuity of bird diversity would converge to zero if the added controls explain the outcome. For example, if the discontinuous change in field size at the former border (Figure ??) explains the decline in bird diversity, then adding field size as a control would explain the change in bird diversity at the former border, and the former border itself had no further impact on the outcome. These controls include land cover types, land cover diversity, field size, crop diversity, and EVI as a measure of land use intensity. We add these controls successively to determine their individual contribution to the biodiversity response to farm size.

Instead of using EVI as proxy for land use intensity we would like to measure fertilizer and pesticide inputs directly, but to our knowledge, these data do not exist. The role of agrochemicals in the relationship between farm size and biodiversity therefore largely remains part of the unexplained variation.

To select our optimal bandwidth we use mean squared error bandwidth selection procedure following the suggestion by Imbens and Kalyanaraman (2012) with robust bias corrected confidence intervals as suggested by Calonico et al. (2014, 2020) clustering our standard errors on district level to account for serial correlation.

4.2 Results

In the following we present our results based on the eBird data and the CBBS data. To address species selection, we then present results based on the same set of cropland birds in both data sets.

eBird: Using data from eBird, we find a large and negative impact of farm size on bird species richness (Table 1). We use the optimal bandwidth from the baseline specification for all specifications of Table 1 to make the estimates directly comparable. We show the impact of bandwidth choice on the results in Appendix D. Our baseline specification indicates that bird richness is reduced by 8.5 species or 20 % relative to the predicted bird diversity at the Western side of the former border. Including land cover, field size, the EVI and crop diversity within a 1×1 km buffer around the centroid of the observation has little impact on this estimate. We chose the 1×1 km buffer based on the 1×1 km sampling polygon of the CBBS, which we discuss below. However, including land-cover diversity reduces the estimate to 1.5 species. The results using the raw non-matched data reported in Appendix E are qualitatively similar.

However, land cover characteristics only imprecisely relate to bird richness observations because the location accuracy of each observation in the eBird data varies from several meters to kilometers. Using the land cover characteristics within a 6×6 km buffer around the

Table 1: Farm size and bird diversity (eBird)

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-8.5	1.7	0	7	41	77
Land cover	-8.7	2.3	0	7	41	77
Field size	-8.2	2.4	0	7	41	77
Crop diversity	-7.6	2.0	0	7	41	77
EVI	-8.1	2.5	0.001	7	41	77
Land cover diversity	-1.5	1.9	0.4	7	41	77

Notes: Regression discontinuity results based on eBird data. The columns report the coefficient estimates, the standard errors (SE), the P-value (P), the bandwidth in km (BW) as well as the sample size in West Germany (NW) and in East Germany (NE). The running variable (distance from the border) is negative for West Germany and positive for East Germany. The baseline specification includes a border dummy, log(experience), log(duration), year fixed effects and quarter fixed effects as controls. We add additional controls in the subsequent specifications. ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within a 1x1 km area around the sample centroid as control, ‘Field size’ adds additionally the mean field size within the sample area as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘EVI’ adds the EVI index as control while ‘Land cover diversity’ adds land cover diversity as control. Standard errors are clustered at the district level. The optimal bandwidth is based on the baseline specification.

observation centroid does not change our findings qualitatively, however (Appendix F).

Beyond location uncertainty, a major concern with the citizen science data is that the selection of study sites may be biased and affected by the landscape composition. In contrast,

the CBBS is based on a stratified random sample and includes the exact outline of the sampling area. Although the number of samples in proximity to the former border is lower, CBBS allows us to exactly match the bird observation to land cover characteristics. Consequently, CBBS provides a means to evaluate the robustness and validity of the results based on the eBird data.

CBBS: Similar to the results based on the eBird data, we find a negative and significant impact of farm size on species richness using data from the CBBS. We follow the same estimation strategy as with the eBird data but drop the observer effort and experience as well as the quarter since effort and timing of the CBBS is the same across all observations.

Table 2 reports the results. Our baseline result suggests that bird species richness declines by 6 species at the former inner German border although the estimate is not precise. Including land cover, field size, crop diversity and the EVI changes the precision of the estimates but has no significant impact on the estimated magnitude of the impact. In contrast, including land cover diversity in the regression as control reduces the estimates to zero. We interpret these results as evidence that changes in the overall land cover complexity explains the reduction in bird species richness in response to increased farm size.

In a robustness test, we show that the bandwidth choice has little impact on the qualitative results (Appendix G). The magnitude of estimates from eBird and CBBS results are not directly comparable because of the different sample means. Expressing the estimates relative to the expected diversity level at the Western side of the former border allows us to compare the estimates. The estimated bird diversity reduction of 8.5 species in the baseline specification using the eBird data suggests that bird diversity declines by 20 % at the former border while

Table 2: Farm size and bird diversity (CBBS)

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-5.8	3.2	0.1	21	86	161
Land cover	-4.4	2.8	0.1	21	86	161
Field size	-5.3	2.6	0.04	21	86	161
Crop diversity	-5.3	2.6	0.04	21	86	161
EVI	-4.9	2.7	0.1	21	86	161
Land cover diversity	-0.4	2.1	0.9	21	86	161

Notes: The impact of farm size on species richness using CBBS data for the years from 2015 to 2017. The columns report the point estimate for the differences in bird diversity between East and West Germany, the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE). The specification ‘Baseline’ includes a border dummy as control, ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within the 1x1km sample polygon as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘Land cover diversity’ adds additionally land cover diversity. Standard errors are clustered at the district level.

the baseline specification using the CBBS data suggests a decline of species richness by 10 %. This difference may be explained by selection bias in the eBird data either with respect to sites or species. We explore these potential biases in the next sub-section.

Cropland birds: To limit the influence of selection bias stemming from the recording (or not recording) of certain species in the eBird data, we estimate the impact of increased farm size at the former border on species richness using the same set of cropland species in both data sets (see Section 2). We repeat the same approach of the two previous sub-sections but using the same set of cropland species in both data sets. Overall, we find a negative and significant decline in the number of cropland species in response to increased farm size at the former inner German border based both data sets.

Table 3 summarizes the results based on the eBird data. The results suggests a decline of cropland bird species by 1.6 to 1.9 species at the former border. Although the estimate is reduced in absolute terms compared to the outcomes using all species, it increased in relative terms. The decline of 1.85 cropland species suggested by the land cover specification implies a decline of 34 % relative to the predicted farmland diversity at the western side of the former border.

Table 4 reports the results for cropland birds based on the CBBS data. The estimates are very similar in absolute terms to the results based on the eBird data but the precision of the estimates is low in the baseline specification. Adding land cover as control largely increases the precision of the estimate. The reduction of cropland birds by 1.74 at the former inner German border in the land cover specification implies a reduction of cropland bird species by 17 % compared to the western side of the former border.

Table 3: Farm size and farmland birds (eBird)

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-1.57	0.28	0	8	43	78
Land cover	-1.85	0.27	0	8	43	78
Field size	-1.93	0.27	0	8	43	78
Crop diversity	-1.90	0.25	0	8	43	78
EVI	-1.83	0.26	0	8	43	78
Land cover diversity	-1.59	0.26	0	8	43	78

Notes: The impact of farm size on farmland bird species richness using eBird data. The columns report the point estimate for the differences in bird diversity between East and West Germany (Est) at the border, the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE). The running variable is negative for West Germany and positive for East Germany. The baseline specification includes a 5 km border dummy as well as log(experience) and log(duration) of the observation as controls. The subsequent specification add additional controls. ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within a 1x1 km square around the sample centroid as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘EVI’ adds the EVIindex as control while ‘Land cover diversity’ includes additionally general land cover patch size and land cover diversity as controls. Standard errors are clustered at the district level.

These results suggest that farm size affects cropland birds substantially more than birds in general. However, they also suggest that species selection does not drive the difference between the results based on CBBS and eBird data. Similar to the results of the previous sub-section,

Table 4: Farm size and farmland birds (CBBS)

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-1.07	0.99	0.28	39	188	234
Land cover	-1.74	0.54	0.001	39	188	234
Field size	-1.95	0.52	0.0002	39	188	234
Crop diversity	-1.80	0.51	0.0005	39	188	234
EVI	-1.71	0.48	0.0004	39	188	234
Land cover diversity	-1.28	0.48	0.01	39	188	234

Notes: The impact of farm size on farmland birds using CBBS data for the years from 2015 to 2017. The columns report the estimated differences in bird diversity between East and West Germany, the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE). The running variable is negative for West Germany and positive for East Germany. The specification ‘Baseline’ includes a 5 km border dummy as control, ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within the 1 km² sample polygon as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘Land cover diversity’ adds additionally land cover diversity. Standard errors are clustered at the district level.

land cover and land cover diversity are the control variables with the largest impact on the results. We provide more evidence for the importance of land cover and land cover diversity for biodiversity in the next section.

5 Land use and bird diversity

To explore the relationship between bird diversity and land cover simplification further, we use a cross-sectional regression with the complete geographic range of the CBBS survey. To match these data to the land cover data from 2016, we restrict the sample to the period between 2015 and 2017.

5.1 Estimation

Our estimation is based on spatial differences of land cover controlling for a range of geographic variables. The baseline regression equation is

$$Y_{ijt} = \alpha_1 LC_{ij} + \alpha_2 FS_{ij} + \alpha_3 CD_{ij} + \alpha_4 EVI_{ij} + \alpha_5 LD_{ij} + X_{ij} + \theta_t + \varepsilon_{it} \quad (2)$$

where Y is our outcome (bird diversity) in sample area i in district j and year t , LC is a vector of land cover shares within the sample areas (cropland, grassland, buildings, water, forest, other) with “forest” being the baseline category, FS measures field size, CD is crop diversity, EVI is the EVI index within the sample area, LD is land cover diversity, X is a vector of controls which includes mean precipitation, mean temperature and elevation, θ_t are year fixed effects and ε_{it} is the error term. The errors are potentially correlated within sample sites over time. We therefore cluster our standard errors at the district (Kreis) level using the method for cluster robust standard errors suggested by (Cameron et al. 2011) and implemented in the `lfe` package Gaure (2013). The independent variables may be correlated with other landscape characteristics, which could also affect bird diversity directly and may therefore omit variable bias. We therefore include district level fixed effects in the second specification and thus use

only differences of land cover characteristics and bird diversity across sample areas within the same districts to estimate our coefficients.

5.2 Results

The results show that general bird diversity declines with increasing cropland extent and it increases with land cover diversity (Figure 9). All other land cover types do not change bird diversity relative to the native vegetation (forests). Field size and crop diversity have no statistically significant impact on bird diversity. We standardize all variables such that the magnitude becomes directly comparable. The results of the baseline specification show that increasing cropland extent by one standard deviation (29%) reduces bird species richness by 0.5 standard deviation (5.4 species). Including district dummies as a fixed effect does not change these results while measuring bird diversity with the Simpson index reduces the estimate to 0.36 standard deviations. In contrast, crop cover increases bird species richness of cropland species as expected. However, the effect of land cover diversity on species richness is larger and more consistent than the impact of crop cover. A one standard deviation increase of land cover diversity increases species richness by 0.91 standard deviations (9.9 species). This estimate reduces to 0.75 and 0.41 respectively, when bird diversity is measured with the Simpson index or by species richness of cropland species. All other variables have no consistent and statistically significant impact on bird diversity.

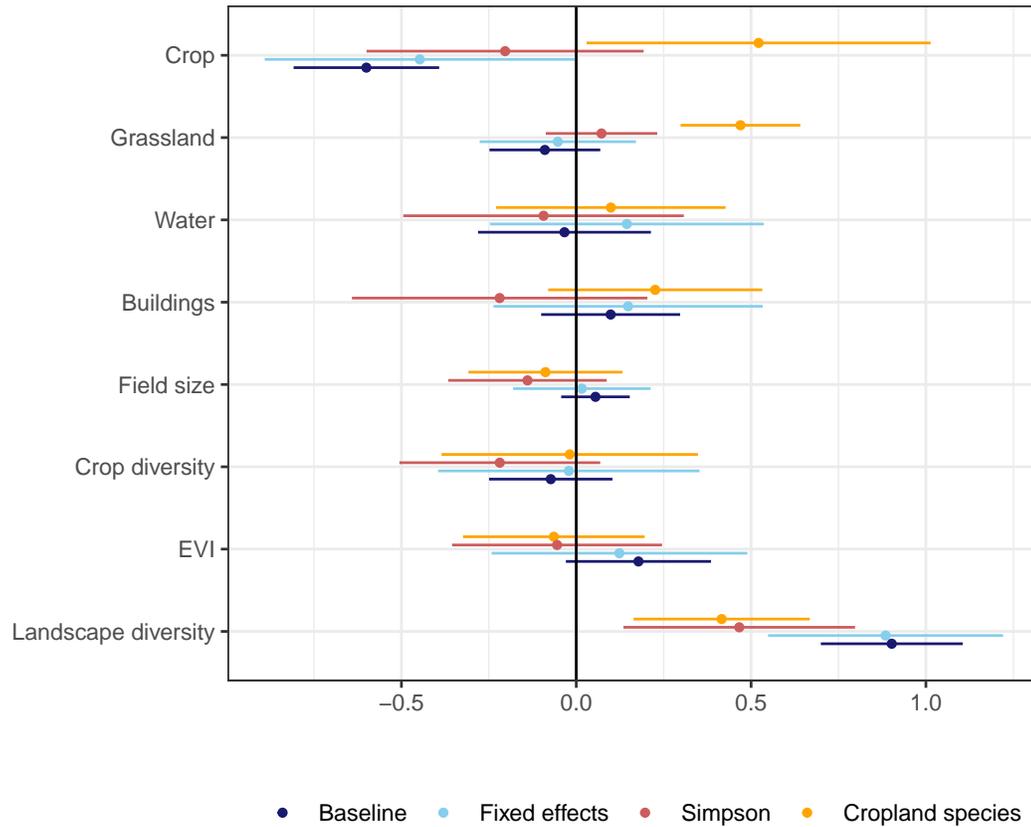


Figure 9: Bird diversity and land cover: The figure shows the point estimates and the 95 % confidence intervals for our cross-sectional regression on bird diversity and land cover characteristics. The ‘Baseline’ specification includes the illustrated variables plus elevation, mean temperatures, mean precipitation levels and year fixed effects. The ‘Fixed effects’ specification includes additionally district level fixed effects. The ‘Simpson’ specification is as the fixed effects specification but measures bird diversity with the Simpson diversity index. The ‘Agriculture’ specification is as the ‘Fixed effects’ specification but measures bird diversity as the number of cropland species. The standard errors of all specifications are clustered at the district level.

6 Discussion

Agriculture is the main driver of global biodiversity loss (Tilman et al. 2017). Underlying the environmental impact of agriculture are both agricultural expansion and changes within the agricultural landscape. Yet, disentangling the contributions of agricultural expansion from changes in management practices has been stymied by a lack of disaggregated production and biodiversity data collected across the same area and at the same scale. The impact of changes within the agricultural landscape are particularly difficult to study because they are complex, data are often private, and causality between these changes and biodiversity loss is difficult to establish. Here we focus on the impact of farm size on bird diversity using a regression discontinuity design that leverages the former inner German border to overcome data limitations and tease apart how on-field and landscape mechanisms associated with farm size affect biodiversity in this agriculturally dominated region.

In this paper we create a new data set combining bird observation from opportunistic citizen science and systematic bird surveys with land cover characteristics from (Preidl et al. 2020) to study the impact of farm size on bird diversity. We use these data in a regression discontinuity approach that exploits the discontinuous change of farm size at the former inner German border to identify the causal impact of farm size on bird diversity. Although Germany has been unified for more than 30 years, the legacy of former farm collectivization in East Germany is still largely visible. After the reunification, farms in East Germany have been privatized leaving a legacy of large private farm operations in East Germany and relatively small family owned farm operations in West Germany. Although this process of agricultural industrialization leading

to larger more mechanized farms is visible in many parts of the world, Germany allows us to compare the environmental outcomes from both regimes at the same time and within the same economic and political environment. Further, Germany's land cover is dominated by agriculture (50.8% of the total surface area) and any changes in management practices have therefore important implications for biodiversity.

Our results show that there is a large and discontinuous decline of local bird diversity at the former inner German border. Matching the bird diversity observations with land cover characteristics allows us to study the pathways through which farm size affects bird diversity. However, adding field size and crop diversity does not explain the decline in bird diversity at the former inner German border. Using the EVI as proxy for land use intensity leads to a small reduction of the estimate, suggesting that differences in land-use intensity can partly explain the impact of farm size on bird diversity. Adding land-cover diversity as control renders the estimated impact of farm size on bird diversity statistically indistinguishable from zero. We interpret this finding as evidence for the importance of the indirect land cover changes associated with increased farm size. Our results suggest that these changes in land cover complexity are more important for explaining changes in bird diversity than other changes associated with farm size including land use intensity and agricultural mechanization. Using the CBBS data in a cross-sectional analysis for Germany helps to interpret these results further. The results based on this cross-sectional analysis suggests that bird diversity declines with cropland extent and it increases with land cover diversity. Even cropland species depend on land cover diversity including non-agricultural habitat. These results therefore suggest that non-crop habitat plays a crucial role for bird diversity. Our findings therefore highlight the importance of analyzing

the agricultural changes in a landscape context. Focusing on biodiversity on agricultural land itself may miss the indirect changes of larger farms and fields on landscape complexity.

These findings are in line with earlier studies that find no effect of crop diversity on bird diversity but instead a large and positive impact of landscape heterogeneity or vegetation structure on bird diversity (Redlich et al. 2018; Josefsson et al. 2017). In addition to being more broad our analysis also establishes causality between land use and bird diversity. Similar to our study, Batáry et al. (2017) and Wuepper et al. (2020) use the discontinuity at the former inner German border to study the impact of land use on environmental outcomes. Batáry et al. (2017) show that the increase in farm size at the former inner German border has a negative effect on invertebrates and plants. While their study is an important contribution it focuses exclusively on field size and management of the respective field. In our study we show that the impact of changes within cropland such as field size on bird diversity are small compared to the indirect impact of changes in the landscape configuration. Using a regression discontinuity design allows us to parse apart the causal impact of the landscape level changes associated with former farm collectivization from underlying continuous changes of geography and climate. Wuepper et al. (2020) also uses a regression discontinuity design, but they lack data on relevant environmental outcomes. The main contribution of the current paper is to assemble a data set of citizen science bird observations, formal bird surveys and high resolution land cover data that allows us to estimate the causal impact of farm size on bird diversity in a regression discontinuity design. We use this approach further to quantify the individual contributions of the associated land cover changes on bird diversity.

In our analysis we focus on common bird species. Rare species such as the great bustard

or agricultural specialists such as skylarks have a minor influence on our results. These species may be sensitive to changes of the agricultural management (Gayer et al. 2019) but since they are either rare or constitute only a small fraction of local bird diversity they have little influence on our results. They are however, important for bird diversity at a larger scale and may require special protection.

Our results mainly concern those species in the agricultural landscape that are common but crucial for the provision of ecosystem services (Kleijn et al. 2015). Increasing the abundance of those species in the agricultural landscape will be important for the sustainable increase of agricultural production. Our results show that providing a mix of non-crop habitat within the agricultural landscape is crucial for biodiversity conservation and can mitigate the negative impact of agricultural industrialization.

References

Adamopoulos, Tasso and Diego Restuccia, “The size distribution of farms and international productivity differences,” *American Economic Review*, 2014, 104 (6), 1667–97.

— **and** — , “The size distribution of farms and international productivity differences,” *The American economic review*, 2014, 104 (6), 1667–1697.

Almond, Douglas, Yuyu Chen, Michael Greenstone, and Hongbin Li, “Winter heating or clean air? Unintended impacts of China’s Huai river policy,” *American Economic Review*, 2009, 99 (2), 184–90.

Ando, Amy W and Christian Langpap, “The economics of species conservation,” *Annual Review of Resource Economics*, 2018, 10, 445–467.

Arata, Linda and Paolo Sckokai, “The impact of agri-environmental schemes on farm performance in five EU member states: a DID-matching approach,” *Land Economics*, 2016, 92 (1), 167–186.

Assunção, Juliano J and Luis HB Braido, “Testing household-specific explanations for the inverse productivity relationship,” *American journal of agricultural economics*, 2007, 89 (4), 980–990.

Barrett, Christopher B, Marc F Bellemare, and Janet Y Hou, “Reconsidering conventional explanations of the inverse productivity–size relationship,” *World Development*, 2010, 38 (1), 88–97.

Batáry, Péter, Róbert Gallé, Friederike Riesch, Christina Fischer, Carsten F Dormann, Oliver Mußhoff, Péter Császár, Silvia Fusaro, Christoph Gayer, Anne-Kathrin Happe, Kornélia Kurucz, Dorottya Molnár, Verena Rösch, Alexander Wietzke, and Teja Tschardt, “The former Iron Curtain still drives biodiversity–profit trade-offs in German agriculture,” *Nature Ecology & Evolution*, 2017, 1 (9), 1279–1284.

Becker, Sascha O, Lukas Mergele, and Ludger Woessmann, “The separation and reunification of Germany: Rethinking a natural experiment interpretation of the enduring effects of communism,” *Journal of Economic Perspectives*, 2020, 34 (2), 143–171.

- Binder, Seth, Forest Isbell, Stephen Polasky, Jane A Catford, and David Tilman**, “Grassland biodiversity can pay,” *Proceedings of the National Academy of Sciences*, 2018, 115 (15), 3876–3881.
- Bolton, Douglas K and Mark A Friedl**, “Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics,” *Agricultural and Forest Meteorology*, 2013, 173, 74–84.
- Buchholz, H**, “The inner-German border: Consequences of its establishment and abolition,” *World boundaries, Eurasia*, 1994, 3, 55–62.
- Burgess, Robin, Francisco J M Costa, and Benjamin Olken**, “Wilderness Conservation and the Reach of the State: Evidence from National Borders in the Amazon,” *NBER Working Paper*, 2018, 24861.
- Burke, Marshall and David B Lobell**, “Satellite-based assessment of yield variation and its determinants in smallholder African systems,” *Proceedings of the National Academy of Sciences of the United States of America*, February 2017, 114 (9), 2189–2194.
- Busch, Malte, Jakob Katzenberger, Sven Trautmann, Bettina Gerlach, Rainer Droeschmeister, and Christoph Sudfeldt**, “Drivers of population change in common farmland birds in Germany,” *Bird Conservation International*, 2020, 30 (3), 335–354.
- Calonico, Sebastian, Matias D Cattaneo, and Max H Farrell**, “Optimal bandwidth choice for robust bias-corrected inference in regression discontinuity designs,” *The Econometrics Journal*, 2020, 23 (2), 192–210.

- , —, and **Rocio Titiunik**, “Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs,” *Econometrica*, 2014, 82 (6), 2295–2326.
- Cameron, A Colin, A Colin Cameron, Jonah B Gelbach, and Douglas L Miller**, “Robust Inference With Multiway Clustering,” *Journal of Business & Economic Statistics*, 2011, 29 (2), 238–249.
- Chabé-Ferret, Sylvain and Julie Subervie**, “How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching,” *Journal of Environmental Economics and Management*, 2013, 65 (1), 12–27.
- Clough, Yann, Stefan Kirchweger, and Jochen Kantelhardt**, “Field sizes and the future of farmland biodiversity in European landscapes,” *Conservation Letters*, 2020, 13 (6), e12752.
- Costello, Christopher, Nicolas Quérou, and Agnes Tomini**, “Private eradication of mobile public bads,” *European Economic Review*, 2017, 94, 23–44.
- Dainese, Matteo, Emily A Martin, Marcelo A Aizen, Matthias Albrecht, Ignasi Bartomeus, Riccardo Bommarco, Luisa G Carvalheiro, Rebecca Chaplin-Kramer, Vesna Gagic, Lucas A Garibaldi et al.**, “A global synthesis reveals biodiversity-mediated benefits for crop production,” *Science advances*, 2019, 5 (10), eaax0121.
- Desiere, Sam and Dean Jolliffe**, “Land productivity and plot size: Is measurement error driving the inverse relationship?,” *Journal of Development Economics*, 2018, 130, 84–98.
- Elsen, Paul R, Laura S Farwell, Anna M Pidgeon, and Volker C Radeloff**, “Landsat 8 TIRS-derived relative temperature and thermal heterogeneity predict winter bird species

richness patterns across the conterminous United States,” *Remote sensing of environment*, January 2020, 236, 111514.

Englander, Gabriel, “Property rights and the protection of global marine resources,” *Nature Sustainability*, 2019, 2 (10), 981–987.

Fahrig, Lenore, Judith Girard, Dennis Duro, Jon Pasher, Adam Smith, Steve Javorek, Douglas King, Kathryn Freemark Lindsay, Scott Mitchell, and Lutz Tischendorf, “Farmlands with smaller crop fields have higher within-field biodiversity,” *Agriculture, Ecosystems & Environment*, 2015, 200, 219–234.

Feder, Gershon, “The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints,” *Journal of development economics*, 1985, 18 (2-3), 297–313.

Foster, Andrew D and Mark Rosenzweig, “Are There Too Many Farms in the World? Labor-Market Transaction Costs, Machine Capacities and Optimal Farm Size,” *NBER Working Paper*, 2017, 23909.

Gaure, Simen, “lfe: Linear Group Fixed Effects,” *The R Journal*, 2013, 5 (2), 104.

Gayer, Christoph, Kornélia Kurucz, Christina Fischer, Teja Tschardt, and Péter Batáry, “Agricultural intensification at local and landscape scales impairs farmland birds, but not skylarks (*Alauda arvensis*),” *Agriculture, Ecosystems & Environment*, 2019, 277, 21–24.

Geiger, Flavia, Jan Bengtsson, Frank Berendse, Wolfgang W Weisser, Mark Emmerson, Manuel B Morales, Piotr Ceryngier, Jaan Liira, Teja Tschardtke, Camilla Winqvist, Sönke Eggers, Riccardo Bommarco, Tomas Pärt, Vincent Bretagnolle, Manuel Plante-genest, Lars W Clement, Christopher Dennis, Catherine Palmer, Juan J Oñate, Irene Guerrero, Violetta Hawro, Tsipe Aavik, Carsten Thies, Andreas Flohre, Sebastian Hänke, Christina Fischer, Paul W Goedhart, and Pablo Inchausti, “Persistent negative effects of pesticides on biodiversity and biological control potential on European farmland,” *Basic and Applied Ecology*, 2010, 11 (2), 97–105.

Gelman, Andrew and Guido Imbens, “Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs,” *Journal of Business & Economic Statistics*, 2019, 37 (3), 447–456.

Hautier, Yann, Eric W Seabloom, Elizabeth T Borer, Peter B Adler, W Stanley Harpole, Helmut Hillebrand, Eric M Lind, Andrew S MacDougall, Carly J Stevens, Jonathan D Bakker, Yvonne M Buckley, Chengjin Chu, Scott L Collins, Pedro Daleo, Ellen I Damschen, Kendi F Davies, Philip A Fay, Jennifer Firn, Daniel S Gruner, Virginia L Jin, Julia A Klein, Johannes M H Knops, Kimberly J La Pierre, Wei Li, Rebecca L McCulley, Brett A Melbourne, Joslin L Moore, Lydia R O’Halloran, Suzanne M Prober, Anita C Risch, Mahesh Sankaran, Martin Schuetz, and Andy Hector, “Eutrophication weakens stabilizing effects of diversity in natural grasslands,” *Nature*, April 2014, 508 (7497), 521–525.

—, **Pascal A Niklaus, and Andy Hector,** “Competition for light causes plant biodiversity loss

after eutrophication,” *Science*, May 2009, 324 (5927), 636–638.

Hesselbarth, Maximilian HK, Marco Sciaini, Kimberly A With, Kerstin Wiegand, and Jakub Nowosad, “landscapemetrics: an open-source R tool to calculate landscape metrics,” *Ecography*, 2019, 42 (10), 1648–1657.

Ho, Daniel E, Kosuke Imai, Gary King, and Elizabeth A Stuart, “Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference,” *Political Analysis*, 2007, 15 (3), 199–236.

—, —, —, —, **and** —, “MatchIt: Nonparametric Preprocessing for Parametric Causal Inference,” *Journal of Statistical Software*, 2011, 42 (8).

Imbens, Guido and Karthik Kalyanaraman, “Optimal Bandwidth Choice for the Regression Discontinuity Estimator,” *The Review of economic studies*, July 2012, 79 (3), 933–959.

Johnston, A, W M Hochachka, M E Strimas-Mackey, V Ruiz Gutierrez, O J Robinson, E T Miller, T Auer, S T Kelling, and D Fink, “Best practices for making reliable inferences from citizen science data: case study using eBird to estimate species distributions,” *bioRxiv*, 2020.

Josefsson, Jonas, Åke Berg, Matthew Hiron, Tomas Pärt, and Sönke Eggers, “Sensitivity of the farmland bird community to crop diversification in Sweden: does the CAP fit?,” *Journal of Applied Ecology*, 2017, 54 (2), 518–526.

Karger, Dirk Nikolaus, Olaf Conrad, Jürgen Böhner, Tobias Kawohl, Holger Kreft, Rodrigo Wilber Soria-Auza, Niklaus E Zimmermann, H Peter Linder, and Michael

Kessler, “Climatologies at high resolution for the earth’s land surface areas,” *Scientific data*, September 2017, 4, 170122.

Kehoe, Laura, Alfredo Romero-Muñoz, Ester Polaina, Lyndon Estes, Holger Kreft, and Tobias Kuemmerle, “Biodiversity at risk under future cropland expansion and intensification,” *Nature Ecology & Evolution*, 2017, 1 (8), 1129–1135.

Kleijn, David, Rachael Winfree, Ignasi Bartomeus, Luísa G Carvalheiro, Mickaël Henry, Rufus Isaacs, Alexandra-Maria Klein, Claire Kremen, Leithen K M’gonigle, Romina Rader et al., “Delivery of crop pollination services is an insufficient argument for wild pollinator conservation,” *Nature communications*, 2015, 6 (1), 1–9.

Koester, Ulrich E and Karen M Brooks, “Agriculture and German reunification,” Technical Report, The World Bank 1997.

Kremen, Claire and Adina M Merenlender, “Landscapes that work for biodiversity and people,” *Science*, 2018, 362 (6412).

Langpap, Christian and JunJie Wu, “Thresholds, perverse incentives, and preemptive conservation of endangered species,” *Journal of the Association of Environmental and Resource Economists*, 2017, 4 (S1), S227–S259.

Larsen, Ashley E and Frederik Noack, “Identifying the landscape drivers of agricultural insecticide use leveraging evidence from 100,000 fields,” *Proceedings of the National Academy of Sciences of the United States of America*, May 2017, 114 (21), 5473–5478.

Li, Yijia, Ruiqing Miao, and Madhu Khanna, “Neonicotinoids and decline in bird biodiversity in the United States,” *Nature Sustainability*, 2020, 3 (12), 1027–1035.

MacDonald, James M, Penni Korb, and Robert a Hoppe, “Farm Size and the Organization of U.S. Crop Farming,” *USDA Economic Research Report*, 2014, *ERR-152*.

Martin, Emily A, Matteo Dainese, Yann Clough, András Báldi, Riccardo Bommarco, Vesna Gagic, Michael P D Garratt, Andrea Holzschuh, David Kleijn, Anikó Kovács-Hostyánszki, Lorenzo Marini, Simon G Potts, Henrik G Smith, Diab Al Hassan, Matthias Albrecht, Georg K S Andersson, Josep D Asís, Stéphanie Aviron, Mario V Balzan, Laura Baños-Picón, Ignasi Bartomeus, Péter Batáry, Françoise Burel, Berta Caballero-López, Elena D Concepción, Valérie Coudrain, Juliana Dänhardt, Mario Diaz, Tim Diekötter, Carsten F Dormann, Rémi Dufrot, Martin H Entling, Nina Farwig, Christina Fischer, Thomas Frank, Lucas A Garibaldi, John Hermann, Felix Herzog, Diego Inclán, Katja Jacot, Frank Jauker, Philippe Jeanneret, Marina Kaiser, Jochen Krauss, Violette Le Féon, Jon Marshall, Anna-Camilla Moonen, Gerardo Moreno, Verena Riedinger, Maj Rundlöf, Adrien Rusch, Jeroen Scheper, Gudrun Schneider, Christof Schüepp, Sonja Stutz, Louis Sutter, Giovanni Tamburini, Carsten Thies, José Tormos, Teja Tschardt, Matthias Tschumi, Deniz Uzman, Christian Wagner, Muhammad Zubair-Anjum, and Ingolf Steffan-Dewenter, “The interplay of landscape composition and configuration: new pathways to manage functional biodiversity and agroecosystem services across Europe,” *Ecology letters*, July 2019, 22 (7), 1083–1094.

—, —, —, —, —, —, —, —, **Michael PD Garratt, Andrea Holzschuh, David Kleijn, Anikó**

Kovács-Hostyánszki et al., “The interplay of landscape composition and configuration: new pathways to manage functional biodiversity and agroecosystem services across Europe,” *Ecology letters*, 2019, 22 (7), 1083–1094.

McGarigal, K, S A Cushman, and Ene E., “FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps,” 2012.

Meehan, Timothy D, Ben P Werling, Douglas A Landis, and Claudio Gratton, “Agricultural landscape simplification and insecticide use in the Midwestern United States,” *Proceedings of the National Academy of Sciences of the United States of America*, July 2011, 108 (28), 11500–11505.

Melstrom, Richard T, “The Effect of Land Use Restrictions Protecting Endangered Species on Agricultural Land Values,” *American Journal of Agricultural Economics*, 2019.

Mitchell, Michael S, Richard A Lancia, and John A Gerwin, “Using landscape-level data to predict the distribution of birds on a managed forest: effects of scale,” *Ecological Applications*, 2001, 11 (6), 1692–1708.

Mitschke, Alexander, Christoph Sudfeldt, Holger Heidrich-Riske, and Rainer Dröschmeister, “Das neue Brutvogelmonitoring in der Normallandschaft Deutschlands—Untersuchungsgebiete, Erfassungsmethode und erste Ergebnisse,” *Vogelwelt, Die*, 2005, 126, 127–140.

Muyanga, Milu and Thomas S Jayne, “Revisiting the farm size-productivity relationship based on a relatively wide range of farm sizes: Evidence from Kenya,” *American Journal of*

Agricultural Economics, 2019, 101 (4), 1140–1163.

Noack, Frederik and Ashley Larsen, “The contrasting effects of farm size on farm incomes and food production,” *Environmental Research Letters*, 2019, 14 (8), 084024.

— **and Martin Quaas**, “Ecology of scope and the productivity of small-scale farming,” *working paper*, 2021.

— , **Marie-Catherine Riekhof, and Salvatore Di Falco**, “Droughts, biodiversity, and rural incomes in the tropics,” *Journal of the Association of Environmental and Resource Economists*, 2019, 6 (4), 823–852.

Preidl, Sebastian, Maximilian Lange, and Daniel Doktor, “Introducing APiC for regionalised land cover mapping on the national scale using Sentinel-2A imagery,” *Remote Sensing of Environment*, 2020, 240, 111673.

Radeloff, V C, M Dubinin, N C Coops, A M Allen, T M Brooks, M K Clayton, G C Costa, C H Graham, D P Helmers, A R Ives, D Kolesov, A M Pidgeon, G Rapacciuolo, E Razenkova, N Suttidate, B E Young, L Zhu, and M L Hobi, “The Dynamic Habitat Indices (DHIs) from MODIS and global biodiversity,” *Remote sensing of environment*, March 2019, 222, 204–214.

Redlich, Sarah, Emily A Martin, Beate Wende, and Ingolf Steffan-Dewenter, “Landscape heterogeneity rather than crop diversity mediates bird diversity in agricultural landscapes,” *PloS one*, August 2018, 13 (8), e0200438.

Semper-Pascual, Asunción, Leandro Macchi, Francesco Maria Sabatini, Julieta Decarre, Matthias Baumann, Pedro G Blendinger, Bibiana Gómez-Valencia, Matías E Mastangelo, and Tobias Kuemmerle, “Mapping extinction debt highlights conservation opportunities for birds and mammals in the South American Chaco,” *Journal of Applied Ecology*, 2018, 55 (3), 1218–1229.

Sirami, Clélia, Nicolas Gross, Alette Boses Baillod, Colette Bertrand, Romain Carrié, Annika Hass, Laura Henckel, Paul Miguet, Carole Vuillot, Audrey Alignier, Jude Girard, Péter Batáry, Yann Clough, Cyrille Violle, David Giralt, Gerard Bota, Isabelle Badenhauer, Gaëtan Lefebvre, Bertrand Gauffre, Aude Vialatte, François Calatayud, Assu Gil-Tena, Lutz Tischendorf, Scott Mitchell, Kathryn Lindsay, Romain Georges, Samuel Hilaire, Jordi Recasens, Xavier Oriol Solé-Senan, Irene Robleño, Jordi Bosch, Jose Antonio Barrientos, Antonio Ricarte, Maria Ángeles Marcos-Garcia, Jesús Miñano, Raphaël Mathevet, Annick Gibon, Jacques Baudry, Gérard Balent, Brigitte Poulin, Françoise Burel, Teja Tschardt, Vincent Bretagnolle, Gavin Siriwardena, Annie Ouin, Lluís Brotons, Jean-Louis Martin, and Lenore Fahrig, “Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions,” *Proceedings of the National Academy of Sciences of the United States of America*, August 2019, 116 (33), 16442–16447.

Strimas-Mackey, M, E Miller, and W Hochachka, *awk: eBird Data Extraction and Processing with AWK* 2018.

Sullivan, Brian L, Christopher L Wood, Marshall J Iliff, Rick E Bonney, Daniel Fink, and

Steve Kelling, “eBird: A citizen-based bird observation network in the biological sciences,”

Biological Conservation, 2009, *142* (10), 2282–2292.

Tilman, David, Michael Clark, David R Williams, Kaitlin Kimmel, Stephen Polasky, and

Craig Packer, “Future threats to biodiversity and pathways to their prevention,” *Nature*,

2017, *546* (7656), 73–81.

Tscharntke, Teja, Yann Clough, Thomas C Wanger, Louise Jackson, Iris Motzke, Ivette

Perfecto, John Vandermeer, and Anthony Whitbread, “Global food security, biodiversity

conservation and the future of agricultural intensification,” *Biological Conservation*, 2012,

151 (1), 53–59.

USGS, “Global 30 Arc-Second Elevation (GTOPO30),” 2004. Accessed: NA-NA-NA.

Wätzold, Frank, Martin Drechsler, Karin Johst, Melanie Mewes, and Astrid Sturm, “A

novel, spatiotemporally explicit ecological-economic modeling procedure for the design

of cost-effective agri-environment schemes to conserve biodiversity,” *American Journal of*

Agricultural Economics, 2016, *98* (2), 489–512.

Weissteiner, Christof J, Celia García-Feced, and Maria Luisa Paracchini, “A new view

on EU agricultural landscapes: Quantifying patchiness to assess farmland heterogeneity,”

Ecological indicators, February 2016, *61*, 317–327.

Wu, Yiyun, Xican Xi, Xin Tang, Deming Luo, Baojing Gu, Shu Kee Lam, Peter M Vi-

tousek, and Deli Chen, “Policy distortions, farm size, and the overuse of agricultural chem-

icals in China,” *Proceedings of the National Academy of Sciences*, 2018, *115* (27), 7010–7015.

Wuepper, David, Stefan Wimmer, and Johannes Sauer, “Is small family farming more environmentally sustainable? Evidence from a spatial regression discontinuity design in Germany,” *Land Use Policy*, 2020, *90*, 104360.

Zabel, Florian, Ruth Delzeit, Julia M Schneider, Ralf Seppelt, Wolfram Mauser, and Tomáš Václavík, “Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity,” *Nature communications*, 2019, *10* (1), 1–10.

A Land cover

This section visualizes the changes in land cover across the former inner German border. Although there is no discontinuous change in crop cover (Figure 10) and forest cover (Figure 11) across the former inner German border, there is a general increase in crop cover from West to East Germany. Crop cover also drops directly at the former border. This change in land cover at the former border motivates our border dummy in our regression specifications. In contrast to crop and forest, the percentage cover of buildings (e.g. residential areas) and land cover diversity show a discrete change at the former inner German border (Figure 12 and 13). However, the change in land cover diversity at the former border is obscured by generally large fluctuations in land cover diversity. We control for land cover and land cover diversity in different specifications of our regression approach.

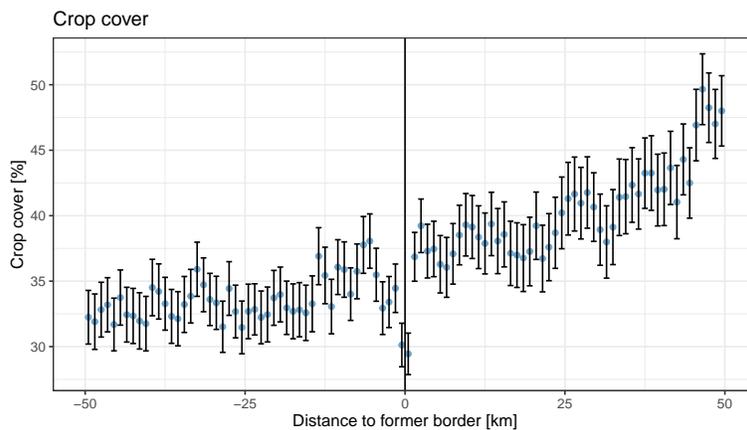


Figure 10: The dots are the mean crop cover of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

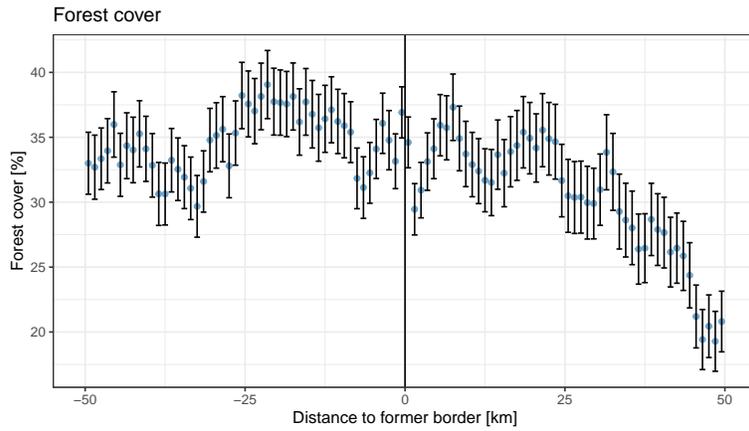


Figure 11: The dots are the mean forest cover of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

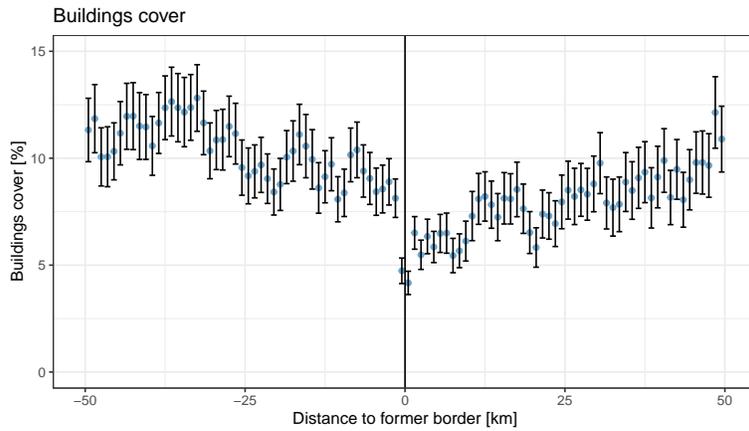


Figure 12: The dots are the mean buildings cover of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

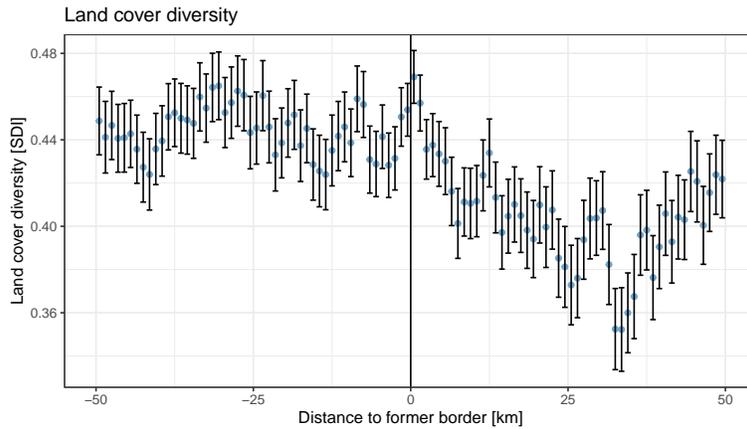


Figure 13: The dots are the mean land cover diversity values of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

B Climate and Elevation

In this section, we illustrate the change of climate and elevation across the former inner German border to explore alternative explanations for our main results. All figures show regression discontinuity plots using 1 km bins, fourth order polynomials and a bandwidth of 50 km. The figures suggest no discontinuous change of these geographic variables at the former border. Also, the change in elevation (Figure 14) and temperature (Figure 15) are modest in absolute terms. Although precipitation levels change contentiously at the former border (Figure 16), they decline rapidly to the East. We therefore include precipitation as control in our RDD estimation.

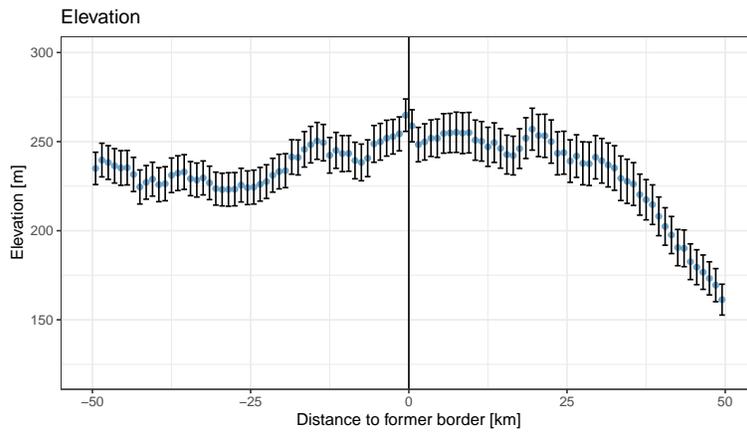


Figure 14: The dots are the mean elevation levels of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

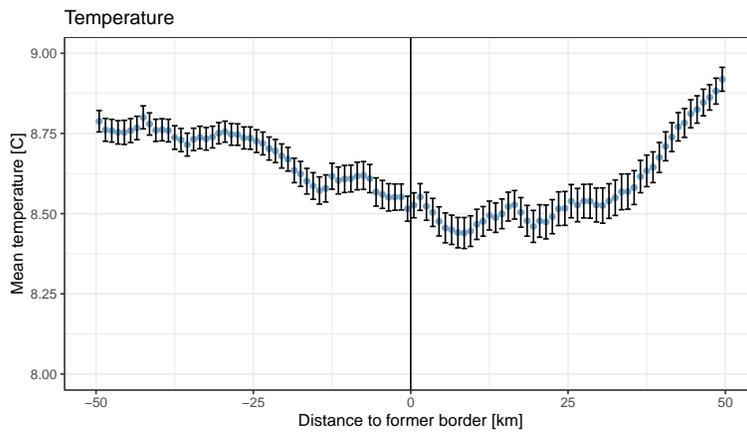


Figure 15: The dots are the mean annual temperature levels of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

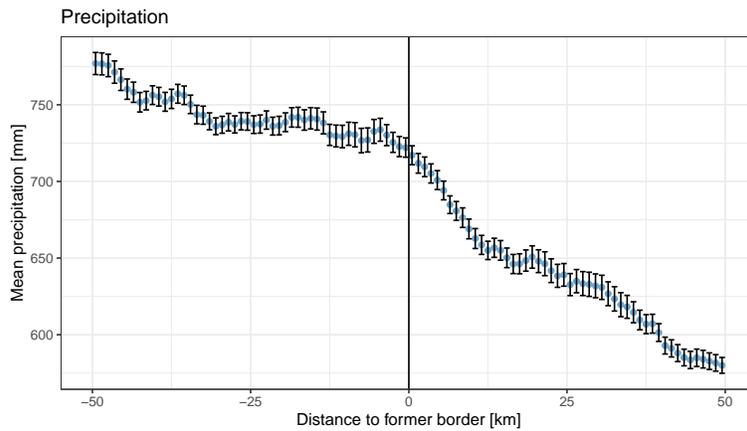


Figure 16: The dots are the mean annual precipitation levels of 1×1 km grid cells within a 50 km distance band on both sides of the former inner German border. West Germany is to the left of the former border, East Germany is to the right of the former border. The bars are 95% confidence intervals.

C Cropland birds

In this section, we report our set of cropland species and compare them to the list of farmland species suggested by Busch et al. (2020). We exclude the common pheasant from our list although it is highly associated with agricultural land because it is introduced and it is commonly released as game bird. Although there is an overlap of species in both list there are also differences. These differences may stem from our exclusive focus on cropland while Busch et al. (2020) focus more widely on farmland birds.

Table 5: Farmland birds

German name	English name	Scientific name	Busch	Own
Wiesenschafstelze	Blue-headed Yellow Wagtail	<i>Motacilla flava</i>	1	1
Dorngrasmücke	Common Whitethroat	<i>Sylvia communis</i>	1	1
Feldlerche	Eurasian Skylark	<i>Alauda arvensis</i>	1	1
Stieglitz	European Goldfinch	<i>Carduelis carduelis</i>	1	1
Sumpfrohrsänger	Marsh Warbler	<i>Acrocephalus palustris</i>	1	1
Kiebitz	Northern Lapwing	<i>Vanellus vanellus</i>	1	1
Neuntöter	Red-backed Shrike	<i>Lanius collurio</i>	1	1
Goldammer	Yellowhammer	<i>Emberiza citrinella</i>	1	1
Feldsperling	Eurasian Tree Sparrow	<i>Passer montanus</i>		1
Bluthänfling	Common Linnet	<i>Linaria cannabina</i>		1
Nachtigall	Common Nightingale	<i>Luscinia megarhynchos</i>		1
Bachstelze	White Wagtail	<i>Motacilla alba</i>		1
Gelbspötter	Icterine Warbler	<i>Hippolais icterina</i>		1
Grauammer	Corn Bunting	<i>Emberiza calandra</i>		1
Rauchschwalbe	Barn Swallow	<i>Hirundo rustica</i>		1
Klappergrasmücke	Lesser Whitethroat	<i>Sylvia curruca</i>		1
Gartengrasmücke	Garden Warbler	<i>Sylvia borin</i>		1
Turmfalke	Common Kestrel	<i>Falco tinnunculus</i>		1
Uferschnepfe	Black-tailed godwit	<i>Limosa limosa</i>	1	
Feldschwirl	Common Grasshopper Warbler	<i>Locustella naevia</i>	1	
Bluthänfling	Common linnet	<i>Carduelis cannabina</i>	1	
Star	Common Starling	<i>Sturnus vulgaris</i>	1	
Turteltaube	European Turtle Dove	<i>Streptopelia turtur</i>	1	
Wacholderdrossel	Fieldfare	<i>Turdus pilaris</i>	1	

D Bandwidth (eBird)

In Table 6 we repeat the regression discontinuity analysis with the eBird data from the main text but double the bandwidth from 7 km to 15 km. Overall, the magnitude of the estimates increases but the results are otherwise similar to those reported in Table 1.

E Results with raw data (eBird)

In this section, we repeat the regression discontinuity analysis with the eBird data of the main text but using the raw non-matched eBird data. For the main article we preprocess the data to ensure comparability between the West German and the East German sample. However, preprocessing depends on the variables and the specifications of the matching algorithm. Table 7 reports the results. The results are, however, very similar to the results reported in the main text of this article.

F Buffer (eBird)

In this section, we repeat the regression discontinuity analysis with the eBird data from the main text of the article but using a 6×6 km buffer to calculate the land cover variables. We can only link the bird diversity observations to land cover characteristics through the centroid of the bird observations but with little information about the size of the actual observation area. Here we show the impact of the buffer size on the regression results. The number of data and consequently the bandwidth differ slightly from the specification reported in the main article

Table 6: Farm size and bird diversity (eBird) with double bandwidth

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-12.1	1.8	0	15	154	93
Land cover	-9.2	2.5	0	15	154	93
Field size	-8.7	2.5	0	15	154	93
Crop diversity	-9.0	2.6	0	15	154	93
EVI	-9.0	2.6	0.001	15	154	93
Land cover diversity	-6.6	2.3	0.004	15	154	93

Notes: Regression discontinuity results using eBird data for all species. The columns report the point estimate for the differences in bird diversity between East and West Germany at the border, the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE).

The running variable is negative for West Germany and positive for East Germany. The baseline specification includes a border dummy, log(experience), log(duration) of the observation, year fixed effects and quarter fixed effects as controls. We add additional controls in the subsequent specifications. ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within a 1x1 km area around the sample centroid as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘EVI’ adds the EVI index as control while ‘Land cover diversity’ adds land cover diversity as control.

Standard errors are clustered at the district level. The optimal bandwidth is based on the baseline specification.

because average field size and the EVI are defined for more observations with the increased buffer around the observations. The results of the baseline specification with the 6×6 km buffer (Table 8) are similar to the results in the main text (Table 1). However, the impact of land cover

Table 7: Farm size and bird diversity (eBird) with raw data

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-7.0	1.3	0.000	10	600	82
Land cover	-4.1	1.6	0.01	10	600	82
Field size	-4.5	1.6	0.004	10	600	82
Crop diversity	-4.4	1.6	0.005	10	600	82
EVI	-4.5	1.5	0.004	10	600	82
Land cover diversity	-2.7	1.5	0.1	10	600	82

Notes: Regression discontinuity results using eBird data for all species. The columns report the point estimate for the differences in bird diversity between East and West Germany at the border, the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE). The running variable is negative for West Germany and positive for East Germany. The baseline specification includes a border dummy, log(experience), log(duration) of the observation, year fixed effects and quarter fixed effects as controls. We add additional controls in the subsequent specifications. ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within a 1x1 km area around the sample centroid as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘EVI’ adds the EVI index as control while ‘Land cover diversity’ adds land cover diversity as control. Standard errors are clustered at the district level. The optimal bandwidth is based on the baseline specification.

diversity on the results is reduced in Table 8 suggesting that the 6×6 km buffer overestimates the observation area.

Table 8: Farm size and bird diversity (eBird) with 6×6 km buffer

Specification	Estimate	SE	P	BW	NW	NE
Baseline	-8.0	1.6	0	9	47	84
Land cover	-5.7	2.2	0.01	9	47	84
Field size	-6.2	2.2	0.005	9	47	84
Crop diversity	-4.6	1.8	0.01	9	47	84
EVI	-4.7	1.8	0.01	9	47	84
Land cover diversity	-5.7	1.5	0	9	47	84

Notes: Regression discontinuity results using eBird data for all species. The columns report the point estimate for the differences in bird diversity between East and West Germany at the border, the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE).

The running variable is negative for West Germany and positive for East Germany. The baseline specification includes a border dummy, log(experience), log(duration) of the observation, year fixed effects and quarter fixed effects as controls. We add additional controls in the subsequent specifications. ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within a 6×6 km area around the sample centroid as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘EVI’ adds the EVI index as control while ‘Land cover diversity’ adds land cover diversity as control.

Standard errors are clustered at the district level. The optimal bandwidth is based on the baseline specification.

G Bandwidth (CBBS)

In this section, we repeat the regression discontinuity analysis with CBBS data from the main text but double the bandwidth to test the impact of bandwidth selection on our results. The results are reported in Table 9

Table 9: Farm size and bird diversity (CBBS) with double bandwidth

Specification	Est	SE	P	BW	NW	NE
Baseline	-4.0	2.6	0.1	42	208	250
Land cover	-5.1	2.4	0.03	42	208	250
Field size	-5.3	2.4	0.02	42	208	250
Crop diversity	-5.4	2.3	0.02	42	208	250
EVI	-5.1	2.3	0.03	42	208	250
Land cover diversity	-2.2	1.9	0.2	42	208	250

Notes: The impact of farm size on species richness using CBBS data for the years from 2015 to 2017. The columns report the point estimate for the differences in bird diversity between East and West Germany (Est), the standard errors (SE), the P-value (P), the bandwidth in km (BW) and the sample size in West Germany (NW) and in East Germany (NE). The running variable is negative for West Germany and positive for East Germany. The specification ‘Baseline’ includes a 5 km border dummy as control, ‘Land cover’ adds the percentage of land cover categories (crop, grassland, forest, water, built up) within the 1x1km sample polygon as control, ‘Field size’ adds additionally the field size as control, ‘Crop diversity’ adds additionally crop diversity as control, ‘Land cover diversity’ adds additionally land cover diversity. Standard errors are clustered at the district level.