Journal of Development Economics 172 (2025) 103402

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Regular article

Blaming the wind? The impact of wind turbine on bird biodiversity☆

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ARTICLE INFO

Keywords:
Wind turbines
Bird biodiversity
Habitat loss
Food chain

ABSTRACT

We quantitatively assess the impacts of onshore wind turbines on bird diversity using citizen science data in China. Results show that a one-standard-deviation increase in wind turbines reduces bird abundance by 9.75% and leads to a 12.2% reduction in bird species richness at the county level. The negative impacts are more significant in migrant birds, birds in forests, urban and farmlands than others. Biodiversity protection helps to safeguard bird abundance against wind turbines. We also find that habitat loss rather than food chain change after the wind turbine installations contributes to biodiversity loss. The net impact of wind turbines on the environment is positive when considering the carbon reduction effects.

1. Introduction

There is a growing consensus that human-caused climate change has led to widespread adverse impacts and associated losses to nature and people. The global average temperature needs to be below 1.5 °C above the pre-industrial level to avoid further catastrophic damages from climate change (IPCC, 2023). As the largest carbon emitter, China has committed to peak carbon emissions by 2030 and reach carbon neutrality by 2060 (i.e., the "double carbon" goal). Wind power with net carbon dioxide benefits has become a popular alternative to fossil fuels and meets the electricity demand (Dammeier et al., 2019; Lu et al., 2014). The installed wind power capacity has increased substantially over the past two decades. China currently has the largest cumulative installed wind power capacity in the world (IEA, 2021), with approximately 281.65 gigawatts (GW) by the end of 2020.[1] The rapid expansion of wind power benefits the national emissions commitment and also contributes to emissions reductions on a global scale (Pörtner et al., 2022).

While wind energy plays a vital role in carbon reductions and mitigating climate change, onshore wind turbines that occupy large areas may negatively impact the environment, including noise and visual pollution (Dong et al., 2024; Dröes and Koster, 2016; Jalali et al., 2016; Mei et al., 2024), destruction of biological habitats (Zerrahn, 2017), and displacement of wildlife (Minderman et al., 2012). Some studies have focused on bird fatalities around wind turbines using infra-red imagery or satellite tagging in specific wind farms or regions (Ellerbrok et al., 2022; Mikami et al., 2022; Popescu et al., 2020). We currently lack empirical evidence on the magnitude of the impact of wind turbines on bird populations, though the potential negative impacts have already been realized by local governments and communities. For example, in 2017, the Changdao[2] county in Shangdong province demolished 80 wind turbines due to concerns on the potential negative impact on bird populations. Changdao county is located at the intersection of the Bohai Sea and Huanghai sea in northeast China, and consists over 150 small islands. Changdao county is also the home to or on the migration route of over 330 different bird species, about 22% of the total bird species observed in China. Local communities have reported reduced bird populations and increased pest activity in nearby forests after the installation of wind turbines, which ultimately led to a complete removal of all wind turbines in the Changdao county.[3]

☆ Lina Meng acknowledges the financial support from the National Natural Science Foundation of China (72173109 and 72274162). Yinggang Zhou gratefully acknowledges financial support from the National Natural Science Foundation of China (71871195, and 71988101) and the Chinese National Social Science Foundation (19ZDA060). Yingdan Mei acknowledges the financial support from the National Natural Science Foundation of China (72373162 and 72473145). We extend our gratitude to Dr. Jiajun Yuan and Yuhan Chi's research assistant for their invaluable contributions to the data collection process.
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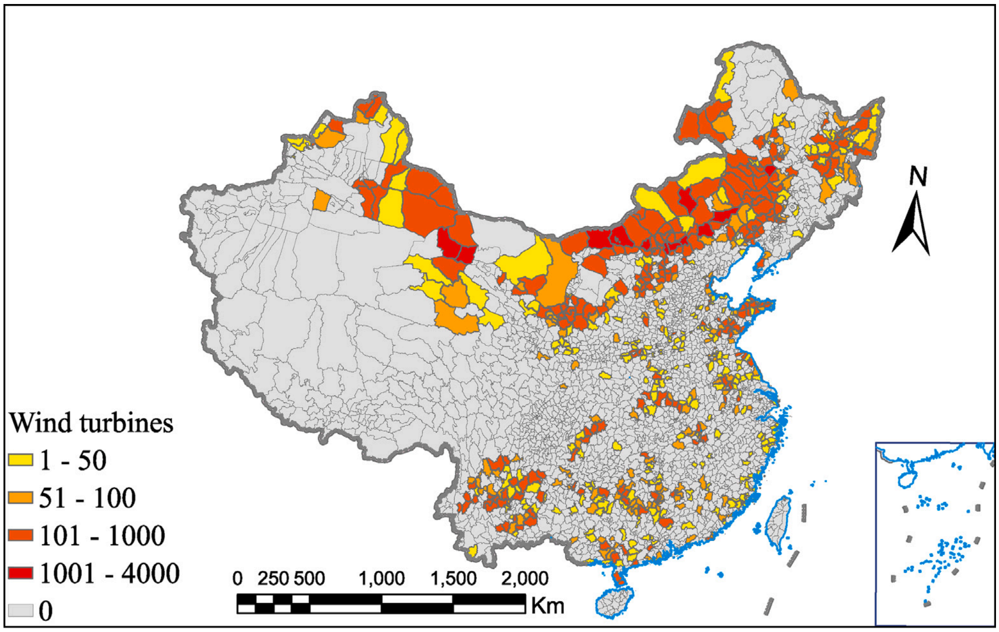
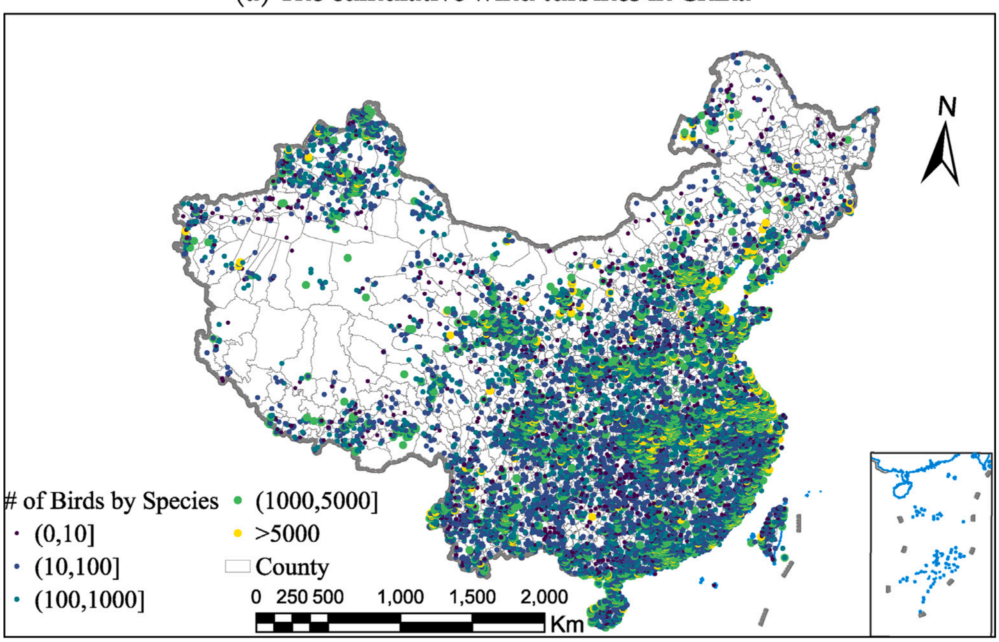
1 Data from *The Chinese Electricity Yearbook* (2021).
2 Changdao means "Long Island" in English, which, by coincidence, located in northeast China, similar to the location of Long Island in the U.S.
3 News report (in Chinese), https://m.bjx.com.cn/mnews/20170821/844599.shtml, last accessed on 10/04/2023.

https://doi.org/10.1016/j.jdeveco.2024.103402
Received 15 April 2024; Received in revised form 1 November 2024; Accepted 3 November 2024
Available online 10 November 2024
0304-3878/



(a) The cumulative wind turbines in China



(b) The number of observed birds by species in the CBR checklists

Fig. 1. The spatial patterns of checklists and wind power installations in China.
(a). The cumulative installed wind turbines in China by the end of 2022. Counties with yellow-to-red colors represent the treatment group with installed capacity from low to high; counties with gray color indicate the control group without wind turbines. (b) The spatial distributions of checklists and the number of observed birds by species from 2015 to 2022. The dots represent the spatial locations of a given checklist. Dots with yellow indicate the higher observed number of birds from 2015 to 2022. The administrative map was acquired from the National Geomatics Center of China (NGCC), GS(2023)2767.

This paper firstly estimates the impact of onshore wind turbines on bird populations using micro-level data in China. We combine three data sources, including the China Bird Watching Report (similar to the eBird Reference Dataset) (CBR, 2023), wind farm installations (Huaxia, 2014), and the official website of the Development and Reform Commission (DRC) in each province. By doing so, we are able to create high-precision distributions of birds and wind turbines across China (see Fig. 1). The results from the instrumental variable (IV) model indicate that a one-standard-deviation increase in wind turbines (approximately 84 turbines) leads to a 9.75% decrease in bird abundance from the mean value of 5.38 and a 12.2% reduction in bird species richness from the mean value of 66 at a county level. The negative impacts are more significant in migrant birds, birds in forests, urban and farmlands than others. Biodiversity protection helps to safeguard bird abundance against wind turbine installations while having minor effects on bird species richness.

Our paper contributes to the burgeoning literature on the impact of wind turbines on biodiversity (Katzner et al., 2019). A group of scientific literature observed a correlation between wildlife collisions and wind turbine installations, using field survey data or infra-red imagery (Desholm and Kahlert, 2005; Loss et al., 2013; Thompson et al., 2017). Another thread of literature focuses on habitat loss due to the construction and operation of wind farms (Barré et al., 2018; Marques et al., 2020). The most closely related works are Miao et al. (2019), which focus on 86 bird observation routes located in 36 states in the United States, though the study lacks sufficient power to conclude a statistical relationship due to limited observations. Our paper is among the first to estimate the impact of wind turbines on bird biodiversity using micro-level data in China, the country which has the largest cumulative installed capacity of wind power in the world. Our IV estimate results provide robust evidence that wind turbines significantly reduce bird biodiversity, using national representative microdata of bird watching. Different from Miao et al. (2019), we show that habitat loss after wind turbine installations is one of the mechanisms contributing to biodiversity loss, while food chain changes play a minor role in bird biodiversity loss.

This paper also adds to the literature on the trade-off between wind and coal power in biodiversity conservation. Many energy policies have emphasized the hazards wind turbines present to birds, but few studies compare bird fatalities caused by different energy sources. A review conducted by Sovacool (2013) shows that, on average, wind farms and nuclear power plants are responsible each for between 0.3 and 0.4 deaths per gigawatts-hour (GW h) of electricity while fossil-fueled power plants are responsible for about 5.2 fatalities per GW h, when bird deaths from coal mining, plant operation, and climate change are added in. Our study shows that, on average, wind turbines are responsible for 1.31 bird fatalities per GW h in 2020, which is much smaller than those caused by fossil-fuel power stations. We further use a back-to-the-envelop method to calculate the net effect of wind turbines, considering the direct economic loss in bird diversity and potential economic benefits from carbon reduction. We find that the benefit of carbon reductions overcomes the economic loss in bird biodiversity, especially when compared to alternative electricity generation from fossil-fueled power plants.

Lastly, this paper speaks to the externalities of renewable energy, focusing on wind energy. Most of the studies have scrutinized the benefits of wind energy by reducing air pollution (Millstein et al., 2017; Novan, 2015), zero carbon emissions (Cullen, 2013; Fell and Kaffine, 2018), and the associated benefits to mitigate climate change (Callaway et al., 2018; Siler-Evans et al., 2013). Kaffine (2019) provides robust evidence that counties with wind turbines have also experienced increased corn yields due to the microclimate effects of wind farms. Song et al. (2023), however, find that increasing wind energy capacity reduced grassland quality in China. The overall impact of wind turbines on the ecosystem is still an open question. We quantitatively assess the expanding onshore wind turbines on bird biodiversity.

The remainder of this paper is organized as follows. Section 2 frames the research hypotheses and introduces the econometric model to identify those hypotheses. Section 3 explains the results as well as the potential mechanisms. Section 4 discusses the trade-off between wind and coal power on bird fatalities. Section 5 concludes.

2. Research design and methodology

2.1. Hypothesis development

Birds are an important indicator of ecosystem health and biodiversity status (Lu et al., 2020; Pimm et al., 2014; Sun et al., 2022). China is located along four of the nine major bird migration routes in the world. Literature shows that wind farms affect bird populations either directly through collisions with turbines (Cabrera-Cruz and Villegas-Patraca, 2016; Marques et al., 2014; Thaxter et al., 2017), or indirectly through displacement, resource exclusion, habitat modification, and increased energy expenditure by blocking regular flight paths (Marques et al., 2020; Santos et al., 2022; Zerrahn, 2017), using infra-red imagery or satellite tagging in specific wind farms or regions (Ellerbrok et al., 2022; Mikami et al., 2022; Popescu et al., 2020). There is no systematic study to quantify the threat of increasing wind turbines on the overall bird populations, which leads to our first hypothesis.

Hypothesis 1. Wind turbine installations negatively affect bird biodiversity.

In addition to collision, wind farm constructions and operations also fragment the earth's surface, such as forest and grassland, which ultimately affect the habitat environment of birds (Marques et al., 2020; Sovacool, 2013). Moreover, the fragmentation of land covers may affect the sources of bird food. Wind turbines also alter the surface meteorology through decreased wind speeds and turbulent mixing (Stevens and Meneveau, 2017). Song et al. (2023) find that an expansion in wind power correlates with a decrease in grassland coverage, which serves as a critical food source for herbivorous bird species. Thus, wind turbine installations may affect bird biodiversity through the channel of food chains. We thus propose our additional hypothesis below, focusing on the impact mechanisms.

Hypothesis 2a. Wind turbines affect bird biodiversity through the channel of habitat loss.

Hypothesis 2b. Wind turbines affect bird biodiversity by reducing crop lands' production.

2.2. Data

2.2.1. Wind turbine installations

Wind energy installation data is provided by Huaxia (2014), a Chinese nongovernmental organization. The dataset includes the location, the number of wind turbines, installed capacity, and the date of assessment completed for each wind farm in China from 1989 to 2011. We collect information on wind farms between 2012 and 2022 from the official website of the Development and Reform Commission (DRC) in each province. The construction of wind farms must be approved by the provincial DRC and posted on the government website. A sample of the approval file is shown in Figure B.1 in Appendix B. In total, we collect information on 1810 wind farms with 109,408 turbines (see Figure B.2 in Appendix B). We then geocode each wind farm with the county-level characteristics using the specific address on the posts. The number of installed wind turbines is aggregated at the county-month-year level. We also use newly released data from *The Wind Power* in the robustness check.[4]

Fig. 1(a) shows the spatial distributions of wind energy capacity at the county level by the end of 2022. The red and yellow colors indicate counties with relatively high and low installed wind energy capacity, respectively. Panel A of Table 1 shows that, on average, 16% of the counties installed wind turbines over the study period. The average installed wind turbines are 18.56 per county.

To account for the potential correlations between wind turbine locations and bird diversity, we instrument the wind turbines by the inner production of the logarithmic value of a county's average wind speed at the 100-meter height in 2004–2014 and the national annual growth rate of wind turbine installation (Brunner et al., 2022). Specifically, a county's average wind speed at the 100-meter height is acquired from ECMWF Reanalysis v5 (ERA5).[5] Panel A of Table 1 shows that, the

[4] *The Wind Power* is a proficient, worldwide, and unique database for people working in the wind turbine sector. The sample's cumulative wind turbines are 140,088. The data collected in the database come from the internet, press releases, professional media, and so on. More details are released via https://www.thewindpower.net/about_en.php.

[5] The data is downloaded from ECMWF website: https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5, and processed by ArcGIS Pro.

Table 1
Summary statistics.
This table reports the summary statistics of variables used in the paper, which are grouped for estimation purposes. Panel A reports the key variables, including the wind turbine installation at a county-by-month-of-year scale and bird biodiversity characteristics. Panel B reports the heterogeneity in bird characteristics and other regional attributes that are used for heterogeneity analysis. Panel C reports other variables that are used for mechanism analysis or control variables. The variable definitions are provided in Table B.1 of Appendix B.

Variable	N	Mean	S.D.	P1	P99
Panel A: Key variables					
Number of checklists	33,777	16.87	39.74	1	191
Bird abundance	1,091,957	5.38	12.32	1	75
Bird species richness	33,777	65.9	49.58	6	252
Predicted bird abundance	515,559	4.99	8.41	1	43.07
Predicted bird species richness	864,608	47.2	42.71	1	209
Average duration per checklist (h)	33,777	14.2	34.63	0	220.3
Treatment	2445	0.16	0.37	0	1
# of wind turbines	33,890	18.56	84.11	0	398
Average wind speed at the 100 m height (mph)	34,135	1.97	0.78	0.31	7.48
Growth rate of wind turbine installations (%)	8	5.78	5.84	0	18.61
Panel B: Bird characteristics and other attributes					
Migrant birds	1,091,957	0.48	0.5	0	1
Habitat: Forest	1,091,957	0.57	0.5	0	1
Habitat: Grassland	1,091,957	0.18	0.38	0	1
Habitat: Urban and farmlands	1,091,957	0.47	0	1	
Habitat: Waterfowl	1,091,957	0.35	0.48	0	1
Mass (g)	1,091,957	246.3	602.07	6.13	2750
IUCN red list	1,062,049	0.06	0.34	0	2
CN key List	1,091,957	0.63	0.48	0	1
Government awareness	260	0.57	0.49	0	1
GDP per capita	260	0.52	0.51	0	1
Panel C: Other variables					
NDVI	174,873	0.46	0.2	−0.04	0.9
Wetland grids	154,463	37,679.58	134,696	3	512,293
Crop grids: maize	6942	1019.44	4936.7	1	14,012
Crop grids: wheat	5510	1218.44	5521.14	1	15,886
Crop grids: rice	6532	750.7	2435.42	1	7448
Phenological duration: maize	6312	113.9	27.06	72	168
Phenological duration: wheat	4468	222.16	28.8	72	168
Phenological duration: rice	4303	120.9	27.27	72	168
Temperature (°F)	33,890	62.09	15.2	22.37	87.48
Visibility	33,890	8.74	4.19	2.7	18.3
Wind speed (mph)	33,890	5.07	1.92	2	11.53
Precipitation (mm)	33,890	3.37	4.09	0	18.85
Ozone (kg kg^{-1})	33,890	0.006	0.0006	0.005	0.008
Population density (person per sq km)	9245	1604	3649	1	16,748
Nighttime light value	9245	6.74	10.05	0.002	42.54
The area of nature reserve (sq km)	9445	67.54	2218.58	0	540

average wind speed at the 100-meter height in 2004–2014 is 1.97 mph, and the national growth rate of wind turbine installations between 2015 and 2022 is 5.78%.

2.2.2. Bird checklist

The bird observation data comes from the China Birdwatching Report (CBR, similar to the eBird Reference Dataset), a citizen science dataset consisting of reports from users, including information on individual bird trips and associated characteristics, such as the specific date and time, location of a specific trip, as well as species and quality of birds encountered developed by CBR (2023). Each birdwatching report in the data set is called a "checklist". We then link the bird classification to the CBR dataset in China based on the existing methodology (Sun et al., 2022). To determine the spatial distribution of birds in China, we geocode each checklist by the reported latitude and longitude information using ArcGIS Pro software. The county of encounter associated with each checklist is also obtained, and the data are then aggregated at the county-of-month-by-year-of-species level. The CBR contains checklists in China from 1995 to the present (see Figure B.3 in Appendix B). The number of checklists before 2015 is relatively small, so we restrict our sample from 2015 to 2022. Fig. 1(b) shows the spatial distribution of checklists, where we find that observations are clustered in eastern and central China. To reduce potential bias caused by outliers, we censor the top and bottom 1% outliers of observed birds and observed durations per checklist. We also perform a robustness check by using the raw data without censoring outliers and our main results remain the same.

We focus on two measures of bird diversity, including bird abundance and bird species richness which are two of the most important indices to measure bird biodiversity in the literature (Liang et al., 2020; Liu, 2022; Rosenberg et al., 2019). Bird abundance is the average number of birds of a given species per checklist observed at a county-month-year-species level. Species richness is the total number of unique species observed in a given county at the month-year level, which better reflects the diversity of the bird populations. Bird abundance and species richness measure the change in bird populations before and after the wind turbines were installed.

One of the major concerns is the efficacy of the CBR dataset caused by the potential sampling issues and bias. The large sample sizes from over 232 million checklists tend to mitigate the bias and increase precision compared to smaller samples (Dickinson et al., 2010). Similar to the eBird ((https://ebird.org)), the CBR data platforms collaborate with researchers from different scientific domains, such as ecology, geography, computer science, and statistics, to help the CBR set up the data process standards in the website and mobile app systems, which ensures the data quality when reporters upload their bird observations. The reports must include the maximum number of birds per species per checklist, the maximum duration of bird watching, maximum observational areas per checklist, and potential species that may be observed within a certain area. The system automatically reviews reporters' inputs and pop-up messages of errors when the inputs do not conform the standards.[6] Those data processing and verification tools help to reduce observer errors, which is an early concern regarding citizen-source data like CBR (Sullivan et al., 2014; Dickinson et al., 2010).

Moreover, in the robustness check, we replace the observed birds with predicted biodiversity measures to account for the potential observation bias (Liang et al., 2020). Predicted bird abundance is estimated using the following specifications,

$$log(\#of\,Birds\,Resported_{ighcdmy}) = \alpha_0 Durations_{ighcdmy} + \rho_h + \Gamma_{icmy} + \varepsilon_{ighcdmy} \quad (1)$$

where the dependent variable is the logarithmic number of birds reported by checklist g in county c at hour h on the d day of month m, in year y. *Duration* is the hours spent in bird watching in checklist g. ρ_h is an hour-of-day fixed effect that controls for time-invariant variables across days within an hour of the day, and $\varepsilon_{ighcdmy}$ is the error term. After estimation, we predict Γ_{icmy} which captures bird abundance of species i at the county-month-year level, after controlling for the effort variables and hour-of-day fixed effects. We then calculate the predicted bird abundance or richness at the county-month-year level by summing up the predicted species in Γ_{icmy} in a given county for a given month-year. The predicted value in bird diversity rules out birding checklist characteristics that may be correlated with month-over-month changes in wind energy installations within a given county. We replace observed bird abundance and species richness with predicted values in the robustness check.

To explore possible heterogeneous effects, we collect a number of explanatory variables. The variable *Red List* is a dummy variable indicating whether the species is listed as "Near Threatened" or more threatened by the International Union for Conservation of Nature (IUCN). Another variable *CN key list* is a dummy variable indicating whether the species is on the *"List of National Key Protected Wildlife"* announced by the Chinese government. *GDP per capita* is a dummy variable that takes a value of one if the GDP per capita in the given province exceeds the mean value of the sample. Additionally, we identify counties with a high level of government awareness of biodiversity based on a higher frequency of the word "biodiversity" in the government reports from 2005 to 2015 compared to the sample mean, as determined through word count analyses.

Panel A in Table 1 summarizes the key variables used in this study. On average, there are 16.87 checklists per county per month, with more than 5 birds per species observed per checklist. Approximately 66 bird species are observed in a given county per month. The pattern of predicted bird abundance and species richness is similar to the observed ones. The average duration per checklist is approximately 14.2 h. Panel B summarizes the heterogeneity of bird characteristics and other attributes. Half of the observed birds are migrant birds, and over 50% of birds are forest birds, followed by urban and farmland birds and waterfowls. Glassland birds represent 18% of the full sample. Among the observed species, only 6% of species are "Near Threatened" or above, while 63% of the observed species are on the *CN Key List.*

2.2.3. Other variables

We calculate the monthly mean normalized difference vegetation index (NDVI) and wetland areas by normalized difference water index (NDWI) at the county level to measure the change in habit environment in the mechanism analysis.[7] NDVI has been a central measurement of plant quality and agricultural outcomes since the emergence of satellite data in 1970s (Ferguson and Kim, 2023; Gao et al., 2023; Song et al., 2023). It is also a common way to map wetlands by satellite data based on the NDWI, due to its sensitivity to moisture contents in the land surface (Yang, 2020). Specifically, grids with a monthly mean NDWI value larger than 0 are regarded as wetland or permanent waterbody areas. We then sum up the areas of wetland grids within a county, which gives the areas of wetlands of a county in a specific month-of-year. More detailed information on NDVI and wetland measurements is available in Appendix A. We also calculate two indices: cultivated-land areas and the duration of the phenological growth period for three main crops, *i.e.,* maize, wheat, and rice, to measure the potential changes in crop phenology and, thereafter, crop yield in the mechanism analysis (Sakamoto et al., 2013). The original data source published by Luo et al. (2020), based on Global Land Surface Satellite (GLASS) leaf area index (LAI) products. The calculation procedures related to crop phenology are available in Appendix A.

Additionally, we include several control variables that may affect bird watcher activities or bird diversity (Katzner et al., 2019; Liang et al., 2020; Loss et al., 2013). Specifically, we obtain the monthly temperature and environment data from ECMWF Reanalysis v5 (ERA5), including mean temperature, visibility, mean wind speed, precipitation, and ozone. Population density is acquired from Oak Ridge National Laboratory,[8] and nighttime light value from Visible Infrared Imaging Radiometer Suite (VIIRS) on the EARTH DATA website.[9] Panel C in Table 1 summarizes the variables used in this study.

2.3. Empirical models

2.3.1. The two-way fixed effects model

We estimate the impact of wind turbine installations on bird diversity using a two-way fixed effects model (TWFE) based on the following specifications,

$$Y_{icmy} = \alpha(Treat_c \times Post_{cmy}) + \theta X_{cmy} + \delta_{py} + \eta_{ps} + \kappa_c + \lambda_{my} + \mu_i + \varepsilon_{icmy} \quad (2)$$

where Y_{icmy} is the logarithmic bird diversity, measured by bird abundance for species i reported in checklists (or bird species richness) in county c of prefecture city p in month m and year y as the data are aggregated at the county(c)-month(m)-year(y)-species(i) level. $Treat_c \times Post_{cmy}$ is an indicator that takes the value of one if a wind turbine is installed after month m year y at county c, and takes the value of zero otherwise. X is a time-varying vector that contains the county-of-month-by-year level characteristics, including average bird observed duration, average temperature, average visibility, average wind speed, total precipitation, average ozone, percentage of natural park areas in the county, average population density, and average night light value. We use a series of fixed effects to control for potential time-constant, unobserved factors. Specifically, city-by-year fixed effects δ_{py} control for unobserved factors common within a city in a given year, such as changes in conservation policy at the city level; city-by-season fixed effects η_{ps} control for city-specific seasonal fluctuations in weather conditions and other factors that may affect observed bird diversity; county fixed effects κ_c account for county-specific time-invariant factors such as elevation, distance to coastline; month-year fixed effects λ_{my} control for common characteristics of months in all sampled counties in a given year; and species fixed effects μ_i account for the species-specific time-invariant factors such as preferred habitat. The regressions are weighted by the number of checklists in a given county-by-month-of-year.

As the number of wind turbine installations varies across counties and increases over time for counties with multiple wind farms, we use a continuous treatment by replacing $Treat_c \times Post_{cmy}$ with the logarithmic number of wind turbines in a given county,

$$Y_{icmy} = \beta Turb_{cmy} + \theta X_{cmy} + \delta_{py} + \eta_{ps} + \kappa_c + \lambda_{my} + \mu_i + \varepsilon_{icmy} \quad (3)$$

[6] More instructions can be found through the *Record Submission Rules* and *User's guideline of China Birdwatching Record App* on the website https://www.birdreport.cn/.

[7] The variables are calculated by MODIS Vegetation Index Products and LANDSAT 8 Collection 2 on the Google Earth Engine Platform, https://code.earthengine.google.com.

[8] Website: https://landscan.ornl.gov/.

[9] https://www.earthdata.nasa.gov/learn/find-data/near-real-time/viirs

where $Turb_{cmy}$ is the logarithmic installed wind turbines in county c, in month m, year y, and equals zero if county c has no wind turbines as of month m, year y. All other variables carry the same definitions as in Eq. (2). Similarly, we weight the regressions by the number of checklists in a given county-of-month-by-year. The coefficients α and β are expected to be negative, according to Hypothesis 1.

2.3.2. The potential endogeneity caused by wind turbine siting

The siting of wind turbines is not random. In 2003, the Chinese government issued a technical regulation on the siting strategy of wind farms, focusing on areas with abundant wind resources and avoiding ecologically sensitive areas.[10] The siting strategy of wind farms may cause the sample to violate the parallel assumption of the TWFE model. Additionally, the enforcement of the siting policy may vary across regions and over time, potentially biasing the estimates of the TWFE model in Eqs. (2) and (3).

To address the potential endogenous caused by wind turbine siting, we instrument the installation of wind turbines by a Bartik-like variable based on the inner production of the logarithmic value of a county's average wind speed at the 100-meter height in 2004–2014 and the national annual growth rate of wind turbine installation (Brunner et al., 2022).[11] Abundant wind resources are one of the key factors determining the wind farm siting. The historical wind speed would not affect the current change in bird biodiversity. Also, the national annual growth rate of wind turbine installation is correlated with the county's wind turbines. The full model, including the first stage, can be described by the following specifications:

$$Y_{icmy} = \tau \widehat{WindFarm}_{cmy} + \theta X_{cmy} + \delta_{py} + \eta_{ps} + \kappa_c + \lambda_{my} + \mu_i + \varepsilon_{icmy} \tag{4}$$

$$WindFarm_{cmy} = \gamma(WindSpeed_c \times NG_y) + \theta X_{cmy} + \delta_{py} + \eta_{ps} + \kappa_c + \lambda_{my} + \mu_i + \nu_{icmy} \tag{5}$$

where $WindFarm_{cmy}$ is the treatment variable of county c in month m of year y, which is either being the interaction of $Treat_c \times Post_{cmy}$ in Eq. (2) or the $Turb_{cmy}$ in Eq. (3). $WindSpeed_c$ is the logarithmic value of the average wind speed at the 100-meter height of the county c during the period of 2004–2014, and NG_y is the national annual growth rate of wind turbine installation in year y. Thus, $\widehat{WindFarm}_{cmy}$ is the predictor derived from the first stage regression, as described by Eq. (5). Similarly, the regressions are weighted by the number of checklists in a given county-by-month-of-year. Our coefficient of interest τ denotes the treatment effect of installed wind turbines on bird biodiversity, which is expected to be negative according to Hypothesis 1. Goldsmith-Pinkham et al. (2020) show that the exogeneity condition of Bartik-like instrument should be interpreted in terms of "share", or the $WindSpeed_c$. We will implement several empirical tests to verify the exogeneity condition of wind turbine IV in Section 3.2.

3. Results

3.1. The impact of wind turbines on bird biodiversity

Panel A of Table 2 reports the baseline estimations for the impact of wind turbines on bird abundance. We first estimate the treatment effects using the TWFE specification of Eq. (2) in Column (1). We then measure the treatment effect of wind turbines by the number of wind turbines in Column (2). We document that wind turbines reduced the number of birds of a given species per checklist at the county-year-month level, estimated by the TWFE model of Eq. (3).

Next, in Column (3), we present the results from the IV estimation of Eq. (4) to address the endogenous concern about wind turbine sitings. The coefficient of $Treat \times Post$ remains statistically negative. Specifically, we find that the presence of wind turbines significantly reduces the number of birds of a given species per checklist by 12.2% at the county-year-month level. When the $Treat \times Post$ dummy variable is replaced with the logarithmic number of wind turbines in Column (5), we find consistent results. A one standard-deviation increases in wind turbines (approximately 84 turbines)[12] in a given county leads to a 9.75% decrease in bird abundance per checklist from the mean value of 5.38.[13] The corresponding magnitude of effects is much smaller than bird abundance loss caused by climate change, which reports a decline in bird abundance by 30% by the 2080s compared to the 2000 level, if there is no other mitigation adopted (Warren et al., 2013). Columns (4) and (6) also report the first stage regressions, which confirm a significant correlation between the county wind turbine installations and the inner product of county wind resources and national annual growth rate of wind turbines. We choose the IV estimation in Column (5) as our preferred specification, given the significant variation in wind turbine installations across the counties and over time. Fig. 2(a) also shows the quantile treatment effects on bird abundance based on the number of wind turbines in the horizontal axis, using the IV estimation in Column (5) of Table 2. The results show that the magnitude of the treatment effect initially increases substantially as wind turbines increase. When the number of wind turbines exceeds 10 percentiles, an increase in cumulative installed wind turbines has a diminishing effect on the bird abundance, which may reflect the potential adaptive behavior of birds (Kumara et al., 2022).

We further explore the impact of wind turbines on bird richness in Panel B of Table 2. The presence of wind turbines significantly decreases the number of unique species by 3.5% (Column 3), while a one standard-deviation increases in wind turbines (approximately 84 turbines) in a given county decreases the number of unique bird species by 17.67% from the mean value of 66, based on the IV estimations in Column (5) of Table 2.[14] The TWFE estimations still lead to a significant negative impact associated with the presence or increasing installations of wind turbines, as shown in Columns (1) and (2) in Panel B. Fig. 2(b) shows the quantile treatment effects on bird richness based on installed capacity in the horizontal axis. Similar to Fig. 2(a), we find that the magnitude of the treatment effect increases slightly as the wind turbines increase with diminishing marginal effect.

To sum up, wind turbines significantly reduce bird diversity, measured by bird abundance and species richness. Hypothesis 1 holds.

3.2. Validity of the instrumental variable

In the IV estimation model described by Eq. (4), we control for city-by-year fixed effects, city-by-season fixed effects, county fixed effects, month-of-year fixed effects, bird-watching efforts, and local weather conditions. This specification helps us mitigate the concern of a spurious correlation between wind turbine installations and bird biodiversity, such as topography and climate. Yet, the historical wind

[10] National Development and Reform Commission. *Circular on the Administrative Measures for the Preliminary Work of Wind Power Concession Projects and Related Technical Regulations*, https://www.nea.gov.cn/2011-11/21/c_131260341.htm.

[11] The average height of wind turbine is approximately 100 m.

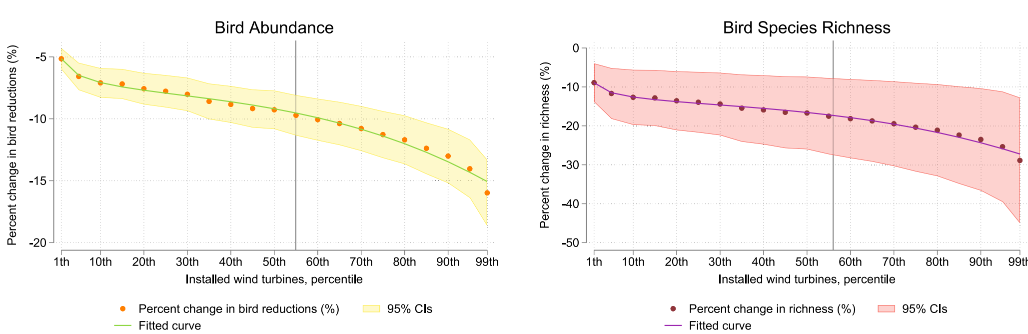
[12] To give a scope of land occupation of the wind turbines, the average land occupied by wind farms is 6070 m^2/windmill (Smeeton, 2022). Given that a one-standard-deviation of installed wind windmills in a county is approximately 84 in our sample, the corresponding land occupation by wind farms in a county is $(84 \times 6070) \div 1000000 = 0.51$ km^2 (about 126 acres). The median value of a county is 1553 km^2, and the percentage of land occupied by 84 windmills in a county territory is 0.03%. Despite the small proportion of land occupations by wind turbines, the wake effects caused by windmills can affect land areas by hundreds of miles (Diffendorfer et al., 2022; Lundquist et al., 2019).

[13] The calculation is given as $Log(84.11) \times 0.037 \div Log(5.38) \times 100\% = 9.75\%$.

[14] The calculation is given as $Log(84) \times 0.167 \div Log(65.90) \times 100\% = 17.67\%$.

Table 2
The impact of installed wind turbines on bird biodiversity.
This table reports the estimations of Eq. (2) and Eq. (3). The dependent variables in Panels A and B are bird abundance and species richness, respectively. Columns (1) and (2) report the two-way fixed effects model (TWFE) estimates; Columns (3) and (5) report the effects of wind turbine installation on bird biodiversity, and Columns (4) and (6) report the first-stage regression results of the IV estimates. *Treat* takes a value of one if a county had wind turbines from 2015 to 2022, and takes a value of zero otherwise. *Post* takes a value of one if the specific month-of-year being or after the month-of-year when the first wind turbine was installed in a given county. The *Wind turbine IV* instruments for wind turbine installation interact with the logarithmic value of a county's average wind speed at the 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. Control variables included logarithmic average duration of a checklist in a given county-by-month-of-your, monthly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of the natural reserve to the county area, county's yearly population density, and average nighttime light value. We also include city-by-year fixed effects, city-by-season fixed effects, year-by-month fixed effects, and county-fixed effects. Panel A further includes species-fixed effects. All regressions are weighted by the number of checklists in a given county-by-month-of-year. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	TWFE estimates		IV estimates			
			Second stage	First stage	Second stage	First stage
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bird abundance						
Treat×Post	0.001		−0.122***			
	(0.002)		(0.013)			
Log (# of Wind Turbines)		−0.004***			−0.037***	
		(0.001)			(0.004)	
Wind turbine IV				0.085***		0.278***
				(0.001)		(0.001)
kaap F_stat				3150		3150
County unit	1880	1880	1880	1880	1880	1880
Observations	1,087,165	1,087,179	1,087,165	1,087,165	1,087,165	1,087,165
R-squared	0.336	0.101				
Panel B: Bird species richness						
Treat×Post	−0.086***		−0.564***			
	(0.015)		(0.192)			
Log (# of Wind Turbines)		−0.022***			−0.167***	
		(0.005)			(0.057)	
Wind turbine IV				0.035***		0.118***
				(0.002)		(0.006)
kaap F_stat				18.35		19.53
County unit	1782	1782	1782	1782	1782	1782
Observations	30,415	30,415	30,415	30,415	30,415	30,415
R-squared	0.769	0.769				
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_by_Month FE	Yes	Yes	Yes	Yes	Yes	Yes



(a) Bird Abundance (b) Bird Species Richness

Fig. 2. Effects of wind turbine installations on bird diversity.
Notes: Bird Abundance is the number of observed birds grouped by species in a given county-year-month. Bird Richness is the number of observed bird species in a given county-year-month. Each dot is the coefficient in column (4) of Table 2, multiplied by the associated percentile installed capacity, respectively. The colored area is 95% confidence intervals.

speeds may correlate with unobserved characteristics that still persist and affect bird populations.

To address this concern, we implement a "Zero-First-Stage" (ZFS) test following Guiso et al. (2016) and Lal et al. (2024). In 2013, the Chinese government unveiled its plan to establish a national park system. Five pilot national parks were set up in 2015, following the "Pilot Program for Establishing a National Park System" jointly issued by 13 ministries and commissions, including the National Development and Reform Commission (NDRC). According to the pilot program, national parks implement the strictest protections for biodiversity; any non-protection-related constructions are forbidden. The strictest regulations on national parks help us design a "Zero-First-Stage" test. Intuitively,

Table 3
Validating the instrument.
This table reports the validating results of the instrument using the "zero-first-stage" (ZFS) test. Panel A reports the reduced-form estimates of two subsamples, observations outside the national parks and the "ZFS" subsample. We then regress a placebo test by randomly assigning treatment status to "ZFS" subsamples and then reduplicate IV estimations by 100 times, instrumented by the interaction of the logarithmic value of a county's average wind speed at the 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. Panel B reports the mean coefficients and 95% CIs in the square brackets. Control variables included logarithmic average duration of a checklist in a given county-your-month, monthly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of natural reserve to the county area, county's yearly population density and average nighttime light value. We also include county fixed effects, city-by-year fixed effects, city-by-season fixed effects, and month-of-year fixed effects. Columns (1) and (2) further include species-fixed effects in the regressions. All regressions are weighted by the number of checklists in a county-by-month-of-year. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A: Reduced-form estimates	Y = Log(Bird abundance)		Y = Log(Bird species richness)	
	Sample in national parks		Sample in national parks	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Wind turbines IV	−0.007***	−0.222	−0.019***	−0.171*
	(0.001)	(0.227)	(0.005)	(0.098)
Observations	1,047,129	39,955	29,215	845
R-squared	0.338	0.366	0.866	0.878
Panel B: Placebo tests	Y = Log(Bird abundance)		Y = Log(Bird species richness)	
	(1)	(2)	(3)	(4)
Treat×Post: mean	−1.551		−6.888	
	[−3.474, 0.372]		[−14.488, 0.711]	
Log (# of Wind Turbines): mean		0.216		4.710
		[−0.451, 0.882]		[−13.141, 3.722]
Controls	Yes	Yes	Yes	Yes
Species FE	Yes	Yes	No	No
County FE	Yes	Yes	Yes	Yes
City_by_Year FE	Yes	Yes	Yes	Yes
City_by_Season FE	Yes	Yes	Yes	Yes
Year_by_Month FE	Yes	Yes	Yes	Yes

if historical wind speed correlates with some unobserved characteristics that still persist and affect bird populations, we could observe a correlation between the wind IV and bird biodiversity in counties within the national parks. To do this, we split the samples into counties outside the national park boundaries and counties within national parks (hereafter, the "ZFS" subsample, see Figure B.4 in Appendix B). Then, we regress bird biodiversity on the wind IV using the two subsamples. The results in Panel A of Table 3 show that, not surprisingly, wind IV has a negative and significant effect on the bird biodiversity in counties outside the national parks, regardless of whether measured by bird abundance in Column (1) or bird species richness in Column (3). Furthermore, we document an insignificant correlation between wind IV and bird biodiversity in the "ZFS" subsample, as shown in Columns (2) and (4) in Panel A. In other words, we reject the hypothesis that some unobserved characteristics may correlate with the historical wind speed, which still persists and affects the bird population.

To further support the exclusion restriction assumption of wind IV, we implement a placebo test in the following steps. First, we randomly select 50% observations from the "ZFS" subsample and assign a treatment status to the selected sample. Second, we randomly select another 50% observations from the control group, that is, counties that have not installed wind turbines until the end of 2022. We then combine the two samples and repeat the IV estimation in Eq. (4). Third, we repeat the previous two steps by randomly selecting observations with the same criteria and performing the IV estimations 100 times. Panel B of Table 3 reports the mean value of estimated τ and the corresponding 95% confidence intervals (CIs) of these estimates. There is no causal effect of wind turbines on bird biodiversity when we conduct the placebo test using the "ZFS" subsample. As a result, our estimation is unlikely driven by unobserved characteristics that correlate with historical wind resources and still persist in affecting bird populations since in counties within national parks, where similar conditions exist but where wind turbines are forbidden to be installed, we do not find a significant correlation with bird populations.

High wind areas, like the coastal areas, may initially have high bird diversity, and the electricity demand may be also high in those areas. The bird diversity in areas with high electricity demand then may also decline without wind turbines. To address this potential concern, we implement two empirical tests to verify the exogeneity condition of historical wind speeds on bird biodiversity, following Goldsmith-Pinkham et al. (2020). Specifically, we use *Night lights* as proxies of the economic activities in 2015, and *Population* as the population conditions of a county in 2015, while *Num. of firms* is the number of firms above the scale of the county in 2015, representing the electricity demand by the industrial sector. We then regress $WindSpeed_c$ and the wind turbine IV ($WindSpeed_c \times NG_y$) on the three variables, respectively.

The results presented in Table 4. We do not find a statistically significant correlation between areas with a high wind speed ($WindSpeed_c$) and rich bird diversity in the base year. But we find that both local economic activities and population size are statistically significant with historical wind speed ($WindSpeed_c$) in Column (1). The significant correlations remain when using $WindSpeed_c \times NG_y$ as the dependent variable in Column (2), which is unsurprising Goldsmith-Pinkham et al. (2020), as "the shares are typically equilibrium objects and likely codetermined with the level of the outcome of interests, and the validity of Bartik-like IV is that the shares are exogenous to *changes* in the outcomes, rather than *levels* of the outcome variables". Thus, we further regress $WindSpeed_c$ and $WindSpeed_c \times NG_y$ on the *changes* in bird abundance, economic activities, population size, and number of firms from 2015 to 2022, respectively. The results in Columns (3)–(4) show that, none of the *changes* in the three local characteristics, including *changes* in night lights, *changes* in population, and *changes* in the number

Table 4
The relationships between wind speed and local characteristics.
The table regresses the wind resource and wind turbine IVs on other local characteristics that may be correlated with electricity demand, including levels of characteristics and changes in the characteristics. Specifically, *Bird abundance* is the logarithmic value of bird abundance of a county in 2015, which is used as a proxy of bird diversity in the base year. *Night lights* is used as proxies of the economic activities in 2015, and *Population* is the population conditions of a county in 2015, while *# of firms* is the number of firms above the scale of the county in 2015, representing the electricity demand by the industrial sector. All the levels of outcome variables are in logarithmic form. *Changes* in the local characteristics are measured by the mean change rate of the three variables between 2015 and 2022. $WindSpeed_c$ is the average wind speed at 100 m height in county *c*, in 2004–2014. $WindSpeed_c \times NG_y$ is the inner production of wind speed and the national annual growth rate of wind turbine installation in 2015. Control variables included average temperature, visibility, precipitation, ozone, and the percentage of the natural reserve in the county area, all of which were level variables in 2015. We also control the average elevation and longitude and latitude of a county's gravity center. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	$WindSpeed_c$ (1)	$WindSpeed_c \times NG_y$ (2)	$WindSpeed_c$ (3)	$WindSpeed_c \times NG_y$ (4)
Bird abundance	−0.008	−0.024		
	(0.006)	(0.017)		
Night lights	0.404***	1.202***		
	(0.041)	(0.124)		
Population	−0.237***	−0.706***		
	(0.026)	(0.078)		
# of firms	0.001	0.004		
	(0.014)	(0.041)		
Changes in bird abundance			0.003	0.048
			(0.007)	(0.063)
Changes in night lights			0.011	0.091
			(0.023)	(0.179)
Changes in population			0.119	0.970
			(0.121)	(1.120)
Changes in # of firms			−0.005	−0.032
			(0.004)	(0.037)
Observations	1833	1833	1519	1519
R-squared	0.314	0.314	0.302	0.276
Controls	Yes	Yes	Yes	Yes

of firms, nor the *changes* in the bird abundance, are correlated with the shares $WindSpeed_c$ and the wind IV ($WindSpeed_c \times NG_y$). Moreover, we employ an event study to explore the pre-trends of bird biodiversity before wind turbine installations, the results in Figure C.1 of Appendix C show that there are no significantly different trends in bird diversity before wind turbine installations. The detailed methodology and results discussions are provided in Appendix C.1. In summary, the proposed wind IV ($WindSpeed_c \times NG_y$) is likely to satisfy the exclusion restriction assumption of instrument variable estimation.

It is also possible that the impacts of wind turbines on bird biodiversity may be driven by the changes in observation patterns of birdwatchers who reported data to the CBR. To address this concern, we regress the number of checklists on the treatment variables to see if the number of observations has changed due to the wind turbine installations. The results are reported in Table C.1 of Appendix C. We do not find a significant impact of wind turbine installations on birdwatcher behaviors regarding the submitted number of checklists, based on the TWFE estimations in Columns (1)–(2) or the IV estimations in Columns (3)–(4) of Table C.1. We further use detailed Global Positioning System (GPS) data from cellphone records in a Chinese city in July and October 2019 and 2021, to measure the differences in visitors to areas with and without wind turbines. The dataset includes 8.41 million grid-cell observations, covering areas with 626 wind turbines in the city (See section B.2 in Appendix B for the details on the cellphone records). We then estimate the results using Equation B.1 described in Appendix C. The results are presented in Figure C.2, which show that there is no significant difference in the volume of visitors to a specific distance grid on a given calendar week-of-year, compared to those located in the distance bin of [9, 10] km (which we use as the control) to wind farms. Thus, our results are unlikely driven by the changes in the birdwatchers and other visitors due to the wind farms. However, it is still possible that our results are affected by the bird visibility change due to the groundcover alterations after wind farm constructions, though this effect is likely small and the reduced NDVI (e.g. lower forest coverage) is more likely to increase the visibility when other conditions remain the same. The availability radar tracking data on bird movements in the future may help to address this concern (Aschwanden et al., 2018; van Erp et al., 2024).

We also conduct several robustness checks, including replacing the dependent variable with the predicted bird biodiversity indices, excluding samples within national parks, and repeating the baseline estimations by another wind turbine data, *The Wind Power*. Further discussions related to the robustness analysis are provided in section C.2 of Appendix C. Overall, the results provide robust evidence that wind turbines have a significant impact on bird biodiversity. Both bird abundance and species richness decrease significantly after the installation of wind turbines at a county level.

3.3. Heterogeneous effects based on migrant patterns, habitat, and mass

Next, we examine how the impacts of wind turbine installation vary across biological conditions. Specifically, we explore the heterogeneous effects of wind turbines based on migrant patterns, habitats, and body mass. We present the estimation results based on IV estimates using the interaction of historical wind speeds and the national annual growth rate of wind turbine installations as the instrumental variable.

The results in Table 5 show that migrant and resident birds are both negatively affected by wind turbines, while the impacts on migrant birds are much higher than those on resident birds. A one standard-deviation increases in wind turbines (approximately 84 turbines) in a given county decreases migrant and resident bird abundance by 38.98% and 2.90% from the mean value of 5.38, respectively (Columns (1) and (2) in Panel A). We also observe consistently negative impacts on both migratory and resident bird richness. (Columns (1) and (2) in Panel B). Four of the nine major bird migration routes in the world are located in China. Despite the implementation of technical regulations governing wind farm siting, which mandate that new wind turbine installations should circumvent ecologically sensitive areas, including the migratory

Table 5
Heterogeneous effects of wind turbine installation on bird biodiversity: Different bird groups.
This table reports the heterogeneous effect of wind turbine installations on bird biodiversity. Panel A uses bird abundance as the dependent variable, and Panel B uses bird richness as the dependent variable. Each column represents a separate IV estimate, instrumented by interaction production of the logarithmic value of a county's average wind speed at 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. Control variables included logarithmic average duration of a checklist in a given county-your-month, monthly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of natural reserve to the county area, county's yearly population density and average nighttime light value. We also include county fixed effects, city-by-year fixed effects, city-by-season fixed effects, and month-of-year fixed effects. Panel A further includes species fixed effects in the regressions. All regressions are weighted by the number of checklists in a county-by-month-of-year. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	Migrant		Habitat				Mass		
	Yes (1)	No (2)	Forest (3)	Grassland (4)	Urban and farm land (5)	Waterfowl (6)	Low (7)	Median (8)	High (9)
Panel A: Bird abundance									
Log (# of Wind Turbines)	−0.148***	−0.011***	−0.055***	0.024***	−0.081***	−0.027**	−0.037***	−0.031***	−0.052***
	(0.008)	(0.004)	(0.004)	(0.008)	(0.008)	(0.006)	(0.007)	(0.008)	(0.005)
County unit	1865	1862	1859	1805	1858	1822	1843	1844	1853
Observations	525,195	561,901	619,562	192,092	351,322	382,916	312,597	382,129	383,778
Species FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Bird species richness									
Log (# of Wind Turbines)	−0.174***	−0.162***	−0.151***	−0.246***	−0.172***	−0.360	−0.240*	−0.017	−0.416***
(0.047)	(0.054)	(0.051)	(0.043)	(0.043)	(0.310)	(0.129)	(0.123)	(0.142)	
County unit	1782	1770	1753	1764	1728	1756	1724	1680	1677
Observations	29,160	29,169	29,109	27,138	28,462	27,148	27,749	28,538	28,667
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year_by_Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

pathways of birds, the substantial presence of migratory birds and their seasonal movements still significantly increase the likelihood of their exposure to wind turbines.

We next explore the impacts of wind turbines on bird populations in different habitats, including forest, grassland, urban and farm land, and waterfowl. We provide supportive evidence that the negative impacts on bird abundance mainly come from birds in three of the four habitats, except grassland (Columns (3)–(6) in Panel A of Table 5). Wind turbines significantly reduce bird species richness in forests, grassland, urban and farmland (Columns (3)–(6) in Panel B of Table 5). The estimations on waterfowl richness are noisy and statistically insignificant at a 10% level. Approximately 60% of bird species live in the forest, which increases the probability of harm by wind turbines. The high fragmentation of urban and farmlands also increases the threat of wind turbines to bird population (Loss et al., 2023; Sun et al., 2022).

We further divide the bird populations into three groups based on their mass distribution: low (mass <=21 g), median (21 g <mass ≤ 108 g), and high (mass >108 g). The results in Columns (7) – (9) of Table 5 show that, wind turbines negatively affect bird abundance in different mass groups, while the estimated impacts on birds with high mass (mass >108 g) are much larger than the others two groups. We also find statistically negative effects of wind turbines on the species richness of birds with high mass (mass >108 g), mainly originating from *Anas*, *Ardea*, and *Spilopelia*. The three genera of birds represent 7.3% of the total population. Large birds like *Anas*, *Ardea*, and *Spilopelia* often have less agility compared to smaller birds and may be less able to quickly avoid turbine blades, increasing the collision risk. We do not find evidence that the species richness of birds with weighing less than 109 g is affected by wind turbines.

3.4. Heterogeneous effects based on protection status and regional characteristics

Next, we explore the heterogeneous effects based on protection status and regional characteristics. We categorize the observation based on the IUCN red list, CN key list, governments' biodiversity awareness, and regional economic conditions. We find that wind turbines only have a significantly negative impact on non-IUCN red list species, while the impact is positive for IUCN red list species, which is marginally significant at a 10% level (Columns (1)–(2) in Panel A of Table 6). A one standard deviation increase in wind turbines (approximately 84 turbines) significantly reduces bird abundance of non-IUCN red list species by 13.43% while also marginally increases bird abundance of IUCN red list species with a larger magnitude of 31.34%. We find evidence that wind turbines significantly reduce bird species richness in the non-IUCN red list (Column (2) in Panel B). According to the siting regulations, the wind turbine construction should be avoided in natural reserves. Wind farms are required to adopt mitigation methods to avoid bird collisions if protected bird species are observed before construction, i.e., painting the blades with warning colors and installing bird repellents.[15] May et al. (2020) find a 72% reduction in bird fatalities at a wind farm by painting one of a wind turbine's three blades black. Miao et al. (2019) show no significant impact for turbines 1600 m away from bird observation sites, which may explain a significantly positive effect of wind turbines on IUCN red list species. Moreover, declines in non-IUCN red-list species reduce the population competition in birds, which may increase the abundance of red list birds. We also divide the bird species by CN List and repeat the IV estimations in Columns (3)–(4). The results are consistent with those in Columns (1)–(2), though the estimations for species richness are noisy and not statistically significant at a 10% level.

Columns (5)–(6) further group the sample based on governments' biodiversity awareness, by the median value of biodiversity words in the annual government reports between 2004 and 2014. The results show that, as expected, government concerns for biodiversity provide protection in terms of bird abundance when harmed by wind turbines, e.g., urging wind farms to take mitigating processes to keep birds away from turbines. The results are consistent with Cazalis et al. (2020), who find that protections only positively affect bird biodiversity of conservation concerns. We also find that bird abundance in regions with relatively low GDP per capita increases after wind turbine

[15] For example, some mitigation methods are reported by the environmental impact statement of the Tianchentuo Wind Farm Project in Tianmen City in August 2022.

Table 6
Heterogeneous effects of wind turbine installation on bird biodiversity: Different biodiversity protection and regional heterogeneity.
This table reports the effects of wind turbine installations on bird biodiversity in regions with different biodiversity protections and economic conditions. Panel A uses bird abundance as the dependent variable, and Panel B uses bird richness as the dependent variable. Each column represents a separate IV estimate, instrumented by the interaction production of the logarithmic value of a county's average wind speed at the 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. *IUCN redlist* is a dummy of whether the species is listed by IUCN as "Near Threatened" or more threatened. *CN key list* is a dummy of whether the species is on the "List of National Key Protected Wildlife". *County with high government awareness* is defined by the county in the province with a higher word frequency of biodiversity in their government reports from 2005 to 2015. *GDP per capita* is defined by the county in the province with a higher GDP per capita than the sample median from 2005 to 2015. Control variables included logarithmic average duration of a checklist in a given county-your-month, monthly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of natural reserve to the county area, county's yearly population density and average nighttime light value. We also include county fixed effects, city-by-year fixed effects, city-by-season fixed effects, and month-of-year fixed effects. Panel A further includes species-fixed effects in the regressions. All regressions are weighted by the number of checklists in a county-by-month-of-year. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	IUCN Redlist		CN Key List		Government awareness		GDP per capita	
	Yes	No	Yes	No	More	Less	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Bird abundance								
Log (# of Wind Turbines)	0.119*	−0.051***	0.007	−0.038**	0.924***	−0.019	−0.015	2.864***
	(0.070)	(0.018)	(0.057)	(0.018)	(0.213)	(0.016)	(0.016)	(0.578)
County unit	1586	1880	1333	1879	1015	865	890	989
Observations	64,175	1,022,600	35,937	1,050,653	630,214	456,860	628,448	458,291
Species FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Bird species richness								
Log (# of Wind Turbines)	−0.156	−0.174***	−0.021	−0.163	−2.165**	−0.355***	−0.261***	−3.235
(0.116)	(0.034)	(0.023)	(0.122)	(0.946)	(0.041)	(0.047)	(2.500)	
County unit	1591	1736	1394	1734	955	808	857	924
Observations	21,374	30,266	52	14,474	30,281	13,332	17,198	13,205
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year_by_Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

construction (Columns (7) – (8) in Panel A). The species richness is significantly affected by wind turbines, regardless of GDP per capita. Regions with lower GDP per capita suffer less from the negative environmental impacts of wind turbines. The results are consistent with the observation that regions with high government biodiversity awareness generally have relatively low GDP per capita such as Yunan province in southwestern China.

3.5. The spillover effect of wind turbines on bird biodiversity

Birds fly across the border. For example, wind turbines installed in Beijing may affect bird biodiversity in Tianjin, a neighboring city of Beijing. To explore the cross-border impacts of wind turbines, we re-estimate the baseline models using wind turbines installed within the county border and wind turbines installed in its neighboring counties as the main explanatory variable, following Du et al. (2024). We define neighboring counties if the geometric center is within K kilometers of the domestic county's geometric center, where $K \in [100, 150, 225]$.[16] The number of wind turbines installed in the neighboring counties is calculated by the inverse distance-weighted mean,

$$NB'sWindTurbines_{cmy} = \frac{\sum^{d_{jc} \in K} \frac{1}{d_{jc}} Turb_{jmy}}{\sum^{d_{jc} \in K} \frac{1}{d_{jc}}} \qquad (6)$$
$$K \in [100, 150, 225].$$

where d_{jc} is the distance between the neighbor county j's geometric center to the domestic county c's geometric center. $Turb_{jmy}$ is the installed wind turbines in neighbor county j in month m, in year y.

Table 7 reports the spillover effects of wind turbines. Using wind turbines in counties within 100 km from the domestic county as the neighbors, we find significant impacts from both the domestic county and neighbors' wind turbines on bird abundance. Specifically, a one standard deviation increases in the county's wind turbines causes a 11.59% reduction in bird abundance from the mean value of 5.38 per checklist. A one standard deviation increases in neighbors' wind turbines also results in a 4.52% reduction in the domestic county's bird abundance. We further address the potential endogenous of the neighbor's wind turbine siting by IV estimations in Column (2). Specifically, we instrument neighbors' wind turbines by the inverse distance-weighted wind IVs of the corresponding counties, as illustrated in Eq. (6). The significant spillover effects of neighbors' wind turbines on bird abundance remain. One standard deviation increase in neighbors' wind turbines significantly reduces the domestic county's bird abundance by 42.81%, from the mean value of 5.38 per checklist. Columns (3) – (6) further extend the neighbors' distance to 150 km and 225 km; the main findings remain. Panel B confirms the significant negative spillovers of wind turbines on bird species richness when instrumented neighbors' wind turbines by the inverse distance-weighted wind IVs in Columns (4) and (6). We also observe statistically negative impacts of the domestic county's wind turbine on bird species richness in Columns (1) – (3), instructed by the inner production of historical wind speeds and national annual growth rate of wind turbines.

Overall, these findings confirm the presence of significant spillover effects from wind turbines, with birds flying across borders. Moreover, we also find that, even considering the spillover effects, the impact of wind turbines within the domestic county is comparable to the baseline results in Column (5) of Table 2. This finding suggests that the presence of spillovers is unlikely to alter our baseline estimation.

3.6. Mechanism analysis

We next discuss the mechanisms through which wind turbines affect bird diversity. Literature shows that the impact of wind turbines on bird diversity is directly through collisions, using infra-red imagery or field survey data in a given wind farm (Ellerbrok et al., 2022; Sovacool, 2013). We develop hypotheses in Section 2.1 that suggest habitat loss and food chains are other potential channels through which bird diversity is impacted. Due to data constrained, we investigate the last two channels in the subsequent discussions.

[16] A 225 km is the mean radius of a climate zone in China.

Table 7
The spillover effects of wind turbines on bird biodiversity.
This table reports the spillover effects of wind turbines on bird biodiversity. Panel A uses bird abundance as the dependent variable, and Panel B uses bird richness as the dependent variable. *Log (# of Wind Turbines)* is instrumented by the interaction production of the logarithmic value of a county's average wind speed at the 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. *# of NBs' wind turbines* is the inverted distance weighted wind turbines in the neighbor counties within K km. In Columns (2), (4) and (6), *Log (# of NBs' Wind Turbines)* is instrumented by the inverse distance weighted wind turbine IV of the neighbor counties. Control variables included monthly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of the natural reserve to the county area, county's yearly population density, and average nighttime light value. We also include province-by-year fixed effects, city-by-season fixed effects, year-by-month fixed effects, and county-fixed effects. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	K = 100 km		K = 150 km		K = 225 km	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bird abundance						
Second-Stage Regression						
Log (# of Wind Turbines)	−0.044***	−0.030***	−0.035***	−0.025***	−0.038***	−0.048***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
Log(# of NBs' wind turbines)	−0.017***	−0.161***	−0.019***	−0.102***	−0.057***	−1.220***
	(0.002)	(0.011)	(0.002)	(0.010)	(0.005)	(0.095)
First-stage regression						
Wind turbines IV	0.246***	0.308***	0.285***	0.205***	0.276***	0.198***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NBs' wind turbines IV		0.120***		0.430***		0.461***
		(0.000)		(0.002)		(0.002)
County unit	1880	1880	1880	1880	1880	1880
Observations	1,087,165	1,087,165	1,087,165	1,087,165	1,087,165	1,087,165
Species FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Bird richness						
Second-Stage Regression						
Log (# of Wind Turbines)	−0.146**	−0.037***	−0.160***	−0.036	−0.166***	0.037
	(0.065)	(0.003)	(0.054)	(0.037)	(0.055)	(0.040)
Log(# of NBs' wind turbines)	0.031**	0.579***	−0.019*	−0.331***	−0.013	−2.813***
	(0.014)	(0.055)	(0.011)	(0.069)	(0.038)	(0.612)
First-stage regression						
Wind turbines IV	0.104***	0.131***	0.125***	0.088***	0.123***	0.086***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
NB's wind turbines IV		0.061***		0.200***		0.255***
		(0.002)		(0.007)		(0.009)
County unit	1782	1782	1782	1782	1782	1782
Observations	30,415	30,415	30,415	30,415	30,415	30,415
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Month_by_Year FE	Yes	Yes	Yes	Yes	Yes	Yes

3.6.1. Habitat loss

Hypothesis 2a predicts that the construction and operation of wind farms alter the surrounding habitat, ultimately impacting bird diversity. Specifically, we measured the changes in vegetation conditions and wetlands through remote sensing data. We use the county's monthly mean value of normalized difference vegetation index (NDVI) to measure the change in forest and grassland Gao et al. (2023), Song et al. (2023). We also define a small grid cell, that is, a 30 m×30 m grid area in a remote sensing image, as a wetland if the corresponding normalized difference water index (NDWI) is larger than zero (Yang, 2020). Both indices are calculated through the Google Earth Engine (GEE) Platform. Section A.1 and A.2 in Appendix A provide details on the data process. We then process the mechanism analysis by replacing the dependent variable in Eq. (2) and (5) with the monthly mean value of NDVI and county's wetland grids, respectively. To ensure the comparability of the sample size, we include only a sample of counties that have reported bird observations over the study period.

Panel A of Table 8 shows a statistically negative effect of wind turbines on NDVI, based on the TWFE estimates in columns (1)–(2) and IV estimates in columns (3) and (4), suggesting the installation of wind turbines significantly impact the vegetation conditions. The loss of forest and grassland habitats is likely to contribute to the decrease in bird diversity in the given county. Panel B reports the impact of wind turbines on wetland grids, measured by NDWI. The results in Columns (1) – (3) show the negative impacts of wind turbines on wetlands despite the estimations being noisy and statistically insignificant at a 10% level. When we instrument the number of wind turbines by the wind IV in Column (4), we find a statistically negative impact of wind turbines on wetlands. Our results provide supportive evidence that wind turbines impact bird diversity through habitat loss, in particular, changes in forests, grasslands, and wetlands. *Hypothesis* 2a is substantiated by the findings.

3.6.2. Food chain changes

In this section, we investigate the potential mechanism of food chain by employing spatially detained crop phenology data, developed by Luo et al. (2020). Specifically, Luo et al. (2020) produced a 1 km × 1 km gridded-phenology dataset for three main crops (i.e., maize, wheat and rice) in China from 2000 to 2019, based on GLASS LAI products. Key phenological stages, including emergence date and maturity date, are mapped in the cultivated-land grids by the value of DOY (date of year) (see Figure A.3 in Appendix A as an example). For each crop, we measure the impact on the food chain by two indices: cultivated-land areas and the duration of the phenological growing period. The longer the phenological growing period of a crop, the higher the crop yield (Sakamoto et al., 2013). Section A.3 in Appendix A describes the data cleaning process. We process the mechanism analysis by replacing the dependent variable in Eq. (5) with the two indices, respectively.

We first investigate whether wind turbine installations affect bird diversity through crop areas. Panel A in Table 9 shows a statistically

Table 8
Mechanism analysis I: Habitat losses.
This table reports the mechanism through which wind turbine installation affects bird biodiversity. Panel A reports the impact of wind turbines on forest and grassland, measured by monthly mean NDVI. The dependent variables are logarithmic($NDVI \times 100+1$). Panel B reports the impact on wetland areas, measured by the number of grids with monthly mean NDWI larger than zero. Columns (1) and (2) report the TWFE estimates; Columns (3) and (4) report the IV estimates. *Treat* takes a value of one if a county had wind turbines from 2015 to 2022, and takes a value of zero otherwise. *Post* takes a value of one if the specific month-of-year being or after the month-of-year when the first wind turbine was installed in a given county. Wind turbine installation is instrumented by the interaction production of the logarithmic value of a county's average wind speed at 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. Control variables included monthly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of the natural reserve to the county area, county's yearly population density, and average nighttime light value. We also include province-by-year fixed effects, city-by-season fixed effects, year-by-month fixed effects, and county-fixed effects. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	TWFE estimates (1)	TWFE estimates (2)	IV estimates (3)	IV estimates (4)
Panel A: dependent variable = Log(NDVI*100+1)				
Treat×Post	−0.002**		−0.333***	
	(0.001)		(0.097)	
Log (# of Wind Turbines)		−0.001*		−0.036***
		(0.000)		(0.009)
County unit	1847	1847	1847	1847
Observations	174,873	174,873	174,873	174,873
R-squared	0.870	0.870		
Panel B: dependent variable = Log(# of wetland grids+1)				
Treat×Post	−0.042		−47.540	
	(0.038)		(69.038)	
Log (# of Wind Turbines)		−0.010		−1.071***
		(0.011)		(0.351)
County unit	1847	1847	1847	1847
Observations	154,463	154,463	154,463	154,463
R-squared	0.581	0.575		
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Province_by_year FE	Yes	Yes	Yes	Yes
City_by_Season FE	Yes	Yes	Yes	Yes
Year_by_Month FE	Yes	Yes	Yes	Yes

negative impact of wind farms on rice-cultivated areas, when measured by the interaction term $Treat \times Post$ in Column (5). Wind turbine installations on the cultivated areas of maize and wheat are statistically insignificant. Panel B uses the duration of the phenological growth period of the three main crops as the dependent variables. The results show that wind farms significantly shorten the phenological growth period of maize (Column (1) in Panel B). The coefficients of the treatment variable on the phenological growth period of wheat and rice, are negative but statistically insignificant. We find limited evidence that wind turbine installations impact bird diversity through the food chain. There has been no systematic change in cultivated-land areas or the phenological growth period of three key crops since the wind turbine installations. *Hypothesis* 2b is not supported by the findings.

4. The trade-off between wind energy and coal power in biodiversity conservation

Bird population is negatively impacted by the electricity industry, through clean energy production like wind energy and solar or dirty energy like coal power (Sovacool, 2013). As commented by Garry George, renewable energy director for Audubon California, "there is no standardized way of doing it that everyone can agree to", pointing to the substantial impact of energy use on the birds, regardless of energy sources.[17] In this section, we compare the impacts of wind energy and coal power on bird biodiversity, using the estimated results in Section 3.

Specifically, the results in Table 2 show that a one standard-deviation increases in wind turbines (approximately 84 turbines) results in a 9.75% decrease in bird abundance per checklist from the mean value of 5.38, and a 17.67% decrease in bird richness from the mean value of 66. Thus, on average, one wind turbine is responsible for 4.94 bird fatalities per year.[18] The cumulative number of onshore wind turbines in China at the end of 2020 was 99,322, which generated 373.2 TW h of electricity and were responsible for 491.22 thousand bird fatalities in 2020. In other words, wind turbines are responsible for 1.31 bird fatalities per GW h in 2020 on average. Note that this is regarded as an upper-bound estimate as birds may change their residency rather than being killed by wind turbines. If the wind-generated power is produced by coal power, the 373.2 TW h coal power will cause 20.53 thousand bird fatalities, due to collisions of power plants and habitat loss.[19] However, this figure will rise to 1.93 million if bird deaths from coal mining and climate change caused by the consumption of fossil fuel are added, which is approximately 4 times higher than the bird fatalities caused by wind turbines.[20]

Given the potential benefits of wind energy in lowering CO_2 emissions and mitigating climate change (Millstein et al., 2017), we further employ a simple back-to-the-envelope model to estimate the net environmental benefits of wind power. First, given 99,322 on shore wind turbines in China in 2020, we estimate the direct economic loss in bird diversity to be between \$1.64 to \$2.33 trillion in 2020, based on the value of willingness to pay (WTP) in the literature (Lundhede et al., 2014; MartÍn-lÓpez et al., 2008; Sharma and Kreye, 2022). Second, we

[17] U.S. News: https://www.usnews.com/news/blogs/data-mine/2014/08/22/pecking-order-energys-toll-on-birds.

[18] The calculation is given as $(5.38 \times 9.75\%) \times 66 \times 12 \div 84 = 4.94$ birds per year.

[19] The data range from 0.02 birds per GW h to 0.09 birds per GW h, with a mean value of 0.055 birds per GW h per year (Sovacool, 2013).

[20] Adding the avian death from coal mining, plant operation, acid rain, mercury, and climate change together result in a total of 5.18 bird fatalities per GW h (Sovacool, 2013).

Table 9
Mechanism analysis II: Food chain changes.
This table reports the mechanism of the food chain through which wind turbine installation affects bird biodiversity. It is a city-by-year unbalanced panel dataset. The dependent variables in Panel A are logarithmic(cultivated area +1), including maize in Columns (1) – (2), wheat in Columns (3) – (4), and rice in the other two columns. The dependent variables in Panel B are the phenology of the corresponding crops, where phenology is calculated as the DOY (date of year) when maturated less than the DOY when the corresponding crops started the seedling stage. Each column represents separated IV estimates, instrumented for wind turbine installation with the interaction production of the logarithmic value of a county's average wind speed at 100 m height in 2004–2014 and the national annual growth rate of wind turbine installation. *Treat* takes a value of one if a county had wind turbines from 2015 to 2022, and takes a value of zero otherwise. *Post* takes a value of one if the specific year being or after the year when the first wind turbine was installed in a given county. Control variables included county's yearly average temperature, visibility, wind speed at the 2 m height, precipitation, ozone, the percentage of the natural reserve to the county area, population density, and average nighttime light value. We also include province-by-year fixed effects and county-fixed effects in the estimations. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	Maize		Wheat		Rice	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: dependent variable = log(cultivated area+1)						
Treat×Post	13.444		3.335		−5.368**	
	(12.626)		(6.004)		(2.356)	
Log (# of Wind Turbines)		9.078		2.025		−2.666
		(17.840)		(4.412)		(1.650)
County unit	1346	1346	1065	1065	1195	1195
Observations	6303	6303	4578	4578	5817	5817
Panel B: dependent variable = log(crop phenology)						
Treat×Post	−0.822**		−0.013		−0.135	
	(0.397)		(0.234)		(0.116)	
Log (# of Wind Turbines)		−0.573		−0.007		−0.065
		(0.560)		(0.134)		(0.058)
County unit	1375	1375	1177	1177	1263	1263
Observations	15,066	15,066	11,700	11,700	13,356	13,356
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
City_by_Year FE	Yes	Yes	Yes	Yes	Yes	Yes

calculate the economic benefits of wind energy in carbon reduction. Specifically, we calculate the economic benefits of carbon reductions of 373.2 TW h of wind energy, assuming that the wind energy would be produced by coal power. Given the average carbon price of $61.3 per ton CO_2 in 2020,[21] the economic benefit of wind energy in carbon reduction thus is approximately $7.02 trillion.[22] Thus, the economic benefit of wind energy in carbon reduction is 3 times greater than the economic loss of bird diversity due to the installation of wind turbines. We also provide the details of the calculation process in Appendix C.3.

Wind power capacity in China is projected to increase two-fold by 2030 and seven-fold by 2060, based on 2020's capacity (IEA, 2021), corresponding to 149.49 and 275.87 thousand wind turbines, respectively.[23] The wind turbines, thus, are projected to respond to 741.00 thousand bird fatalities in 2030, which will increase to 1.36 million in 2060. The impacts are relatively minor if considering the benefits of carbon reductions by wind energy.

5. Conclusion

This paper estimates the causal effects of wind turbines on bird diversity using citizen-sourced, micro-level data in China. The results from the IV model indicate that a one standard-deviation increases in wind turbines in a given county leads to a 9.75% decrease in bird abundance from the mean value of 5.38 and a 17.67% reduction in bird species richness from the mean value of 66. The negative impacts are more significant in migrant birds, birds in forests, urban and farmlands than others. Biodiversity protection helps to safeguard bird abundance against wind turbine installations while having minor effects on bird species richness.

We discuss the trade-off between wind and coal power in biodiversity conservation and potential carbon reductions. We find that, on average, wind turbines are responsible for 0.7 bird fatalities per GW h in 2020, which is substantially smaller than those caused by fossil-fuel power stations, if bird deaths from coal mining and climate change caused by the consumption of fossil fuel are added. The net economic benefits of wind energy in carbon reduction overcome the direct economic loss of bird diversity due to the installation of wind turbines. Nonetheless, the losses in bird diversity due to wind turbine installations may lead to degraded ecosystems from emission reduction efforts. Policymakers should consider the potential biodiversity loss in the cost–benefit analysis of wind energy investments. Moreover, governments in other countries with large wind energy installed capacities, such as the United States, United Kingdom, Netherlands, and Germany, may also carefully quantify the negative impacts of wind turbines on biodiversity and design more effective approaches to wind energy development.

There are several areas for future studies. Although this research is conducted based on observed bird checklists and does not consider the avoidance behavior of birds to wind turbines, it is noteworthy that Santos et al. (2022) find that birds show avoidance behavior to wind turbines when flying within 750 meters of turbines. While we provide upper bound estimates of wind turbines on bird diversity due to data limitations, it is plausible that the long-term impacts of wind turbines on bird diversity may be smaller when considering the avoidance behavior of birds. The citizen science dataset opens the door to use comprehensive, micro-level datasets to investigate similar research questions, despite potential limitations caused by observers and recordings. The availability of adequate monitoring datasets across different sites may potentially reduce the bias caused by sampling errors in the citizen science dataset in the future as current progress in

[21] We use the average carbon price in the European market reported by World Bank (https://carbonpricingdashboard.worldbank.org/compliance/price), to ensure it to be comparable with the WTP value.

[22] The economic benefit of wind energy in carbon reduction is $0.66 trillion, if measured by the carbon price of $5.13 per ton CO_2 in 2020 in China.

[23] We assume the power of a newly installed wind turbine is 5 MW per turbine, according to the newly constructed report of wind farms.

monitoring datasets are insufficient to study the bird population change on a national scale (Aschwanden et al., 2018; van Erp et al., 2024).

CRediT authorship contribution statement

Lina Meng: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Pengfei Liu:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yinggang Zhou:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yingdan Mei:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2024.103402.

Data availability

Data will be made available on request.

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