Evaluating the External Effect of Wind Power Development on Grassland Quality

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Abstract

This study employs a difference-in-differences approach to investigate the effect of county wind power development on grassland quality in China. We find robust evidence that increasing wind power capacity density by 0.02 MW/km^2 leads to a 0.5% reduction in the normalized difference vegetation index from its mean value. Excluding economic activities as a transmission channel, heterogeneous effects suggest that higher latitude areas with shorter nighttime hours in the growing season are less affected by the negative externality, supporting microclimate effects as the main mechanism. In addition, scarce wind resources and abundant precipitation may help weaken the negative effect.

Appendix materials can be accessed online at:
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Evaluating the Externality Effect of Wind Power Development on Grassland Quality

1. Introduction

Land degradation affects people and ecosystems throughout the planet and is both affected by and contributes to climate change (Gang et al. 2014; Intergovernmental Panel on Climate Change 2019). One way to fight global climate change is to develop renewable energy including wind power. However, wind farms can change local climate such as temperature, moisture and CO_2 levels and thus impose externalities and cause potential damage to the ecosystem. Covering 20–40% of world's land surface, grasslands not only play a key role in providing important ecosystem services, but also afford the livelihood of millions of herders (Food and Agricultural Organization 2008; Hou et al. 2021). Due to favorable construction conditions and low market values, grasslands are good locations for wind farms and thus are highly likely to be affected by externalities of wind power development. However, the negative externality effects of wind farms on the ecosystem have not raised enough attention in academic research.

According to the scientific literature (Baidya Roy, Pacala, and Walko 2004; Baidya Roy and Traiteur 2010; Zhou et al. 2012; Rajewski et al. 2013), by changing wind speed, turbulence, and vertical mixing, wind turbines can affect the surface meteorology band and thus the vertical distribution of energy and exchange between land surface and atmosphere (Armstrong et al. 2014; Rajewski et al. 2014). The local effects a wind farm has on temperatures, moisture, and CO_2 concentrations can extend beyond 10 km of where the wind turbines are located (Fitch, Lundquist, and Olson 2013; Lundquist et al. 2019) and thus, have externalities to the growth of vegetation in a relatively large surrounding area. On one hand, some of these externalities are beneficial for vegetation. For example, enhanced CO_2 levels in vegetation canopies during daytime hours can stimulate vegetation growth and higher nighttime temperatures can increase

vegetation productivity by reducing the frequency of frost. On the other hand, higher nighttime temperatures also reduce vegetation productivity by enhancing plant respiration and the nutrient metabolism rate. Hence, although there is a consensus that microclimate effects from wind turbines exist, their net effect on vegetation growth is still an open question.

In our study, we aim to fill the knowledge gap by examining the externality effect of wind farms on grassland quality in China's setting as it has a large scale of wind power capacity distributing across the country and grasslands covering vast geographical areas of various types. We design a difference-in-differences study with varying treatment intensities to investigate the effect of wind power development on grassland quality. Specifically, we compare counties with and without wind power development before and after the operation of wind farms with different cumulative wind power capacity densities (i.e., treatment intensities). We obtain a rich panel dataset by combing county-level data of cumulative wind power capacity, remote sensing data on the normalized difference vegetation index (NDVI) and other county level characteristics. It allows us to clearly identify the causal effect measuring the ecological externality of wind power development at the county level by controlling for many covariates such as time-invariant county characteristics, national and provincial level shocks, and weather fluctuation.

We find that wind power development has a negative effect on grassland quality indicated by NDVI, which is robust to potential spillovers on neighboring counties. We further explore the underlying mechanism. In addition to the microclimate effect, wind power may affect grassland quality indirectly by encouraging more economic activities, as pointed by several studies (Brown et al. 2012; De Silva, McComb, and Schiller 2016; Xia and Song, 2017b). After controlling for labor input and livestock output, we find that the negative correlation between wind power density and grassland quality is still significant. We also explore three sources of heterogeneity by county location, wind endowment, and vegetation conditions. Relevant

results suggest that grassland quality is less negatively affected in counties with higher latitude, fewer wind resources, and more precipitation. Taken together, these findings suggest that microclimate changes induced by wind power development play the important channel to reduce grassland quality.

We contribute to the existing literature in two aspects. First, we identify a new mechanism of grassland degradation, which, to our knowledge, has not been rigorously addressed. In many countries, there are payment-for-ecosystem-services (PES) programs designed to protect this important ecosystem from over-exploitation (Landell-Mills and Porras 2002; Adhikari and Agrawal 2013). They may face simultaneous issues of fragile ecosystem protection and wind power development. Identifying and measuring the externalities of wind power development on grasslands can help enhance coordination of the public policies to support renewable energy and ecological protection, and thus make more efficient usage of public funding.

Second, our study contributes to the growing literature on the externalities of wind energy or even more broadly renewable energy. A growing body of literature explores various sources of externalities of wind energy or even more broadly renewable energy. Wind energy has gained global support because it contributes to climate mitigation and pollution control goals. From 2005 to 2019, global electricity supplied by wind power increased from 0.6% to 5.6%, making a significant contribution to the transition to a low-carbon economy (International Energy Agency 2019). Economic theory suggests that the efficient public support such as subsidy for wind power critically depends on the overall externalities it brings to the society. While the positive environmental externalities are well recognized, the negative externalities of wind power development are worth in-depth investigating. Existing studies have examined wind farm externalities such as noise impacts and visual disamenities (Heintzelman and Tuttle 2012; Jensen, Panduro, and Lundhede 2014; Gibbons 2015).

The remainder of the paper is organized as follows. Section 2 introduces the relevant

literature and discusses grassland use and wind power development in the context of China. Section 3 describes the data used for the analysis and outlines the identification strategy. Section 4 discusses the main results with robustness checks and heterogeneous effects. Section 5 concludes with the policy implications of the findings.

2. Background

Grassland degradation and protection in China

China has a natural grassland area of nearly 400 million hectares, accounting for 41.7% of the country's total land area and 13% of the world's grassland area, ranking second in the world. Similar to many developing countries, China has experienced serious grassland degradation as 90% of its natural grasslands has degraded in varying degrees, with more than 1/3 of them being moderately and severely degraded (Gang et al. 2014; Zhou et al. 2022). Previous studies explain the causes of degradation mainly from the perspectives of overgrazing driven by population growth, economic development, and land tenure reforms (Briske et al. 2015; Li et al. 2018; Liu et al. 2020; Zhou et al. 2022).

To cope with grassland degradation, the Chinese government invested in several national programs when it realized the severity of the issue. For example, the Conversion of Cropland to Forest and Grassland Program (CCFGP) implemented between 2000 and 2012 involved the return of marginal cultivated land to forestry, shrub land, or artificial grasslands. The CCFGP paid land user households in cash or through supply of grain commensurate with the income or grain production that was foregone (Hua and Squires 2015). Focusing on the pastoral areas, the Returning Grazing to Grassland Program (RGGP) was implemented between 2000 and 2013. In addition to the compensation paid to households for grazing restrictions, resources were invested in fence construction, pasture improvement, and more intensive livestock production systems (Brown, Waldron, and Longworth 2008)

The most recent and largest program is regulated by the Grassland Ecological Compensation Policy (GECP). The first 5-year program, GECP-I, was implemented in eight grassland-rich provinces (Gansu, Inner Mongolia, Ningxia, Qinghai, Sichuan, Tibet, Xinjiang, and Yunnan) between 2011 and 2015. As the first pastoralist-focused PES program, the Chinese government invested 77.4 billion RMB (over 10 billion US dollars), with most of the funding paid directly to herders to compensate for the reduction in grazing intensity or the cessation of grazing activities (Ministry of Agriculture 2011; Ministry of Finance of China 2016). The second 5-year program, GECP-II, was expanded to include additional five provinces in 2016 and was supported with a larger budget of 93.8 billion RMB (nearly 15 billion US dollars).[1]

While academic studies and government policies mainly focus on grazing-related human activities for the investigation on grassland degradation and the measures for grassland protection, issues such as wind farm deployment have never been noticed. Our study therefore contributes to the literature on the sustainable use of grasslands by exploring the ecological effect of wind power development.

China's wind power development and potential externalities

China is the world's largest installed base of wind power capacity. Its cumulative capacity reached 237,029 MW in 2019, accounting 36% of the world's total capacity.[2] Meanwhile, the wind resources also show dramatic regional disparity, mainly concentrated in the Northeast, North, and Northwest ("Three North") areas of the country (He and Kammen 2014). To promote wind power development, a feed-in-tariff was introduced in 2009 that divides China into four pricing zones, reflecting different wind resources and engineering-related factors. The concentration of wind resources in Zone I and Zone II encouraged China's early development strategy focusing on the favorable regions (Xia and Song 2017a; Dong et al. 2018). Appendix Figure A1 shows that wind resource rich regions (Zone I and II) greatly overlap with major

grassland areas. In the eight grassland-rich provinces covered by the GECP-I, the installed capacity accounts for 47% of China's total capacity during the study period.

While the primary focus of the literature on wind power is its emission reduction effects as a clean energy (Cullen 2013; Kaffine, McBee, and Lieskovsky 2013; Novan 2015), there has been a growing number of studies that attempt to identify externalities of wind power development from economic and social perspectives. Noise effects and visual disamenities from wind turbines are often capitalized into property values or captured by reported health problems. Relevant literature shows that nearby wind facilities reduce property values (Heintzelman and Tuttle 2012; Jensen, Panduro, and Lundhede 2014; Gibbons 2015; Dres and Koster 2016) and increase the risk of annoyance and self-reported sleep disturbance (Knopper and Ollson 2011; Schmidt and Klokker 2014).

Measured by employment, personal income, tax, or public goods, Brown et al. (2012) and De Silva, McComb, and Schiller (2016) find local economic benefits from wind farms in the US. However, wind power development in China does not benefit the local economy as much as in the US. While wind power capacity increases GDP per capita, it has negative effects on local fiscal income due to tax exemption policies, large-scale investment by non-locally registered state-owned enterprises, and the high wind power curtailment rate (Xia and Song, 2017b).

More specific economic outcomes, such as crop yields, have been examined by several studies. Rajewski et al. (2013) and Rajewski et al. (2014) are part of the Crop Wind Energy Experiment project, aiming to understand the scientific links between wind turbines, local climate, and crops through field experiments at a large wind farm in the US state of Iowa. Although they have proposed mechanisms that influence surface micrometeorological conditions in the near lee of turbines, the more accurate measurements of plant growth and yield influences of turbines have not been provided. Kaffine (2019) conducts the first

econometric analysis of the net effect of wind farm microclimates on crop yields. Using US county-level data, the study finds that wind power development increases yields of corn, soy, and hay, but has no significant impact on wheat yields. Focusing on farms in the US state of Illinois, Chen (2019) also find a positive effect of wind development on crop returns. The heterogeneous effects of microclimates on vegetation growth documented by Kaffine (2019) highlight the need for more studies to draw conclusions about more extensive ecological effects of wind farms.

3. Data and Identification Strategy

We use the counties mainly engaged in livestock production as the sample of analysis and focus on seven provinces in China, namely Gansu, Inner Mongolia, Ningxia, Qinghai, Sichuan, Xinjiang, and Yunnan (provinces highlighted in Appendix Figure A1, but excluding Tibet). As the first provinces targeted by the GECP, these provinces have the most abundant grassland resources and are also rich in wind resources.[3] The sample period is from 2004 to 2010.

NDVI and grassland type

Derived from infrared channel and near-infrared channel remote sensing data, NDVI has been widely used as an indicator to quantify grassland quality (Piao et al. 2006; Gong et al. 2015). The relatively simple structure of the grassland ecosystems renders the use of remote sensing data attractive in studying vegetation dynamics. The value of NDVI ranges between 0 and 1, with a larger value indicating a more healthy and dense vegetation canopy. Monthly NDVI data at a spatial resolution of 1×1 km^2 are acquired from the MOD13A3 product from NASA's Earth data for the period of 2004–2010.[4] We use the mean monthly NDVI within a year to measure the grassland conditions in the growing season, which is the outcome variable of primary interest.

In our study area, grasslands can be divided into four types according to the characteristics of the grassland plant community, namely meadow, steppe, shrub, and desert (China Vegetation Editorial Committee 1980). Information on grassland types comes from the 1:1 million Vegetation Atlas of China, published in 2001. To obtain the area of different types of grassland for each county, we overlay the county map with the digitized Vegetation Atlas provided by the Environmental and Ecological Science Data Center for West China and the National Natural Science Foundation of China. To generate the share of grasslands by type for each county, the area of different types of grasslands is divided by the total area of grasslands.

Wind power capacity and wind resource

We aggregate the wind power capacity of wind plants over 6,000 KW located in the same county, which is obtained from China Electricity Statistics. This represents over 85% of total capacity during the sample period. The cumulative wind power capacity is divided by county size to generate wind power capacity density, which provides a normalized measure of wind power development for counties of different sizes. While no sample county had plants over 6,000 KW in 2004, wind power capacity grew rapidly from 0.25 KW/km^2 in 2005 to 33.15 KW/km^2 in 2010 (reported in Appendix Table A1). Appendix Figure A2 shows the distribution of wind power capacity from 2005 to 2010, suggesting the agglomeration effect and the geographical expansion of wind power investment.

Wind resource is a key determinant of wind power capacity installed in a county. Wind resources are categorized into seven classes by wind power density (from 0 W/m^2 to 2,000 W/m^2), with class four and above suitable for developing wind farms (Chinese national standard (GB/T 18710-2002)).[5] According to this classification, we set the class of wind resources for each county by overlaying the county map with data on wind power density from the National Meteorological Administration. Counties categorized as class four and above are

considered to be rich in wind resources.

Meteorological and socioeconomic data

Daily precipitation (mm) and temperature (°C) measured at the county level are originally obtained from the National Meteorological Information Center of China. A widely used spatial interpolation method proposed by Thornton, Running, and White (1997) is first applied to impute data for counties without national stations. A cross-validation analysis is then performed to validate the accuracy of the imputations (Zhang, Huang, and Yang 2013). Precipitation is calculated as the cumulative rain in the growing season from April 1 to September 30. Growing degree days (GDD) are calculated as:

$$\sum_{d=Apr1}^{Sept30}\left(\frac{T_{max,d}+T_{min,d}}{2}-5\right) \quad [1]$$

where $T_{max,d}$ is the daily maximum temperature, and $T_{min,d}$ is the daily minimum temperature. Following previous studies, the maximum temperature is fixed at 30 °C. Using 5 °C (41 °F) as the base temperature, negative GDDs are recorded as zero.

Information on labor for livestock production come from the China County Statistical Yearbook. Information on the year-end livestock inventory come from the China Database on County-level Agricultural and Rural Indicators, which are compiled by the Ministry of Agriculture and managed by the Institute of Agricultural Information of the Chinese Academy of Agricultural Sciences. The original data were collected by each county's statistical station and then reported to upper-level statistical bureaus.

Descriptive statistics

The variables above are summarized in Appendix Table A1, with Panel A reporting counties without wind power development, and Panel B reporting counties with wind power development. The descriptive statistics show differences between the two groups in most

variables. With less precipitation (273 mm vs. 513 mm), counties with wind power development had a smaller NDVI (0.4 vs. 0.6). Normalized by county size, in counties with wind power development, less people were engaged in livestock production (13 people per km^2 vs. 31 people per km^2) and less cattle were raised (10 heads per km^2 vs. 21 heads per km^2). These differences may create a bias in our fixed-effect estimation if they change over time.

To test whether the time trend of the two groups was parallel before the operation of any wind farm, we compare NDVI between counties with and without wind power development in the pre-operation period. The subsample includes counties with wind power development in the pre-operation years and all counties without wind power development.[6] Using 2004 as the baseline year, we regress NDVI on a vector of year dummies, a binary variable for counties that experienced wind power development, and their interaction terms. While the coefficient on the year dummies suggests whether variables from counties without wind power development changed significantly over time, the coefficient on the interaction terms indicates the difference in the time trend and its significance between counties with and without wind power development. Figure 1 plots the coefficient estimates for the interaction terms and the corresponding 95% confidence intervals. The estimates are near zero and statistically insignificant in all the years, suggesting that there was no significant difference in the time trend between the two groups before the operation of any wind farm.

[Insert Figure 1 Here]

Identification strategy

In addition to the comparison between counties with and without wind power development, the variations in cumulative capacity density within counties that experienced wind power development also allow us to explore the intensity of treatment. Our basic estimation equation is as follows:

$$y_{czpt} = \alpha_{czp} + \beta w_{czpt} + x_{czpt} + \theta_{zt} + \lambda_{pt} + \epsilon_{czpt} \quad [2]$$

where y_{czpt} is the NDVI for county *c* in zone *z* and province *p* in year *t*, w_{czpt} is cumulative wind power capacity density, and x_{czpt} is weather variables (i.e., precipitation and growing degree days). Following Kaffine (2019), we include quadratic weather variables in the preferred specification, with robustness checks controlling for linear or cubic weather variables, interactions between quadratic weather variables, or province-specific quadratic weather variables. α_{czp} is county fixed effects that controls for time-invariant county characteristics. The fixed benchmark pricing policy implemented in 2009 divides China's onshore wind resource into four zones, each with a different benchmark tariff (Appendix Figure A1). To ensure that the division is not correlated with NDVI either directly or through other channels, we control for zone-specific year fixed effects, denoted by θ_{zt}. λ_{pt} is province-specific year fixed effects, capturing time-variant characteristics at the province level such as the RGGP or other shocks.[7] ϵ_{czpt} is the error term. Standard errors are clustered by prefecture to allow spatial correlation. β is the coefficient of interest that captures the effect of wind power capacity density on NDVI.[8]

As we also use the variation in capacity density to identify the effect, the underlying assumption is that counties that experienced wind power development with different levels of intensity had a parallel NDVI trend before the initial operation. To test this assumption, we used the sample of counties that experienced wind power development to estimate:

$$y_{czpt} = \alpha_{czp} + \beta_1 D_{czpt}(-6 \le t - T_{czp} \le -4)W_{czp} + \beta_2 D_{czpt}(-3 \le t - T_{czp} \le -1)W_{czp} + \beta_3 D_{czpt}(1 \le t - T_{czp} \le 3)W_{czp} + \beta_4 D_{czpt}(4 \le t - T_{czp} \le 6)W_{czp} + x_{czpt} + \theta_{zt} + \lambda_{pt} + \epsilon_{czpt} \quad [3]$$

where T_{czp} is the last year before the initial operation, W_{czp} is the annual average of cumulative capacity density during the operation period, which indicates the intensity of treatment, and $D_{czpt}(-6 \le t - T_{czp} \le -4)$ is a binary variable indicating 4–6 years prior to

the last year before the initial operation. Similarly, $D_{czpt}(-3 \leq t - T_{czp} \leq -1)$ is a binary variable indicating 1–3 years prior to the last year before the initial operation, $D_{czpt}(1 \leq t - T_{czp} \leq 3)$ is a binary variable indicating the year of the initial operation and 2 years post, and $D_{czpt}(4 \leq t - T_{czp} \leq 6)$ is a binary variable indicating 3–5 years after the initial operation. x_{czpt}, α_{czp}, θ_{zt}, λ_{pt}, and ϵ_{czpt} are defined the same as in Equation [2]. Compared with the last year before the initial operation, we expect β_1 and β_2 to be close to zero and β_3 and β_4 to be different from zero.

To test the robustness of our estimate, we further augment the preferred specification of Equation [2] from three aspects. First, we control for prefecture-specific year fixed effects, trim our sample, or examine the relationship between current NDIV and future wind power development to show that our estimate is robust to potential variations in local grassland policies.[9] Comparing estimate controlling for prefecture-specific year fixed effects with that controlling for province-specific year fixed effects helps us investigate policy variations at the prefecture level. Moreover, considering that counties with marginal farmland or conserved land can be treated differently for wind power development, we run regressions with a trimmed sample, where the 5% of observations with the smallest NDVI and the 5% of observations with the largest NDVI are dropped from our sample. Finally, if counties with declining grassland quality were more likely to be targeted for wind power development, there would be a concern of reverse causality. We add capacity under construction (the difference between cumulative capacity density in year t +1 and year t) to investigate its relationship with wind power development. Second, we use the logarithm of NDVI as the outcome variable to test whether our estimate is robust to different measures of grassland quality. Third, we add density of labor for livestock production and livestock density to examine whether wind power capacity density affects NDVI through economic channels. The argument that renewable energy can stimulate economic growth and create jobs is often used to justify supportive policies. There have been

many studies estimating the impact of wind power development on local economies (Brown et al. 2012; De Silva, McComb, and Schiller 2016; Xia and Song 2017b). We focus on labor input and livestock output for two reasons. First, although there can be many economic channels through which the impact of wind power development is translated into the change in grassland quality,[10] livestock production is the last node in the transmission path that directly affects grassland quality. Hence, as long as we control for livestock production, potential economic channels are likely to be closed. Second, as the traditional semi-nomadic pastoralism prevalent in our study area uses very little external inputs such as seedling, irrigation, and haying (Xia et al. 2020), livestock production is measured by labor input and livestock output. Therefore, we add density of labor for livestock production and livestock density to explore the economic channels.

4. Results

The estimates provide robust evidence that wind power capacity density has a negative effect on NDVI. As we do not find that wind power capacity density significantly changes labor input and livestock output, the economic factors are unlikely to transmit the effect of wind power capacity on NDVI. In addition to the main results, we examine the potential spillover issue and explore the heterogeneity of the effect.

Main results

Table 1 reports the basic results from estimating Equation [2]. With a point estimate of -0.144, the effect from estimating the preferred specification is negative and significant (Column 1); increasing capacity density by one standard deviation (0.02 MW/km^2) would be expected to lead to a reduction in NDVI of 0.5% from the mean value of 0.57. This estimate is robust to controlling for precipitation and growing degree days in various specifications (Columns 2 to

5).[11] Regardless of the specifications, the estimates consistently support the negative relationship between wind power development and NDVI with similar magnitudes.

[Insert Table 1 Here]

A key assumption underlying the analysis above is that counties that experienced wind power development were not on a different NDVI trend before the operation of wind farms. To examine this assumption, we estimate Equation [3] with a subsample including only counties that experienced wind power development. Let Year 0 be the last year before the initial operation, and Figure 2 plots the coefficient estimates (β_1-β_4) and the corresponding 95% confidence intervals before and after the initial operation as explained in Section 3. As we expect, the estimates in the pre-operation periods are close to zero and statistically insignificant, suggesting that there was no significant difference in the NDVI trend before the operation of wind farms. By contrast, in the post-operation periods, particularly in the long term, wind power development has a negative and significant effect on NDVI.

[Insert Figure 2 Here]

In the absence of a different pre-trend, Table 2 further tests the robustness of our estimate. Columns 2 to 5 consider the variations in grassland policies across counties. Compared with the result from estimating the preferred specification using province-specific year fixed effects to capture variations in grassland policies, the inclusion of more disaggregated prefecture-specific year fixed effects only slightly increases the point estimate from -0.144 to -0.135 (Column 1 vs. Column 2). This suggests that policy variations across prefectures within a province are limited, and/or there are policy variations across prefectures within a province but the variations are not correlated with wind power development. Although the comparison cannot provide solid evidence to conclude policy variations at the county level, it increases our confidence that local governments seem implement comparable policies and/or policies not correlated with wind power development. If there are county-level variations in grassland

policies, we suppose that counties with marginal farmland or conserved land are most likely to be treated differently for wind power development. Hence, we estimate the effect of wind power development using the trimmed sample with province- and prefecture-specific year fixed effects included respectively. Relevant results are reported in Columns 3 and 4, suggesting that after dropping counties with the smallest and largest NDVI, the effect remains statistically significant and of a similar magnitude to the estimates using the entire sample. In Column 5, we add capacity under construction in the preferred specification to examine whether counties with declining grassland quality are more likely to be targeted for wind power development. As new investment is not significantly correlated with NDVI and adding it does not substantially change the coefficient on wind power capacity density, reverse causality is not a serious concern for our estimation.

Finally, we report the log-linear estimate of the preferred specification in Column 6 of Table 2. The coefficient on wind power capacity density can be interpreted as a 29% reduction in NDVI due to one MW additional increase in capacity density. It is equivalent to a 0.6% reduction in NDVI due to one standard deviation (0.02 MW/km^2) increase in capacity density, which is comparable with the 0.5% reduction from the mean value estimated by the linear specification.

[Insert Table 2 Here]

The preceding estimates establish robust evidence of a negative effect of wind power capacity density on NDVI. Table 3 further examines whether economic factors rather than the microclimate change drive the effect. We first estimate the effect of wind power development on economic activities. We do not find that wind power development has a significant impact on labor input (Column 1) and livestock output (Columns 2 and 3). Next, we regress NDVI on wind power capacity density controlling for labor input and livestock output. The estimate reported in Column 4 is similar to that from the preferred specification (Column 1 of Table 1),

suggesting that labor density is not a channel through which wind power development affects NDVI. Although the estimates reported in Columns 5 and 6 are half of that from the preferred specification (Column 1 of Table 1), they do not support livestock output as a channel, as the smaller estimates are due to missing data on livestock output in 2004 and 2005 (refer to Column 7 as a comparison).[12] However, the estimates varying by sample years indicate that the long-term effect seems larger than the short-term effect, which is also illustrated by Figure 2. We speculate that the results indicate a long-term cumulative effect of microclimate changes on grassland vegetation. There is supporting evidence from the biology literature showing that the climate factors have chronic and significant cumulative impact on vegetation growth (Wen et al., 2019; Zhao, et al., 2020). But as we do not have data to test the effect in a longer period or examine specific mechanisms, we acknowledge that this is a limitation of our study.

[Insert Table 3 Here]

Accounting for out-of-county spillovers

Given that microclimate effects from wind turbines can extend for 10 km or more (Fitch, Lundquist, and Olson 2013; Lundquist et al. 2019), wind farms in one county may have spillover effects on the NDVI of neighboring counties and bias our estimate to the externality. In the absence of wind farm locations, we are unable to calculate the distance between the wind farm and the county centroid to accurately quantify potential spillovers. Instead, we use the distance between the centroids of two counties as an approximation and allow variations in the cut-off distance to examine whether potential spillovers significantly bias our estimate. Neighboring capacity density is defined as wind power capacity in neighboring counties within a certain distance divided by own county size.[13] From Table 4, it does not appear that out-of-county spillovers substantially alter our conclusion about the effect of own capacity density, with the estimates varying between -0.146 and -0.135. Consistent with the effect of own wind

power development, wind power capacity in neighboring counties also reduces NDVI, supporting the existence of out-of-county spillovers.[14]

[Insert Table 4 Here]

Heterogeneous effects and microclimate effect

Exploring heterogeneity further helps us detect whether the microclimate change is the main mechanism of the negative effect of wind power on grassland. Three sources of heterogeneity are explored, including county location, wind endowment and vegetation conditions. As variables used to divide sample counties are often correlated with geographic location, investigating heterogeneous effects from each source separately may bias the estimate due to omitted variables. Therefore, we included different sources of heterogeneity in one regression to avoid the potential endogenous problem. Table 5 reports the results with the three sources of heterogeneity interacted with wind power capacity density.

County location: The first heterogeneity source considered is the county location indicated by the GPS coordinates of the county centroid. Several studies find that enhancing plant respiration and nutrient metabolism rate during nighttime hours can inhibit vegetation growth (Zhou et al. 2012; Rajewski et al. 2013). The northern hemisphere nighttime decreases with the increase of latitude from the vernal equinox (around March 20) to the autumnal equinox (around September 23). This period is the growing season for grasslands in China. We expect that high latitude areas are less affected by wind power development than low latitude areas.

Columns 1 to 4 of Table 5 reports the results with both the longitude and the latitude interacted with wind power capacity density. The results in all the specifications consistently show that the negative effect of wind power development on NDVI is weakened by about 0.03 as latitude increases by an additional degree. The change of longitude does not have any significant effect. As our study area has a large span from north to south (Appendix Figure A3),

this heterogeneous effect is large. Given the same level of capacity density, moving southward by one standard deviation (7.46 degrees) leads to a reduction in NDVI of 39% from the mean value of 0.57.

Wind endowment: As wind speed affects the efficiency of wind turbines which further determines the magnitude of the microclimate effect, the negative effect may be more significant in windier counties. As we expected, wind endowment reinforces the negative effect of wind power development on NDVI (Column 1), although its statistical significance depends on how we measure the heterogeneity of vegetation conditions (Columns 2 to 4).

Vegetation conditions: We use four variables to measure vegetation conditions. The first variable divides grasslands according to the characteristics of the grassland plant community, among which meadow or steppe with high soil moisture are compared with shrub and desert with low soil moisture. The second and third variables use the 800 mm annual precipitation as the cutoff to investigate heterogeneous effects by the moisture level.[15] While the third variable indicates counties with average annual precipitation during our sample period exceeding 800 mm, the fourth one indicates those with minimum annual precipitation during our sample period exceeding 800 mm. The fourth variable is constructed by NDVI in 2003 to capture the initial condition of grassland. We use the standard deviation of initial NDVI of counties with wind power development to divide sample counties into three groups. Counties with initial NDVI between the negative and positive one standard deviation are set to be the reference group, which is compared with counties with initial NDVI smaller than the negative one standard deviation and those with initial NDVI larger than the positive one standard deviation, respectively.

We do not find vegetation conditions divided by the characteristics of the grassland plant community (Column 1) or measured by initial NDVI (Column 4) significantly alters the negative effect of wind power development on NDVI. However, with a point estimate of 0.588,

a large amount of precipitation exceeding 800 mm in each year during our study period significantly weakens the negative effect of wind power development on NDVI (Column 3). This is consistent with Kaffine (2019) that finds no effect on wheat yields in semi-arid conditions and increasing corn yields in more humid areas.

[Insert Table 5 Here]

In addition to supporting the microclimate mechanism, these heterogeneous effects in terms of different geographical characteristics have implications for policy making. Since governments are unlikely to implement policies based on each specific geographical characteristic, we further run zone-specific regressions to provide simple suggestions that can be incorporated into wind power policies. From Appendix Table A3, we cannot conclude on Zone III because its coefficient is insignificant but very comparable with that of Zone II. However, a comparison of the other three zones suggests that the negative effect of wind power development on NDVI is larger in Zone IV and Zone I than Zone II.

5. Conclusions

Grassland degradation and subsequent adverse environmental consequences are an important global concern, especially for developing countries. Though climate change is recognized as one of the contributing factors to grassland degradation, the overall effects and underlying mechanisms are not fully understood. In this paper, we reveal a new mechanism of the interaction between climate change and grassland degradation differing from previous studies. The wind power, which is considered as a key technology to address the concerns of the climate change, may cause damage to grassland vegetation through changing the local climate. Using China's county-level data, we estimate the effect of wind power development on grassland quality. The econometric analysis shows that the wind power capacity density is negative associated with the NDVI, which is an indicator of the quality of grassland. Increasing capacity

density by one standard deviation (0.02 MW/km^2) would be expected to lead to a 0.5% reduction in NDVI. The results are robust to potential spillovers on neighboring counties.

Excluding economic activities as a transmission channel, heterogeneous effects by county latitude consistently suggest that higher latitude areas with shorter nighttime hours in the growing season are less affected by the negative externality. The correlation between nighttime hours and the size of the externality supports microclimate effects as the main mechanism. In addition, less consistent heterogeneous effects by wind endowment and vegetation conditions suggest that scarce wind resources and abundant precipitation may help weaken the negative externality of wind power development to NDVI.

Many developing countries have support policies for both ecosystem protection and renewable development. Economic theory suggests that an efficiency subsidy to support wind power should be equal to the social cost of environmental damage it can avoid. As grasslands play a key role in providing ecosystem services and afford the livelihood for millions of herders, future wind power policies and ecological policies may include a relevant compensation scheme. According to Hou et al. (2021), the GECP-I invested 77.4 billion RMB (over 10 billion US dollars) between 2011 and 2015 and led to a 3% increase in NDVI. As the GECP mainly compensates herders for their economic losses due to the reduction in grazing intensity or the cessation of grazing activities (Ministry of Agriculture 2011), potential ecological benefits are not completely captured by the payment. In the absence of literature on valuing ecological consequences of NDVI change, we could not directly infer the externality costs of wind power on grasslands. But our study shows that the compensation could target for specific areas, to achieve a more efficient outcome.

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Table 1. Effect of wind power capacity density on NDVI

	(1) NDVI	(2) NDVI	(3) NDVI	(4) NDVI	(5) NDVI
Capacity density (MW/sq.km)	-0.144***	-0.137***	-0.145***	-0.147***	-0.138***
	(0.039)	(0.041)	(0.039)	(0.037)	(0.034)
County fixed effects	Yes	Yes	Yes	Yes	Yes
Zone-year fixed effects	Yes	Yes	Yes	Yes	Yes
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes
Quadratic weather	Yes	No	No	No	No
Linear weather	No	Yes	No	No	No
Cubic weather	No	No	Yes	No	No
Weather interactions (quadratic)	No	No	No	Yes	No
Province-weather (quadratic)	No	No	No	No	Yes
Observations	3,066	3,066	3,066	3,066	3,066
R-squared	0.993	0.993	0.993	0.993	0.994
Mean of NDVI	0.573	0.573	0.573	0.573	0.573
Sd. of NDVI	(0.238)	(0.238)	(0.238)	(0.238)	(0.238)
Mean of capacity density	0.001	0.001	0.001	0.001	0.001
Sd. of capacity density	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)

Notes: Weather variables are precipitation and growing degree days from April to September. Robust standard errors in parentheses are clustered at prefecture level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 2. Robustness check for the preferred specification

	(1) NDVI	(2) NDVI	(3) NDVI	(4) NDVI	(5) NDVI	(6) Log(NDVI)
Capacity density (MW/sq.km)	-0.144***	-0.135***	-0.142***	-0.136***	-0.148***	-0.291***
	(0.039)	(0.019)	(0.036)	(0.018)	(0.042)	(0.095)
Capacity density under construction (MW/sq.km)					-0.032	
					(0.061)	
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Zone-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Province-year fixed effects	Yes	--	Yes	--	Yes	Yes
Quadratic weather	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year fixed effects	No	Yes	No	Yes	No	No
Trim	No	No	Yes	Yes	No	No
Observations	3,066	3,066	2,761	2,761	3,066	3,066
R-squared	0.993	0.996	0.992	0.995	0.993	0.994

Notes: Weather variables are precipitation and growing degree days from April to September. Robust standard errors in parentheses are clustered at prefecture level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 3. Test for the economic channel

	(1) Labor density (K/sq.km)	(2) Cattle density (K/sq.km)	(3) Sheep density (K/sq.km)	(4) NDVI	(5) NDVI	(6) NDVI	(7) NDVI
Capacity density (MW/sq.km)	0.002	-0.003	-0.053	-0.148***	-0.080***	-0.077***	-0.080***
	(0.002)	(0.004)	(0.048)	(0.042)	(0.029)	(0.026)	(0.026)
Labor density (K/sq.km)				0.210		0.063	
				(0.193)		(0.130)	
Cattle density (K/sq.km)					-0.042	-0.043	
					(0.054)	(0.054)	
Sheep density (K/sq.km)					0.045**	0.045**	
					(0.017)	(0.017)	
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zone-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,050	2,164	2,165	3,050	2,164	2,152	2,152
R-squared	0.983	0.783	0.831	0.993	0.995	0.995	0.995
Mean of dependent variable	0.028	0.019	0.056	0.572	0.575	0.575	0.575
Sd. of dependent variable	(0.035)	(0.021)	(0.072)	(0.238)	(0.237)	(0.237)	(0.237)
Mean of capacity density	0.001	0.002	0.002	0.001	0.002	0.002	0.002
Sd. of capacity density	(0.016)	(0.019)	(0.019)	(0.016)	(0.019)	(0.019)	(0.019)

Notes: Weather variables are precipitation and growing degree days from April to September. Robust standard errors in parentheses are clustered at prefecture level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 4. Robustness check for spillovers

	(1) Neighboring Counties <=40km	(2) Neighboring Counties <=60km	(3) Neighboring Counties <=80km	(4) Neighboring Counties <=100km	(5) Neighboring Counties <=120km
Capacity density (MW/sq.km)	-0.146***	-0.145***	-0.145***	-0.144***	-0.135***
	(0.040)	(0.038)	(0.035)	(0.032)	(0.025)
Neighboring capacity density (MW/sq.km)	-0.078	-0.052	-0.086*	-0.091***	-0.071***
	(0.112)	(0.094)	(0.050)	(0.034)	(0.021)
County fixed effects	Yes	Yes	Yes	Yes	Yes
Zone-year fixed effects	Yes	Yes	Yes	Yes	Yes
Province-year fixed effects	Yes	Yes	Yes	Yes	Yes
Quadratic weather	Yes	Yes	Yes	Yes	Yes
Observations	3,066	3,066	3,066	3,066	3,066
R-squared	0.993	0.993	0.993	0.993	0.993

Notes: Weather variables are precipitation and growing degree days from April to September. Robust standard errors in parentheses are clustered at prefecture level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Table 5. Heterogeneous effects of wind power capacity density on NDVI

	(1) NDVI	(2) NDVI	(3) NDVI	(4) NDVI
Capacity density (MW/sq.km)	-0.277	-0.258	-0.218	-0.267
	(0.353)	(0.372)	(0.274)	(0.255)
Capacity density*Longitude	0.008	0.010	0.011	0.016
	(0.009)	(0.008)	(0.009)	(0.011)
Capacity density*Latitude	0.028*	0.034**	0.030**	0.027*
	(0.016)	(0.015)	(0.014)	(0.015)
Capacity density*High wind endowment (wind power class >= 4)	-0.487*	-0.402	-0.423	-0.406
	(0.267)	(0.316)	(0.283)	(0.285)
Capacity density*Share of meadow or steppe	0.199			
	(0.454)			
Capacity density*Average annual precipitation >= 800 mm		0.202		
		(0.418)		
Capacity density*Minimum annual precipitation >= 800 mm			0.588**	
			(0.294)	
Capacity density*NDVI in 2003 < 0.24				0.136
				(0.357)
Capacity density*NDVI in 2003 > 0.59				-0.034
				(0.082)
County fixed effects	Yes	Yes	Yes	Yes
Zone-year fixed effects	Yes	Yes	Yes	Yes
Province-year fixed effects	Yes	Yes	Yes	Yes
Quadratic weather	Yes	Yes	Yes	Yes
Observations	3,066	3,066	3,066	3,066
R-squared	0.993	0.993	0.993	0.993

Notes: The omitted category for wind endowment is wind power class <=3. The omitted category for grassland type is grassland with lower soil moisture (shrub or desert). The omitted category for NDVI in 2003 is between 0.24 and 0.59, which is between the negative and positive one standard deviation of NDVI in 2003 for counties with wind power development. The omitted category for precipitation is annual precipitation below 800 mm. Weather variables are precipitation and growing degree days from April to September. Robust standard errors in parentheses are clustered at prefecture level. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

Figure 1. Difference in NDVI in the pre-operation period

Notes: To test the parallel trend assumption, we compare NDVI between counties with and without wind power development in the pre-operation period. The subsample includes counties with wind power development in the pre-operation years and all counties without wind power development. Using 2004 as the baseline year, we regress NDVI on a vector of year dummies, a binary variable for counties that experienced wind power development, and their interaction terms. The coefficient on the interaction terms indicates the difference in the time trend and its significance between counties with and without wind power development. The figure reports the coefficient estimates for the interaction terms. The figure also shows the 95% confidence intervals with standard errors clustered at county level.

Figure 2. Difference in NDVI before and after the initial operation

Notes: To examine whether counties that experienced wind power development with different levels of intensity were on a parallel NDVI trend before the operation of wind farms, we estimate Equation [3] with a subsample including only counties that experienced wind power development. Let Year 0 be the last year before the initial operation, and the figure reports the coefficient estimates (β_1-β_4) for different time periods before and after the initial operation as explained in Section 3. The figure also shows the 95% confidence intervals with standard errors clustered at county level.

Footnotes

[1] The five provinces are Hebei, Shanxi, Liaoning, Jilin, and Heilongjiang.

[2] Data were obtained from Global Wind Statistics at https://library.wwindea.org/global-statistics/

[3] Tibet is excluded as it had no installed wind power and low development potential.

[4] More detailed information about the dataset can be found in Didan (2015).

[5] GB/T 18710-2002 is specified in the methodology of wind energy resource assessment for wind farms, which can be obtained from the National Library of Standards at http://www.nssi.org.cn/nssi/front/gbdetail.jsp?A001=NTE0ODkx

[6] Descriptive statistics on data from the subsample are reported in Appendix Table A2.

[7] Among the grassland policies that we introduced in the background section, the relevant program is the RGGP implemented in pastoral areas between 2000 and 2013. The CCFGP targeted cropland in agricultural areas (i.e., non-pastoral areas). Our sample counties are from pastoral areas and thus not affected by the CCFGP. The GECP has been implemented since 2011. Our research period is 2004-2010 and thus not affected by the GECP.

[8] A prefecture is an administrative unit at the next higher level than a county. We have 76 prefectures in our sample.

[9] From the perspective of decision-making process, the grassland policy during our sample period was unlikely to be correlated with the wind power development. The wind power development in China had been largely driven by policy support. Therefore, the government played an important role in developing wind farms, including the location choice (many studies have reviewed the supporting policies for China's renewable energy, refer to Liu and Kokko 2010; Zhao, Wang, and Wang 2012; Hu et al. 2013; Liu 2013, etc). The location selection criteria considered were mainly the wind resource and the grid connection conditions. The grassland policy was in charge of National Forestry and Grassland Administration. There was

no banning of wind development until 2019 when a new policy was released by National Forestry and Grassland Administration. The new policy bans wind power development in the critical ecological function areas. The policy can be found on the official website at https://www.forestry.gov.cn/main/72/20190328/102937724393971.html

[10] For example, economic growth may improve the consumption level of local residents with more meat demanded. This can stimulate livestock production and reduce grassland quality. Meanwhile, employment opportunities in other industries with higher wages may attract herders to abandon livestock production, which can increase grassland quality.

[11] Column 2 controls for linear precipitation and linear growing degree days. Column 3 controls for cubic precipitation and cubic growing degree days. Column 4 interacts quadratic precipitation and quadratic growing degree days. Column 5 interacts the quadratic weather variables with province fixed effects.

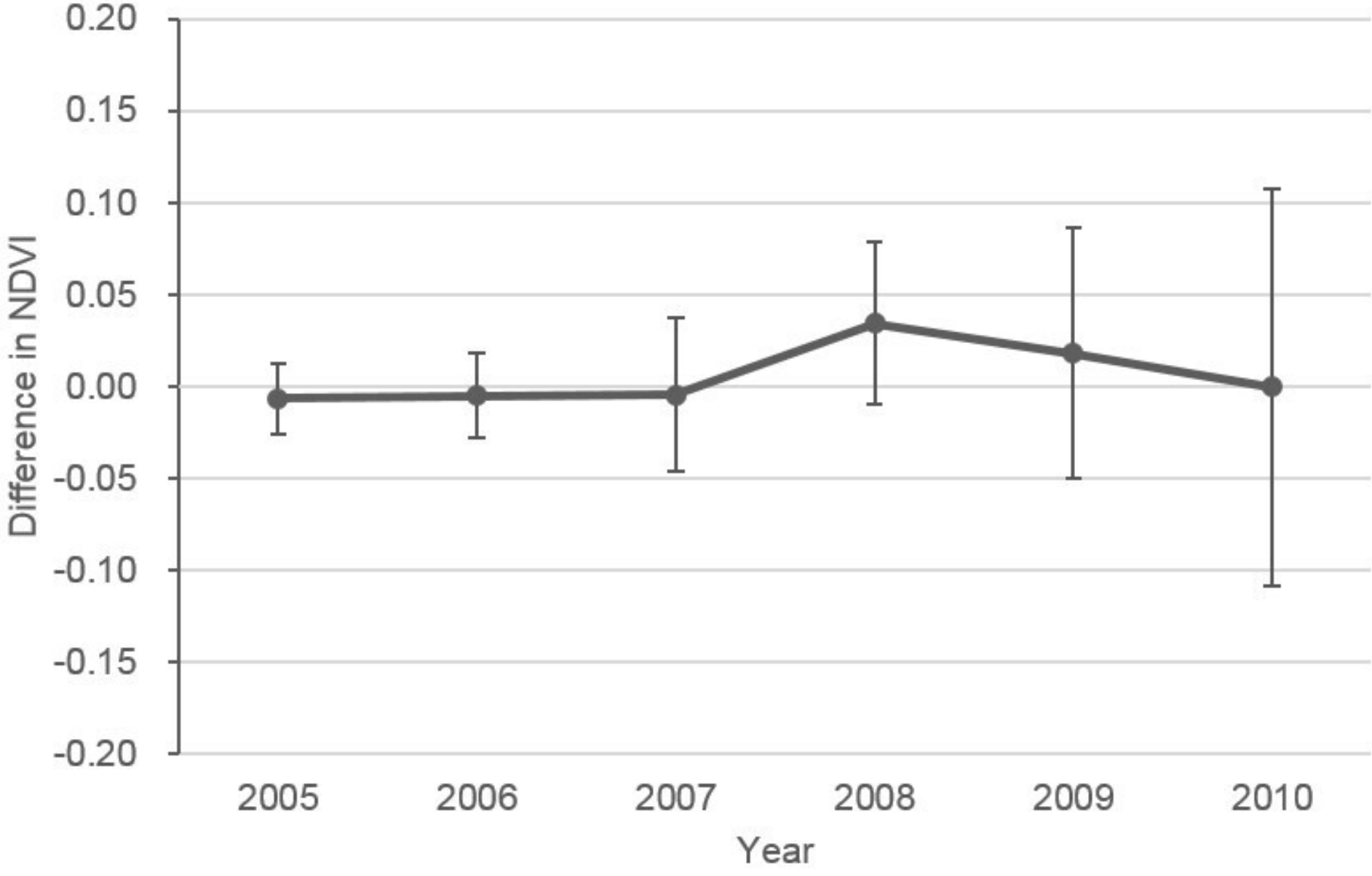
[12] Column 7 uses the same sample as Column 6. Column 7 does not control for labor input and livestock output.

[13] Neighboring counties included counties in provinces not selected as sample provinces for our main analysis. For example, some counties in Inner Mongolia share boundaries with counties in Heilongjiang. If the counties in Heilongjiang experienced wind power development, we included their wind power capacity as neighboring capacity, although we do not study NDVI for counties in Heilongjiang.

[14] With an average county size of 10,048 km^2, 60 km seems too small to identify spillovers from neighboring counties, so we do not find significant spillovers for within 40 km and 60 km in Table 4.

[15] The 800 mm annual precipitation line is of great significance to the geographical boundary of China. It is the boundary between North and South China, the boundary between paddy fields and dry lands, the boundary between subtropical and warm temperate zones, the

boundary between subtropical monsoon climate and temperate monsoon climate, and the boundary between freezing and non-freezing rivers.


0.20
0.15
0.10
0.05
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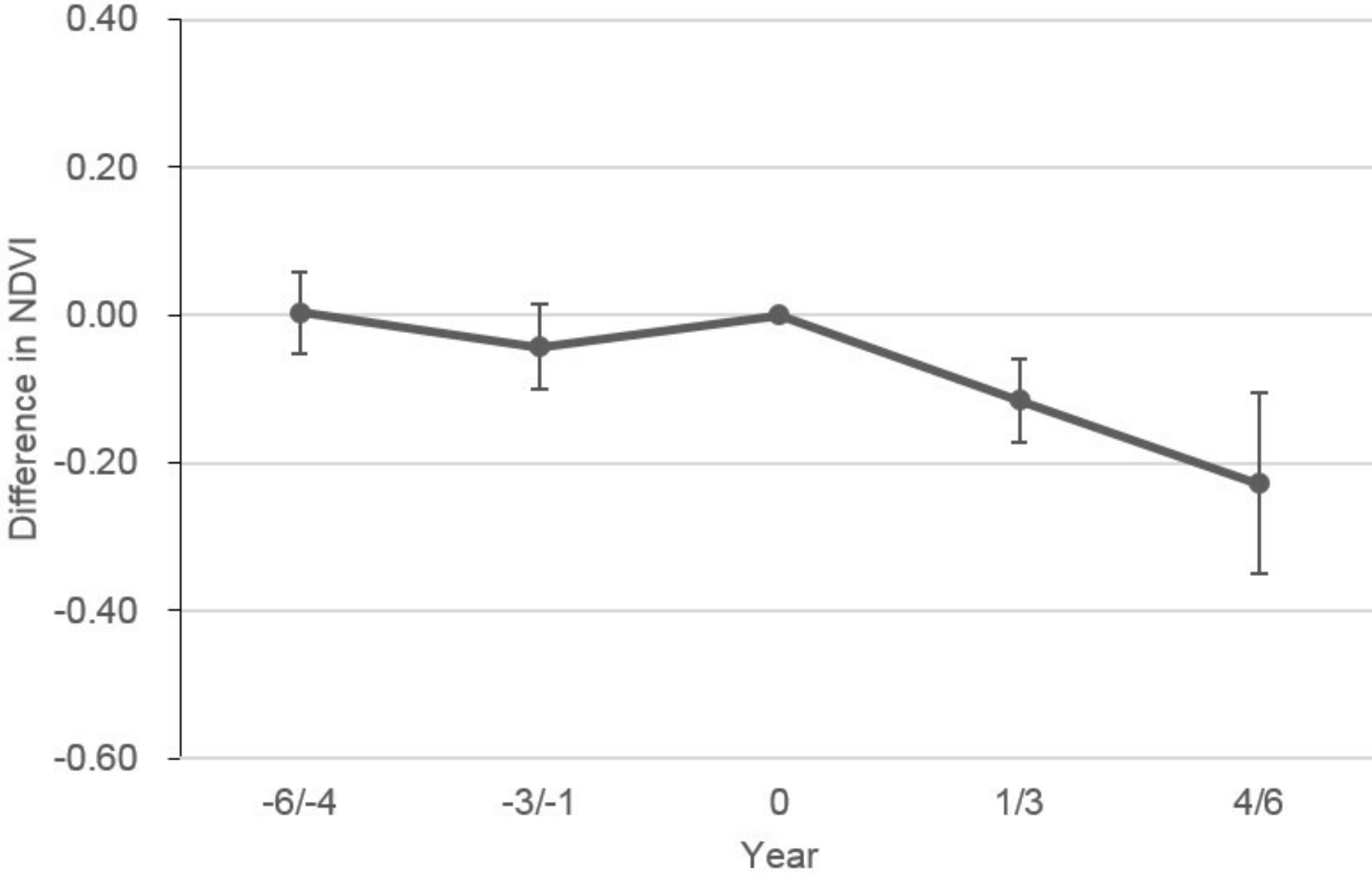
Difference in NDVI
2005
2006
2007
2008
2009
2010
Year


0.40
0.20
0.00
-0.20
-0.40
-0.60
Difference in NDVI
-6/-4
-3/-1
0
1/3
4/6
Year