# Three Essays on Applied Environmental Economics

by

**Hsing-Hsiang Huang**

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Natural Resources and Environment)
in the University of Michigan
2016

**Doctoral Committee:**

Professor Michael R. Moore, Chair
Associate Professor Johannes Foufopoulos
Adjunct Associate Professor Gloria E. Helfand
Associate Professor Ryan M. Kellogg

# Acknowledgements

I am very grateful to my advisor, Dr. Michael Moore, for his advice, kindness, patience, and supports.  I am truly blessed to have had the opportunity to work with him.  I also thank my committee members, Drs. Johannes Foufopoulos, Gloria Helfand, and Ryan Kellogg for the friendly and thought-provoking suggestions.  Finally, I would like to express my deep gratitude to my wife, Diana, and my parents in Taiwan for their love and supports.

**Table of Contents**

## List of Tables

## List of Figures

## List of Appendices

# Chapter 1

# Government Agricultural Programs, Moral Hazard, and Land-Use Adaptation to Weather Risk in the U.S. Midwest

## 1 Introduction

As the climate system is unequivocally warming, extreme precipitation and drought are more likely to occur both in the short-run and in the long-run in North America (IPCC 2013; Christensen et al. 2013; Climate Prospectus 2014). Questions about changes in local temperature and precipitation events have been of practical importance to most of society (Brooks, 2013). Agricultural production is of particular importance due to its direct connection to local weather and its related economic and societal impacts on, for instance, economic growth (e.g., Dell et al. 2012; Burke et al. 2015), migration (e.g., Feng et al. 2010; Hornbeck 2012), and human conflict (e.g., Miguel et al. 2004; Hsiang et al. 2013). Understanding the impact of climate change on agriculture requires knowing how farmers might adapt to the risk of climate change.

In the climate economics literature, voluminous work examining adaptation to climate change is largely linked to climate change impact assessments that identify the extent to which agricultural outcomes are sensitive to climate variables (e.g., Mendelsohn et al. 1994; Schlenker et al. 2005; Deschenes and Greenstone 2007; Burke and Emerick 2015). Yet, specific adaptation strategies through which the agricultural outcomes might be sensitive to climate variables have not been explicitly identified. For instance, in both Mendelsohn et al. (1994)'s seminal paper and Burke and Emerick (2015)'s recent paper, crop switching is only implicitly suggested to be a possible reason for their relatively low estimates of climate impact. As a result, the little direct evidence about behavioral adaptation from the climate change impact assessment literature is of limited use to decision makers (Tol et al. 1998).

While the underlying adaptation mechanisms are not well known via the climate impact studies, recent studies in development economics have shown that farmers' response to weather risk may help to insure them against climate change (Kala 2014; Miller 2014), even though their responses are not sensitive to climate change (Kala 2014). Estimating the link between behavioral adaptation and weather risk is a crucial step for explaining why crop yields may or may not be sensitive to climate change, and examining how crop choice and supply ultimately may shift in response to climate change.

Understanding farmers' private adaptation decision to weather risk will also be useful for designing government programs to efficiently deal with the risk (Mendelsohn 2000). Existing government programs, such as disaster payment or crop insurance programs, are mainly aimed at smoothing the impact of extreme temperature and precipitation and have been provided generously in the United States and other developed countries (Smith and Goodwin 2010). The importance and cost of these government programs will likely increase given that, induced by climate change, extreme temperature and precipitation are more likely to occur. However, government programs may distort farmers' adaptation decisions and thus may actually make farmers more sensitive to changes in extreme weather (Annan and Schlenker 2015). Moral hazard is assumed to play a significant role in this increased sensitivity to extreme weather. Yet, empirical evidence explicitly examining the effect of government programs on farmers' adaptation to weather risk and climate change is limited. While Annan and Schlenker (2015) suggest that the U.S. federal crop insurance program gives farmers a disincentive to reduce the damage of extreme heat during the growing season, which adaptation strategies involve moral hazard is ambiguous. In fact, most adaptation strategies to possible weather shocks must be taken by farmers before the growing season in the U.S. Corn Belt (Haigh et al. 2015). Because farmers' adaptation choices are unobserved by researchers, whether government programs affect an adaptation strategy that farmers should have engaged against weather risk is an open question.

The purpose of this paper is to fill this gap by focusing on the crop-choice decision related to land use (hereafter labelled cropping pattern, or how much cropland to allocate to various crops), which potentially is an adaptation strategy to weather risk and, in addition, is also susceptible to moral hazard created by government agricultural programs. This paper examines the effect of precipitation on cropping pattern, as well as whether a change in federal disaster assistance policy in 2008 distorts these decisions, i.e., a moral hazard problem due to the policy change. Not only do most farmers make crop decisions by the early spring, farmers in the U.S. Corn Belt also make federally-sponsored crop insurance decisions by the March 15 deadline for corn and soybeans. Thus, our identification strategy relies on the exogenous variation in pre-plant precipitation. To test whether the moral hazard behavior occurs after the policy change in 2008, we interact random variation in pre-plant precipitation with the policy change in 2008. By exploiting the two natural experiments, we can identify the effect of the policy change in 2008 on cropping pattern adaptation to pre-plant precipitation.

In this setting, in which weather variation is plausibly unrelated to farmers' behavior, unobserved characteristics of land and farmers may be correlated with both cropping pattern and the level of pre-plant precipitation. For instance, the level of pre-plant precipitation is more likely to be lower in an arid area where farmers have adapted to the higher probability of low precipitation. We control for this time-invariant unobserved heterogeneity with fixed effects. By using fine-scale spatial data, we pair a panel of crop-based land use with pre-plant precipitation for 2001 to 2011 at a one-square-mile level, containing 640 acres. According to the Public Land Survey System (PLSS), the one-square-mile blocks of farmland, called *sections*, tend to have only a few owners within a section.[1] In addition to accounting for unobserved heterogeneity with the section fixed effects, use of the section as the unit of analysis also takes advantage of fine-scale weather data. This avoids the problem in many earlier studies of a small variation in precipitation variables when using spatially aggregated data.

The problem of small variation in precipitation variables may arise when large-scale weather data and/or location fixed effects are used. While temperature is a large-scale weather event, precipitation tends to be a micro-scale weather event because it can be affected by local vegetation and geography, and it intrinsically varies more spatially than does temperature.

[1] A section contains four quarter sections. A quarter section, 160 acres with one-half mile on each side, is the land unit that was distributed for free through the 1862 Homestead Act to individuals who promised to settle and farm the land. It is foundation of ownership. We do not use quarter section as our analytical unit because it does not cover all parts of our study areas in North Dakota and Iowa. In addition, in 2010 the average farm size in North Dakota and Iowa is 1,241 and 333 acres, respectively. Both are larger than 160 acres. Though we cannot observe the actual farm size and ownership of each farm, the use of section-level observations can ensure that the section is owned by limited owners or operators who are the farmers sensitive to the variation in pre-plant precipitation.

Mearns et al. (2001) and Fezzi and Bateman (2015) show that past climate impact studies that analyze a large spatial scale, such as county level or country level, and that use aggregated precipitation data may fail to capture the high variation of precipitation and underestimate the importance of the effect. Fisher et al. (2012) also shows that the use of fixed effects can absorb a significant amount of weather variance. Here, we use micro-scale precipitation data to avoid this problem, and we follow Fisher et al. (2012) to test the variation of precipitation under fixed effects. The fine-scale data in weather and crop choice also facilitate estimation of a flexible model that can detect nonlinearities and breakpoints in the effect of pre-plant precipitation on cropland allocated to four major crops, similar to the methodology used by Schlenker and Roberts (2009) and Burke and Emerick (2015).

The states of North Dakota and Iowa are selected for analysis because both states have fine-scale cropland use data dating back to 2001. In North Dakota, we focus on the region east of the 100th meridian where farming is possible without irrigation. Moreover, we allow heterogeneous behavioral adaptation to pre-plant precipitation by state. For example, a wide variety of crops are planted in North Dakota, implying that farmers there have relatively more crop substitution options when facing drought risk. Also, evidence shows that North Dakota has experienced substantial land conversion from grassland to cropland in recent years (e.g., Mehaffey et al. 2012; Wright and Wimberly 2013), implying that farmers in North Dakota may be more sensitive to weather variance given that the converted cropland tends to be marginal land. Our results confirm that farmers in North Dakota are much more sensitive to pre-plant precipitation than farmers in Iowa. When pre-plant precipitation is too little or too much, they plant fewer acres in corn, which is relatively water-sensitive, and more acres in soybeans and wheat. This implies that farmers are risk-averse and cropping pattern is a major adaptation strategy in North Dakota.

In the analysis of the effect of government programs, we focus on a federal disaster assistance policy shock in 2008 from the Supplemental Revenue Assistance Payments (SURE) program. After 2008, the SURE program that was included in the federal crop insurance program substantially reduced deductibles. Moreover, the SURE program that was based on a whole-farm revenue approach was likely to favor farmers with a single crop (Shields 2010). We compare the two regimes before and after 2008 to find that, in North Dakota after 2008, farmers experiencing deficit or excess pre-plant precipitation plant more acres in corn and fewer acres in other crops than farmers experiencing the same pre-plant precipitation before 2008. Moral hazard associated with *ex ante* crop insurance provides a plausible explanation of the distorted risk-taking behavior. It implies that farmers in North Dakota are able to insure against adverse weather outcomes. It also implies that the highly subsidized crop insurance program can crowd out other means of risk management like cropping pattern.

In the case of Iowa, we find that the moral hazard problem might have occurred slightly before 2008, as cropping pattern is not sensitive to pre-plant precipitation. After 2008, the moral hazard problem is apparent only under excess pre-plant precipitation. The small relative effect implies that this policy change in 2008 exerts only a minor effect on cropping pattern in Iowa.

The paper proceeds as follows. Section 2 details the behavioral and institutional background. Section 3 describes the empirical strategy. The data are discussed in section 4. Section 5 presents the empirical results. Section 6 offers concluding remarks.

# 2 Background

## 2.1 Cropping pattern adaptation to precipitation in the U.S. Corn Belt

Crops need water to grow. The amount of water available for crop growth depends on the interaction between precipitation and soils' water-holding capacity. In the western Corn Belt states, the amount of rainfall is usually favorable and the soil is deep with a high water-holding capacity for corn to grow without irrigation or with only supplemental irrigation. However, relative to other crops, corn is sensitive to water stress (Steduto et al. 2012). Anderson et al. (2012) compare the sensitivity of crop growth to water inputs and report that corn is more sensitive to drought than other major crops in this region, such as soybeans, wheat, and alfalfa. Hence when farmers expect a water deficit, other crops should substitute for corn.[2]

Both precipitation prior to the growing season and precipitation during the growing season are important for crop growth, as the total precipitation from both seasons largely supplies the water available for crops. However, relative to precipitation during the growing season, three specific incentives are provided by pre-plant precipitation for farmers' adaptation decisions. First, pre-plant precipitation can affect root growth. Precipitation from October through April is

[2] In Table 2 of Anderson et al. (2012), the index of water-use efficiency (WUE) is compared between major crops in the United States. The WUE index is used to proxy for a crop's average sensitivity to water. The WUE index of corn is set to be 1 as a baseline. Relative to corn, the WUE indices of the major crops in the region of our study are: 0.65 for soybeans, 0.71 for wheat, 0.43 for alfalfa, 0.85 for barley, and 0.48 for sunflower. That is, in comparison to corn, other major crops have smaller WUE values, indicating those crops are relatively less sensitive to water supply.

important in this region for recharging soil moisture for root growth (Neild and Newman 1990). Water from precipitation must be stored in soils prior to the growing season, so it is available for root growth during the growing season.

Second, pre-plant precipitation can affect crop growth through indirect mechanisms. Iowa experienced exceptionally warm winters in 2011 and 2012. Research shows that lower pre-plant precipitation affected insect ecology and water quality, which resulted in poor crop production in those years (Al-Kaisi et al 2013). On the other hand, excess pre-plant precipitation can increase the risk of seedling diseases. Farmers may delay or extend the planting period, but this increases the risk of losing yields in the late summer (Steduto et al. 2012; Urban et al. 2015).

Third, pre-plant precipitation can affect farmers' expectation of total water available for crop growth. Evidence shows that positive (negative) snowfall anomalies in winter are associated with wetter (drier) than normal conditions during the summer in this region (Quiring and Kluver 2009). Our data also support this relationship. Thus, while precipitation during the growing season is unobserved prior to planting, the realized lower (higher) precipitation prior to the growing season should directly signal to farmers that the likelihood of experiencing drier (wetter) condition for crops growth is higher.

Previous research in a development context documents that ambiguity-averse and risk-averse farmers are able to adjust to abnormal precipitation prior to the growing season. For instance, Miller (2014) demonstrates that farmers in India adapt to the expected precipitation during the growing season by changing crops, based on information about precipitation in recent years, soil types, and weather forecasts. Kala (2014) shows that farmers in India use the onset signals, such as the first date of monsoon plantings in recent years, for optimal planting time, suggesting that past precipitation information can proxy for prior expectation of monsoon onset in the current year.

In the U.S. Corn Belt, farmers make most weather-sensitive decisions before and during winter (Haigh et al. 2015). Yet, empirical evidence on whether pre-plant precipitation affects adaptation decisions is limited. In response to water stress based on the realized pre-plant precipitation, adaptation decisions may include changes in crops, rotations, tillage, cover crops, land use, fertilizer and pesticide purchase, and crop insurance (e.g., Haigh et al. 2015; Malcolm et al 2012). In this paper, we focus on crop-choice decisions due to the availability of high-resolution agricultural land-use data.

This paper is related to an immense agronomic and economic literature on crop choice, in which climate/weather conditions are the main explanatory factors. Many of these studies are based on a profit-maximizing model with either assumed or unknown adaptation by farmers. Many studies also use either annual precipitation or precipitation during the growing season, from March to September in the United States, but ignore behavioral adaptation to pre-plant precipitation. Our work examining behavioral adaptation to pre-plant precipitation is related to the development economics literature mentioned above (e.g., Miller 2014; Kala 2014; Rosenzweig and Udry 2014), which allows farmers to react to precipitation prior to the growing season. Like Miller (2014), crop choice (i.e., planting area) is the adaptation strategy investigated in this paper. Unlike Miller (2014), which attempts to explicitly model predicted growing-season precipitation and its effect on crop-choice decisions, our variable of interest is local pre-plant precipitation. We treat the realized pre-plant precipitation as a random shock for farmers that signals precipitation risk and estimate whether farmers respond to the shock by changing cropping pattern decisions.

## 2.2 The Supplemental Revenue Assistance Payments Program

Governments in developed countries have long provided agricultural disaster assistance programs to help crop producers recover from financial losses stemming from natural disasters. Since the 1980s, the U.S. federal government has primarily relied on two policy tools, crop insurance and *ad hoc* crop disaster payments (Chite 2008). Two advantages of crop insurance, according to policymakers, are its ability to replace costly disaster payments and to provide assistance to more producers. Relative to disaster payments, crop insurance is also viewed as providing lower incentives for moral hazard and for planting crops on marginal lands (Glauber and Collins 2002). Hence, since the federal crop insurance program was first instituted in 1938, major legislative programs in 1980, 1994, and 2000 made the program more affordable to farmers, and thereby increased farmer participation levels, in expectation of reducing reliance on *ad hoc* disaster payments (Shields and Chite 2010). However, the program failed to replace disaster payments despite substantial growth in the participation rates. The two policy tools have co-existed as ways for farmers to manage the risk of natural disaster, as Congress continued to establish *ad hoc* disaster assistance primarily through emergency supplemental appropriations for a wide array of USDA programs. Thirty-nice acts established disaster payments to farmers between 1989 and 2007, and such payments were provided every year during this period (Chite 2010).

In an effort to terminate disaster payments and to deal with risk management in pre-designed rather than *ad hoc* programs, Congress authorized a new program in the 2008 Farm Bill, the Supplemental Revenue Assistance Payments (SURE) program (Shields 2010). The SURE program supplemented the crop insurance program by compensating producers for that portion of crop losses that was ineligible for an insurance indemnity payment, i.e., that portion of losses that was part of the deductible on the policy. The SURE payment level increased with the amount of the farmer's insured coverage. To be eligible for the SURE payment, a farmer had to purchase crop insurance on all planted crops. Then to qualify for a payment, the relevant farm had to be located in a county declared as a disaster by the USDA Secretary, to be located in a county bordering a disaster county, or to have experienced crop losses that exceeded 50% of expected yield. The SURE program was in place from 2008 through 2011.

Prior research has argued that the SURE program was likely to encourage moral hazard by both increasing crop insurance participation rates and changing crop-choice decisions. First, farmers could insure close to 100 percent of their expected yields when they combined SURE payments and the indemnities received from their insurance policies (Smith and Watts 2010). Before 2008, farmers were not allowed to insure more than 75 or 85 percent of their expected crop yields with the federal crop insurance program. The virtual absence of a deductible creates moral hazard. Empirical evidence by Bekkerman et al. (2012) shows that the SURE program substantially increased crop insurance participation rates, measured by the ratio of net insured acres to total planted acres at the county level, especially in counties where producers were more likely to receive SURE payments and thus to exploit opportunities for moral hazard.

Second, SURE payments were based on a whole-farm revenue approach whereas, prior to 2008, disaster payments were based on crop-specific losses. As a result, the SURE program was likely to favor farmers with a single crop, which increased the chance that a farm would drop below its guaranteed revenue threshold that triggered program payments. In order to take advantage of SURE payments, farmers might eliminate crops from their rotations, thereby reducing the diversity inherent in a portfolio of crops (Shields 2010).

Empirical evidence is limited on the effect of the SURE program on land use or land use adaptation to weather risk. Here, we investigate whether the SURE program affects farmers' cropping pattern decision in response to pre-plant precipitation. The treatment period for the program runs from 2009 through 2011, at which time the program was discontinued due to pressure on the federal budget. If the program affected cropping pattern and crop choice, this is new evidence on how government programs can distort adaptation to extreme weather and climate change.

Our study relates to numerous studies examining the effect of crop insurance program on land use and a few studies examining the effect of disaster payments in the agricultural economics literature (e.g., Goodwin et al. 2004; Langpap and Wu 2014; Schoengold et al. 2014) . The effect of these types of programs on farmers' response to weather risk has not been studied. We select the SURE program as our case study because fine-scale land use data is available before and after the program was enacted.

Our work is also related to few recent studies in development economics that conduct a randomized controlled trial in India to elicit the effect of a rainfall insurance program on farmers' response to pre-plant weather (e.g., Cole et al. 2014; Mobarak and Rosenzweig 2014). We use the SURE program as a quasi-natural experiment to examine the effect of an agricultural risk assistance program on farmers' response to pre-plant weather risk. Part of our results is consistent with their findings that a risk assistance program induces farmers to switch to riskier crop production.

## 3 Empirical model

The objective of this paper is to investigate farmers' cropping pattern adaptation to pre-plant precipitation that signals potential water available for crop growth, as well as to investigate the role of government-provided crop disaster assistance in farmers' cropping pattern adaptation. We accomplish these by exploiting random year-to-year variation in pre-plant precipitation and an exogenous change in disaster payment policy induced by the 2008 Farm Bill.

Prior research has demonstrated strong nonlinearity in the relationship between precipitation during the growing season and crop yield outcomes (e.g., Burke and Emerick 2015). The fact that both water shortage and water excess limit crop growth may motivate farmers to change farmland use based on the realized precipitation, as explained in Section 2.1. Many of the previous studies use higher order terms of precipitation to capture the nonlinear effect. However, using these functional forms in a panel setting means that a unit-specific mean re-enters the estimation, raising omitted variables concerns, as identification in the panel models is no longer limited to location-specific variation over time (McIntosh and Schlenker 2006). In order to identify both the effects of water-shortage and water-excess risk on farmers' cropping pattern response to realized pre-plant precipitation, we use a piecewise linear approach following Schlenker and Roberts (2009) and Burke and Emerick (2015).

We model log planting area of a crop $y_{it}$ in section *i* in year *t* as a simple piecewise linear function of total pre-plant precipitation from October 1 to March 15 with a kink at $p_0$. The effect of the disaster payment policy change in 2008 on cropping pattern adaptation to precipitation risk is identified with the interaction terms between our precipitation variables $prec_{it}$ and a policy dummy $d_{it}$ equal to 1 if the year is after 2008. We estimate the fixed effects model:

$$y_{it} = \alpha_i + \beta_1 prec_{it;p<p_0} + \beta_2 prec_{it;p>p_0} + \beta_3 prec_{it;p<p_0} d_{it} + \beta_4 prec_{it;p>p_0} d_{it} + \gamma temp_{it} + \delta_t + t^2 + \epsilon_{it} \quad (1)$$

where the variable $prec_{it;p<p_0}$ is the difference between pre-plant precipitation and $p_0$ interacted with an indicator variable for pre-plant precipitation being below the threshold $p_0$. $prec_{it;p>p_0}$ is similarly defined for pre-plant precipitation above the threshold. We allow the data to determine $p_0$ by looping over all possible thresholds and selecting the model with the lowest sum of squared residuals. The variable $temp_{it}$ is the average pre-plant temperature from October 1 to March 15. $\alpha_i$ is a section fixed effect that controls for unobserved time-invariant characteristics that affects cropland use, such as climate and land quality. Because the PLSS aligns with ownership and farm-management patterns, the section fixed effect can also control for farmer characteristics such as management skills, risk perception, and adaptation ability (Holmes and Lee 2012). Year fixed effects $\delta_t$ account for unobserved common year-specific effects across sections, such as crop prices. Similar to Annan and Schlenker (2015), we include a quadratic time trend $\delta_t^2$, which is common to a state, to control for a yield trend that might affect the cropland use decision.

Our key parameters of interest are the set of $\boldsymbol{\beta}$. $\beta_1$ and $\beta_2$ provide estimates of how farmers respond to pre-plant precipitation. $\beta_3$ and $\beta_4$ provide estimates of whether the crop disaster payment policy change in 2008 gives farmers a disincentive to change crops in response to the risk of deficit or excess precipitation.

There is a concern with this empirical approach. The inclusion of section fixed effects can absorb a significant amount of the variation of interest in our precipitation variables (Fisher et al. 2012). We follow Fisher et al. (2012) to explore this issue, and demonstrate that the residual variation in our pre-plant precipitation changes of interest remains large after accounting for section fixed effects, as shown in Section 5.1.

# 4 Data

## 4.1 Sections

The Public Land Survey System (PLSS) imposed a grid of squares on the acquired lands of the early United States. It provides the basic ownership reference system for all states except for 18 eastern states, Hawaii, and Texas. The Fifth Principal Meridian was planned in 1815 to govern the origin of the grid for North Dakota and Iowa (Committee on Integrated Land Data Mapping 1982). The PLSS typically divides land into 6-mile-square townships. Each square mile in a township is a section, and a section consists of 640 acres. A section is further subdivided into four one-half-mile-square, 160-acre, quarter sections. The legal description of land starts with a quarter section. Hence, the PLSS provides the foundation for land ownership within the two states.

We analyze farmers' cropping pattern at the section level, although our data on cropland use, weather, soil, and irrigation has a higher resolution than the section level, and even higher than the quarter section level. The 1-by-1 mile section grid scale facilitates comparison of grids across years when the grid spacing of the cropland data changed from 56m to 30m during the 2001-2012 study period. The grid scale also makes the local precipitation impact analysis tractable.

We study cropping pattern in the entire state of Iowa and in the area east of the 100th meridian in North Dakota, including 28 counties. We exclude the sections that do not consist of a regular 1-by-1 mile square. Many of the excluded sections are near a county border. Sections that have irrigated land are also excluded.[3] The study area includes 27,151 and 50,020 sections in North Dakota and Iowa, respectively.

## 4.2 Cropland use

The cropland use data are from the National Agricultural Statistics Service's Cropland Data Layer (CDL) program, which provides raster-formatted geospatial data on crops planted and other non-agricultural types of land cover for the United States. Each grid corresponds to a specific crop planted or a type of land cover. The CDL's land cover classifications include over 50 crops and come with a spatial resolution of 30 m or 56 m. The CDL program started producing the annual land cover data for some states in 1997 and has covered the entire United States since 2008. North Dakota and Iowa are two states with a relatively long panel of annual CDL data. We begin the study in 2001 because the entire state of Iowa is first covered that year and, in addition, a major change in crop insurance policy that increased subsidies for premiums was enacted with the 2000 Agricultural Risk Protection Act (ARPA).

Using Python language for ArcGIS, we intersect CDL data with the PLSS sections, and calculate planting area for each crop planted within a section as an aggregation of the CDL grids within the section. We construct a balanced panel of planting area for the crops chosen within the PLSS sections for 2001-2012. Since CDL data before 2006 are less reliable, we focus on crops with high classification accuracy, ranging from 85% to 95%, including corn, soybeans, and spring wheat. In addition, as setting aside farmland or planting alfalfa is also a strategy for replacing water-sensitive crops, we create a variable of non-cropland land cover from CDL data, called grassland. Since CDL data are less reliable for differentiating among alfalfa, fallow/idle cropland, unmanaged grassland, pasture, and hay, these land covers are reclassified and combined into a single grassland land cover category.

[3] The sections containing irrigated agriculture are obtained based on the 250-m scale irrigation map in 2007 from the Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US). The fine-scale irrigation data is publicly available. See Brown and Pervez (2014) for documentation.

Table 1.1 presents summary statistics for mean area by state for corn, soybeans, spring wheat, and grassland, averaged over the sections and sample period. The most common crops in eastern North Dakota are spring wheat and soybeans, which have about 228 acres per section. While corn is not planted extensively in many sections in North Dakota, it is the most common crop in Iowa. Soybeans are next, while wheat is not a major crop in Iowa. Moreover, grassland is a major type of land cover in both states, especially in North Dakota. Figure 1.1 presents acreage change of major types of cropland use across years. On average, acreages of corn and soybeans in North Dakota are larger after 2008 than those before 2008, while acreages of corn and soybeans are relatively stable between the two periods in Iowa. Besides, grassland acreage decreases after 2008 in the both states.

## 4.3 Weather

Our weather data are drawn from Schlenker and Roberts (2009), which consist of daily precipitation and maximum and minimum temperatures at 4-by-4 kilometer grid cells for the entire United States over the period 1950-2013.[4] For each cell, we obtain pre-plant precipitation by calculating the accumulated precipitation from October 1 in the previous year to March 15 in the current year. We also obtain pre-plant temperature by averaging over the same period for each cell. The temperature data begin as the daily-average temperature. Using the Python language for ArcGIS, these weather data cells are intersected with the PLSS sections. The pre-plant precipitation and temperature at the section level are then computed by averaging over the intersected cells' pre-plant precipitation and temperature, respectively.

Mean pre-plant precipitation in North Dakota is 124.96 mm, which is lower than 234.34 mm of Iowa, as shown in Table 1.1. Iowa also has relatively larger variation in pre-plant precipitation. In North Dakota relatively low pre-plant precipitation occurred during 2001-2008, while relatively high pre-plant precipitation occurred after 2008, as can be seen in Figure 1.2. This figure also presents different forms of nonlinear relationship between pre-plant precipitation and land use before and after 2008 for each crop. Figure 1.3 shows that there were relatively high and low pre-plant precipitation events before 2008 in Iowa. Moreover, the relationships between pre-plant precipitation and land use before and after 2008 in Iowa are somewhat similar for each crop.

[4] We thank Wolfram Schlenker for sharing the weather data.

## 4.4 Soil

We obtain soil characteristics from USDA's Soil Survey Geographic (SSURGO) database. This spatially high-resolution database provides 10-by-10 meter grid cells for the entire United States. We extract data on land capacity classification and calculate area-weighted average land capacity for each section. Land capacity classification shows the suitability of soils for most kinds of field crops. The criteria used in grouping the soils involve the landscape location, slope of the field, depth, texture, reaction of the soil, erosion hazard, wetness, rooting-zone limitations, and climate, which are associated with both soil water-holding capacity and farmers' cropping pattern decisions. Class 1 and Class 2 are defined as good quality soils for cropping. Class 3 and Class 4 are moderate quality soils that have severe limitations for cropping and/or require careful conservation practices. Poor quality soils in Class 6, Class 7, and Class 8 have very severe limitations that make them generally unsuited to cultivation. The time-invariant soil data set is used for testing farmers' heterogeneous behavioral adaptation by soil quality.

As shown in Table 1.1, both the mean and standard deviation of weighted land capacity are larger in North Dakota, indicating that land quality in Iowa is generally better than in North Dakota. Figure 1.4 presents the distribution of weighted land capacity for our sample in North Dakota and Iowa. Iowa has about 20 percent good quality land, while North Dakota does not have any good quality land with weighted land capacity less than 2. Iowa has no poor quality land, while North Dakota has a small amount of poor quality land.

# 5 Results

This section is divided into three subsections. The first explores the extent of variation in the precipitation variables in the statistical models we employ. The second provides estimation results for North Dakota. The third provides estimation results for Iowa.

## 5.1 The variations in pre-plant precipitation

Our empirical approach relies on inter-annual variation in pre-plant precipitation after adjustment for section and year fixed effects. Following Fish et al. (2012), we explore how much of the variation is absorbed by the fixed effects. Table 1.2 summarizes regressions of pre-plant precipitation against different sets of fixed effects: (i) an intercept; (ii) section fixed effects; (iii) section plus year fixed effects. The table reports $R^2$, the standard deviation of the residual pre-plant precipitation variation not absorbed by the fixed effects in millimeter equivalent, and the fraction of residuals with an absolute value larger than 10 mm.

In North Dakota, the standard deviation of pre-plant precipitation is 47.0 mm with section fixed effects. Although the variation declines after including year fixed effects, the remaining variation of 19.9 mm provides enough residual variation in the data to proceed with the semi-parametric approach. The subsequent standard errors support this conclusion. The same conclusion applies for the variation in pre-plant precipitation in Iowa, as the remaining variation with section and year fixed effects is 27.6 mm.

## 5.2 Empirical results in North Dakota

Figure 1.5 graphically presents our main results for estimates of the impact of pre-plant precipitation and whether the policy change in 2008 affects cropping pattern adaptation to pre-plant precipitation in North Dakota. Tables 1.3-1.6 report estimates based on equation (1) for corn, soybeans, spring wheat, and grassland, respectively, using data from 2001 to 2011. In the piecewise linear approach, we allow the data to determine the threshold for each crop by looping over all possible thresholds based on equation (1) and selecting the model with the lowest sum of squared residuals. The threshold of pre-plant precipitation obtained is 110 mm for corn, 70 mm for soybeans, 90 mm for spring wheat, and 120 mm for grassland. Because corn is relatively water-sensitive, corn planting acreage is expected to increase linearly up to an endogenous threshold of pre-plant precipitation and then decrease linearly above that threshold. At the same time, the change in acreage response of other crops to pre-plant precipitation is expected to go in an opposite way to the change in corn acreage.

In the following subsections, we report our main results by crop with several robustness checks. The first check examines whether our results are sensitive to soil characteristics. Both the water holding capacity and intrinsic productivity of soil varies by soil quality type. We estimate the impact separately for three types of soil based on weighted land capacity. Good-quality soil covers the sections with weighted land capacity from 1 to 2.99. Moderate-quality soil covers the sections with weighted land capacity from 3 to 4.99. Poor-quality soil covers the sections with weighted land capacity from 5 to 8.

The second robustness check examines whether our results are sensitive to the observations from 2008. We consider observations from 2008 as not subject to the policy change because the

SURE program was enacted on May 22, 2008, long after farmers made cropping decisions for 2008. Moreover, this program was the most complex program that USDA's Farm Service Agency had undertaken. It took some time to educate farmers about the program (Shields 2010). But we might worry that some farmers had reacted to policy debates on this program that occurred during 2007. We thus drop the observations from 2008 and compare the results.

The third robustness check examines potential endogenous variables that are correlated with both pre-plant precipitation and cropping decisions. These variables include the interaction term between pre-plant precipitation and temperature, aggregated precipitation from March 16 to May 31 (where May 31 is the last planting date in this region as required by the crop insurance policy), average temperature from March 16 to May 31, and precipitation in the prior growing season from April to September.

### 5.2.1 Estimates for corn

The main estimation results from equation (1) show that corn acreage is sensitive to pre-plant precipitation both below and above the threshold (see column (1) of Table 1.3 and panel (A) of Figure 1.5). Before the policy change in 2008, a 1 mm decrease in pre-plant precipitation below the threshold would decreases corn acreage by 0.6 percent, while a 1 mm increase in pre-plant precipitation above the threshold decreases corn acreage by 0.8 percent. The results imply that farmers adapted to abnormal pre-plant precipitation that signals the risk of growing conditions by planting fewer acres in corn. Moreover, the inverted-V-shape effect of pre-plant precipitation before 2008 from our estimation results is similar to the results regarding the effect of precipitation during the growing season on corn yields from past climate impact studies (e.g., Annan and Schlenker 2015; Burke and Emerick 2015).

After the policy change in 2008, however, the inverted-V-shape effect of pre-plant precipitation does not appear. We find that after 2008, a 1mm increase in pre-plant precipitation above the threshold actually *increases* corn acreage by 0.3 percent, while the estimated coefficient on the interaction term of pre-plant precipitation below the threshold is insignificant. The results imply that farmers choose to grow corn despite the risks of both deficit precipitation and excess precipitation. The policy change after 2008 introduces moral hazard into decision-making in North Dakota.

The results for precipitation above the threshold (both the non-interacted and interacted terms) are generally robust to the three soil quality types (columns 2-4 of Table 1.3). The estimated coefficients are highly significant and similar in magnitude to the main results. Below the precipitation threshold, however, an interesting results occurs with good-quality soil: the estimated coefficient on pre-plant precipitation is insignificant, which suggests that farmers can tolerate the risk of deficient precipitation when growing corn in these soils.

The main results remain robust when observations from 2008 are skipped, as can be seen in column 5 of Table 1.3. Lastly, when more control variables are included in the analysis, farmers remain sensitive to pre-plant precipitation above the threshold as in the main results.

### 5.2.2 Estimates for soybeans

The main estimation results are shown in column (1) of Table 1.4 and panel (B) of Figure 1.5. Note first that the threshold for pre-plant precipitation for soybeans is 70 mm, which is lower than the minimum pre-plant precipitation in the data after 2008, or 83.5 mm. We thus are not able to estimate the change of soybean acres in response to pre-plant precipitation below the threshold during the post-policy period.

We find that before 2008, a 1 mm decrease in pre-plant precipitation below the threshold increases soybean acreage by 5.1 percent, while a 1mm increase in pre-plant precipitation above the threshold increases soybean acreage by 0.5 percent. The V-shaped effect of pre-plant precipitation before 2008 is opposite to results on the effect of precipitation during the growing season on soybean yields from past climate impact studies (e.g., Annan and Schlenker 2015). Our findings suggest that, before 2008, when farmers faced abnormal pre-plant precipitation they chose to plant soybeans to mitigate the risk of crop productivity losses.

After 2008, and consistent with our expectation, the estimate of the interaction term shows that farmers plant fewer acres in soybeans when pre-plant precipitation is excessive; they should have planted more to mitigate the risk of losses, as before 2008. The estimates show that a 1 mm increase in pre-plant precipitation above the threshold decreases soybeans acreage by 0.2 percent. The estimates of the interaction term are robust to the soil quality types, the removal of observations from 2008, and the inclusion of other control variables (Table 1.4).

The results below the precipitation threshold prior to 2008, in contrast, are sensitive to moderate-quality soil and poor-quality soil.  Here, relatively low soil quality reduces the use of soybeans as an adaptive response to the risk of deficit precipitation.

### 5.2.3 Estimates for spring wheat

The main estimation results are shown in column (1) of Table 1.5 and panel (C) of Figure 1.5. We find that before 2008, a 1 mm decrease in pre-plant precipitation below the threshold decreases spring wheat acreage by 1 percent.  Also, a 1mm increase in pre-plant precipitation above the threshold increases spring wheat acreage by 0.4 percent.  Wheat thus is distinct from both corn and soybeans before 2008.  Farmers use wheat and corn comparably below their respective precipitation thresholds by substituting away from them, and they use wheat and soybeans comparably above their thresholds by substituting toward them.  After 2008, when farmers experience relatively high pre-plant precipitation, farmers plant less acreage in spring wheat.  The estimates show that a 1mm increase in pre-plant precipitation above the threshold decreases spring wheat acreage by 0.4 percent.

The robustness checks for spring wheat show that, like with soybeans, farmers use the moderate-quality and low-quality soils somewhat differently than the good-quality soil.  For example, wheat acreage on these soils does not change in response to pre-plant precipitation above the threshold, either before or after 2008, in contrast to wheat acreage on good-quality soil. The main results are sensitive to other controls, as shown in column (6), as pre-plant temperature and its interaction with pre-plant precipitation are also important for the spring wheat planting decision.

### 5.2.4 Estimates for grassland

The main estimation results are shown in column (1) of Table 1.6 and panel (D) of Figure 1.5. As expected, the direction of the estimates for grassland acreage are similar to soybeans but completely opposite to the results for corn.  Before 2008, below the threshold a 1 mm decrease in pre-plant precipitation would imply a 0.7 percent increase in grassland acreage, while above the threshold a 1 mm increase in pre-plant precipitation increases grassland acreage by 1 percent. Our findings suggest that, when farmers faced abnormal pre-plant precipitation before 2008, they planted acreage in grass-like crops, such as alfalfa, pasture and hay, to mitigate the risk of crop losses.

After 2008, the estimates of the interaction terms show that farmers plant fewer acres in grass-like crops when pre-plant precipitation is both relatively low and relatively high. The estimates show that below the threshold a 1 mm decrease in pre-plant precipitation decreases grassland acreage by 0.2 percent, while above the threshold a 1 mm increase in pre-plant precipitation decreases grassland acreage by 0.7 percent. The estimates of the interaction terms are sensitive to soil quality. After 2008, sections with good quality soil reduce much more grassland acreage when pre-plant precipitation is relatively low before the threshold, and when pre-plant precipitation is relatively high above the threshold. The results suggest that farmers with good quality land undertake crop choices influenced by moral hazard. Other robustness checks for grassland show that our main results are not very sensitive to the loss of observations in 2008 and the inclusion of other controls, as shown in columns (5) and (6), respectively, of Table 1.6.

## 5.3 Empirical results in Iowa

Figure 1.6 presents our main results for estimates of the impact of pre-plant precipitation and whether the policy change in 2008 affects cropping pattern adaptation to pre-plant precipitation in Iowa. Tables 1.7-1.9 report estimates based on equation (1) for corn, soybeans, and grassland, respectively, using data from 2001 to 2011. The threshold of pre-plant precipitation is 430 mm for corn, 180 mm for soybeans, and 240 mm for grassland. In the following subsections, we report our main results by crop with several robustness tests, as in Section 5.2.

### 5.3.1 Estimates for corn

Unlike the results in North Dakota, the main results in Iowa show that corn acreage is not sensitive to pre-plant precipitation both below and above the threshold, as seen in column (1) of Table 1.7 and panel (A) of Figure 1.6. Before 2008, the effect of pre-plant precipitation, below the threshold or above the threshold, is close to zero. North Dakota's inverted-V-shape effect of pre-plant precipitation for corn is not found, implying that farmers in Iowa are not risk averse to weather risk and may be influenced by moral hazard created by the federal crop insurance program.  This especially holds true for sections with poor quality land when they experience too much pre-plant precipitation, as can be seen in column (4) of Table 1.7.

After 2008, while the pre-plant precipitation effect below the threshold continues to be minor, as shown in column (1) of Table 1.7, the pre-plant precipitation effect above the threshold is significant.  We find that after 2008 a 1 mm increase in pre-plant precipitation increases corn acreage by 1.2 percent above the threshold, suggesting that when farmers experience relatively high pre-plant precipitation they might adopt moral-hazard behavior by switching to corn, in addition to the moral-hazard behavior created by crop insurance program.  This occurs in sections with good- and moderate-quality soil according to our robustness checks of soil-quality types.

The robustness checks show that our main results of interaction terms are somewhat sensitive to soil quality.  An unexpected decrease in corn acreage after 2008 occurs below the threshold estimates of the interaction term with poor-quality land.  In contrast, before 2008 the estimates of pre-plant precipitation below the threshold are consistent in all columns.  Our robustness checks also show that above the threshold the estimate of pre-plant precipitation before 2008 is sensitive to the observations in 2008, while our main results are not sensitive to the inclusion of other controls.

### 5.3.2 Estimates for soybeans

The main estimation results are shown in column (1) of Table 1.8 and panel (B) of Figure 1.6. We find that soybean acreage is not sensitive to pre-plant precipitation both below and above the threshold.  After 2008, estimates of the interaction terms show that soybean acreage decreases slightly when there is relatively low pre-plant precipitation below the threshold, or when there is relatively high pre-plant precipitation above the threshold.  For instance, below the threshold a 1 mm decrease in pre-plant precipitation decreases soybean acreage by 0.4 percent.

While our main results are not sensitive to the observations of 2008 and the inclusion of other controls, the estimates below the threshold are sensitive to soil quality.  Before 2008, PLSS sections with moderate- and poor-quality soil plant more soybeans when pre-plant precipitation is low.  However, soybeans acreage decreases after 2008 in these sections, suggesting that farmers with moderate- and poor-quality soil are more sensitive to pre-plant precipitation and the policy change in 2008.

### 5.3.3 Estimates for grassland

The main estimation results are shown in column (1) of Table 1.9 and panel (C) of Figure 1.6. As corn and soybeans in Iowa, before 2008 grassland acreage is not sensitive to pre-plant precipitation above the threshold. Below the threshold, a small pre-precipitation effect is found. A 1 mm decrease in pre-plant precipitation would imply a 0.2 percent increase in grassland acreage, implying that before 2008 when farmers faced relatively low pre-plant precipitation, they plant grass-like crops to mitigate the risk of crop productivity losses.

After 2008, the estimates of the interaction terms below and above the threshold are also very small. The robustness checks show that our main results are consistent in all columns, except the interaction terms for poor-quality land. The estimates for poor-quality land show that, after 2008, below the threshold a 1 mm decrease in pre-plant precipitation increases grassland acreage by 0.7 percent, while above the threshold a 1 mm increase in pre-plant precipitation decreases grassland acreage by 0.2 percent. The results suggest that in Iowa grassland in the sections with poor-quality soil is sensitive to the policy change in 2008.

## 6 Conclusion

Direct evidence about farmers' behavioral adaptation to weather risk is crucial for understanding the impact of climate change and for designing efficient adaptation policy. While past climate and weather impact studies suggest that adaptation would affect the magnitude of impacts, which specific adaptation strategies are adopted in response to weather risk and whether government programs affect the adaptation strategies, are not well known. A common limitation to examining the importance of adaptation strategies is that researchers cannot observe local weather and farmers' behaviors in a large-scale impact assessment study. With fine-scale cropland and weather data from 2001 to 2011 at the PLSS section level, this study analyzes how local pre-plant precipitation and federal agricultural programs influence farmers' cropping-pattern adaptation to weather risk in the U.S. Midwest. We control for unobserved heterogeneity with section fixed effects, and we exploit exogenous variations in pre-plant precipitation that signals weather risk and a 2008 policy change in the federal disaster assistance program.

Our results demonstrate that farmers' planting decisions are responsive to pre-plant precipitation in North Dakota. When faced with relatively low or relatively high pre-plant precipitation, farmers in North Dakota plant more land in soybeans, spring wheat, or grass-like crops, instead of planting water-sensitive corn. The results imply that farmers in North Dakota were risk-averse to weather risk before 2008, even in the presence of highly-subsidized federal crop insurance program that had created moral hazard problems (e.g., Roberts et al. 2011). With the advent of the Supplemental Revenue Assistance Payments (SURE) program in 2008, these cropping-pattern adjustments are largely reversed. The government risk-management policy change thus provided North Dakota farmers a disincentive to change cropping pattern as a mechanism for adapting to precipitation risk. This incremental moral hazard created by the SURE program is consistent with past studies that argue the SURE program provided incentives for farmers to exploit opportunities for moral hazard (e.g., Bekkerman et al. 2012; Shields 2010)

In Iowa, we find that farmers' planting decisions are generally insensitive to pre-plant precipitation and the introduction of the SURE program. Moral hazard problems might have occurred before 2008. After 2008, incremental moral hazard is apparent only under excess pre-plant precipitation. The small relative effect implies that this policy change in 2008 exerted only a minor effect on cropping pattern in Iowa. The inelasticity of Iowa farmers' cropping pattern to both pre-plant precipitation and the policy change in 2008 may not be surprising, as Livingston et al. (2015) suggest that crop choice in Iowa is close to optimal, regardless of both transitory and permanent price changes.

Crop switching has long been recognized as a major adaptation strategy to weather risk and climate change in the agricultural sector. Government risk-management programs can distort this private adaptation to extreme weather and climate change. The problem will grow more important as future climate change increases the frequency of extreme weather events. Our study is an initial step to uncover distortions in the mechanisms of adaptation. Future research includes investigating what drives heterogeneous behavioral responses to weather/climate risk interacted with government programs, and identifying whether land-use distortions affect the sensitivity of yields to climate change.

## References

**Al-Kaisi, Mahdi M., Roger W. Elmore, Jose G. Guzman, H. Mark Hanna, Chad E. Hart, Matthew J. Helmers, Erin W. Hodgson, Andrew W. Lenssen, Antonio P. Mallarino, Alison E. Robertson, and John E. Sawyer.** 2013. "Drought Impact on Crop Production and the Soil Environment: 2012 Experiences from Iowa." *Journal of Soil and Water Conservation*, 68(1): 19-24.

**Anderson, Soren, Chenguang Wang, and Jinhua Zhao.** 2012. "Let Them Eat Switchgrass? Modeling the Displacement of Existing Food Crops by New Bioenergy Feedstocks." Michigan State University, Department of Economics, Working Paper.

**Annan, Francis, and Wolfram Schlenker.** 2015. "Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat." *American Economic Review*, 105(5): 262-266.

**Bekkerman, Anton, Vincent H. Smith, and Myles J. Watts.** 2012. "The SURE Program and Incentives for Crop Insurance Participation: A Theoretical and Empirical Analysis." *Agricultural Finance Review*, 72(3): 381-401.

**Brooks, Harold E.** 2013. "Severe Thunderstorms and Climate Change." *Atmospheric Research*, 123(1): 129-138.

**Brown, Jesslyn F., and Mid Shahriar Pervez.** 2014. "Merging Remote Sensing Data and National Agricultural Statistics to Model Change in Irrigation Agriculture." *Agricultural Systems*, 127: 28-40.

**Burke, Marshall and Kyle Emerick.** 2015. "Adaptation to Climate Change: Evidence from US Agriculture." *American Economic Journal: Economic Policy*, Forthcoming.

**Burke, Marshall, Solomon M. Hsiang, and Edward Miguel.** 2015. "Global Non-Linear Effect of Temperature on Economic Production." *Nature*, 527: 235-239.

**Chite, Ralph M.** 2008. "Crop Insurance and Disaster Assistance in the 2008 Farm Bill." Congressional Research Service, Working Paper RL34207.

**Chite, Ralph M.** 2010. "Emergency Funding for Agriculture: A Brief History of Supplemental Appropriations, FY1989-FY2009." Congressional Research Service, Working Paper RS31095.

**Christensen, J.H., K. Krishna Kumar, E. Aldrian, S.-I. An, I.F.A. Cavalcanti, M. de Castro, W. Dong, P. Goswami, A. Hall, J.K. Kanyanga, A. Kitoh, J. Kossin, N.-C. Lau, J. Renwick, D.B. Stephenson, S.-P. Xie and T. Zhou.** 2013. "Climate Phenomena and their Relevance for Future Regional Climate Change," in Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley, eds., *Climate*

*Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

**Climate Prospectus.** 2014. *American Climate Prospectus: Economic Risks in the United States.* Columbia University Press.

**Cole, Shawn, Xavier Gine, and James Vickery.** 2014. "How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment." Harvard Business School Working Paper, No. 13-080.

**Committee on Integrated Land Data Mapping.** 1982. *Modernization of the Public Land Survey System.* National Academy Press.

**Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken.** 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, 4(3): 66-95.

**Deschenes, Olivier, and Michael Greenstone.** 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *American Economic Review*, 97(1): 354-385.

**Feng, Shuaizhang, Alan B. Krueger, and Michael Oppenheimer.** 2010. "Linkages among Climate Change, Crop Yields and Mexico-US Cross-Border Migration." *Proceedings of the National Academy of Sciences of the United States*, 107(32): 14257-14262.

**Fezzi, Carlo, and Ian Bateman.** 2015. "The Impact of Climate Change on Agriculture: Nonlinear Effects and Aggregation Bias in Ricardian Models of Farmland Values." *Journal of the Association of Environmental and Resource Economics*, 2(1): 57-92.

**Fisher, Anthony C., W. Michael Hanemann, Michael J. Roberts, and Wolfram Schlenker.** 2012. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment." *American Economic Review*, 102(7): 3749-3760.

**Glauber, Joseph W. and Keith J. Collins.** 2002. "Crop Insurance, Disaster Assistance, and the Role of the Federal Government in Providing Catastrophic Risk Protection, *Agricultural Finance Review*, 62(2): 81-101.

**Goodwin, Barry K., Monte L. Vandeveer, and John L. Deal.** 2004. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program." *American Journal of Agricultural Economics*, 86(4): 1058-1077.

**Haigh, Tonya, Eugene Takle, Jeffrey Andresen, Melissa Widhalm, J Stuart Carlton, and Jim Angel.** 2015. “Mapping the Decision Points and Climate Information Use of Agricultural Producers across the U.S. Corn Belt.” *Climate Risk Management*, 7: 20-30.

**Holmes, Thomas J.**, **and Sanghoon Lee.** 2012. “Economies of Density versus Natural Advantage: Crop Choice on the Back Forty.” *Review of Economics and Statistics*, 94(1): 1-19.

**Hornbeck, Richard.** 2012. “The Enduring Impact of the American Dust Bowl: Short- and Long-run Adjustments to Environmental Catastrophe.” *American Economic Review*, 102(4): 1477-1507.

**Hsiang, Solomon M., Marshall Burke, and Edward Miguel.** 2013. “Quantifying the Influence of Climate on Human Conflict.” *Science*, 341: 1235367.

**Intergovernmental Panel on Climate Change (IPCC).** 2013. “Summary for Policymakers,” in Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley eds., *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

**Kala, Namrata.** 2014. “Ambiguity Aversion and Learning in a Changing World: The Potential Effects of Climate Change from Indian Agriculture.” Yale University, Working Paper.

**Langpap, Christian, and JunJie Wu.** 2014. “Impacts of Changes in Federal Crop Insurance Programs on Land Use and Environmental Quality.” Oregon State University, Department of Applied Economics,Working Paper.

**Livingston, Michael, Michael J. Roberts, and Yue Zhang.** 2015. “Optimal Sequential Plantings of Corn and Soybeans under Price Uncertainty.” *American Journal of Agricultural Economics*, 97(3): 855-878.

**Malcolm, Scott, Elizabeth Marshall, Marcel Aillery, Paul Heisey, Michael Livingston, and Kelly Day-Rubenstein.** 2012. “Agricultural Adaptation to a Changing Climate: Economic and Environmental Implications Vary by U.S. Region.” United States Department of Agriculture, Economic Research Service, Economic Research Report Number 136.

**McIntosh, Craig T. and Wolfram Schlenker.** 2006. Identifying Non-Linearities in Fixed Effects Models." University of California, San Diego, School of International Relations and Pacific Studies, Working Paper.

**Mearns, L.O., W. Easterling, C. Hays, and D. Marx.** 2001. ”Comparison of Agricultural Impacts of Climate Change Calculated from High and Low Resolution Climate Change Scenarios: Part I. The Uncertainty Due to Spatial Scale.” *Climatic Change*, 51: 131-172.

**Mehaffey, Megan, Elizabeth Smith, Rick Van Remortel.** 2012. **"**Midwest U.S. Landscape Change to 2020 Driven by Biofuel Mandates." *Ecological Applications*, 22(1):8-19.

**Mendelsohn, Robert.** 2000. "Efficient Adaptation to Climate Change." *Climatic Change*, 45: 583-600.

**Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw.** 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *American Economic Review*, 84(4): 753-771.

**Miguel, Edward, Shanker Satyanath, and Ernest Sergenti.** 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy*, 112(4): 725-753.

**Miller, Benjamin M.** 2014. "Does Validity Fall from the Sky? Observant Farmers and the Endogeneity of Rainfall." University of California, San Diego, Department of Economics, Working Paper.

**Mobarak, Ahmed Mushfiq, and Mark R. Rosenzweig.** 2014. "Risk, Insurance and Wages in General Equilibrium." National Bureau of Economic Research, Working Paper 19811.

**Neild, Ralph E. and James E. Newman.** 1990. "Growing Season Characteristics and Requirements in the Corn Belt." Purdue University, Cooperative Extension Service. National Corn Handbook-40.

**Quiring, Steven M. and Daria B. Kluver.** 2009. "Relationship between Winter/Spring Snowfall and Summer Precipitation in the Northern Great Plains of North America." *Journal of Hydrometeorology*, 10: 1203-1217.

**Rosenzewig, Mark R. and Christopher Udry.** 2014. "Rainfall Forecasts, Weather, and Wages over the Agricultural Production Cycle." *American Economic Review: Papers & Proceedings*, 104(5): 278-283.

**Roberts, Michael J., Erik O'Donoghue, and Nigel Key. 2011.** "Separating Moral Hazard from Adverse Selection: Evidence from the U.S. Federal Crop Insurance Program." University of Hawaii, Manoa, Department of Economics, Working Paper.

**Schlenker, Wolfram, and Michael J. Roberts.** 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States*, 106(37): 15594–15598.

**Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher.** 2005. "Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." *American Economic Review*, 95(1): 395-406.

**Schoengold, Karina, Ya Ding, and Russell Headlee.** 2014. "The Impact of AD HOC Disaster and Crop Insurance Programs on the Use of Risk-Reducing Conservation Tillage Practices." *American Journal of Agricultural Economics*, aau073, 1-23.

**Shields, Dennis A.** 2010. "A Whole-Farm Crop Disaster Program: Supplemental Revenue Assistance Payments (SURE)." Congressional Research Service, Working Paper RS40452.

**Shields, Dennis A. and Ralph M. Chite.** 2010. "Agricultural Disaster Assistance." Congressional Research Service, Working Paper RS21212.

**Smith, Vincent H., and Barry K. Goodwin.** 2010. "Private and Public Roles in Providing Agricultural Insurance in the United States," in Brown, Jeffrey R. eds., *Public Insurance and Private Markets*. The AEI Press.

**Smith, Vincent H., and Myles J. Watts.** 2010. "The New Standing Disaster Program: A SURE Invitation to Moral Hazard Behavior." *Applied Economic Perspectives and Polic*y, 32(1): 154-169.

**Steduto, Pasquale, Theodore C.Hsiao, Elias Fereres, and Dirk Raes.** 2012. *Crop Yield Response to Water.* Rome, Italy: Food and Agriculture Organization of the United Nations.

**Tol, Richard S. J., Samuel Frankhauser, and Joel B. Smith.** 1998. "The scope for adaptation to climate change: what can we learn from the impact literature?" *Global Environmental Change*, 8(2): 109-123.

**Urban, Daniel W., Michael J. Roberts, Wolfram Schlenker, and David B. Lobell.** 2015. "The Effect of Extremely Wet Planting Conditions on Maize and Soybean Yields." *Climatic Change*, 130: 247-260.

**Wright, Christoher K. and Michael C. Wimberly.** 2013. "Recent Land Use Change in the Western Corn Belt Threatens Grasslands and Wetlands." *Proceedings of the National Academy of Sciences of the United States*, (110): 4134-4139.

Table 1.1: Summary Statistics of Crop Planting Area at the Section Level

| | Unit | North Dakota | | | Iowa | | |
|---|---|---|---|---|---|---|---|
| | | Mean | Median | S.D. | Mean | Median | S.D. |
| Corn[a] | acre | 42.48 | 5.49 | 79.34 | 218.96 | 218.93 | 132.98 |
| Soybeans[a] | acre | 109.59 | 59.58 | 127.56 | 171.92 | 161.78 | 164.64 |
| Spring wheat[a] | acre | 118.50 | 83.93 | 122.37 | 0.08 | 0 | 1.64 |
| Grassland[a] | acre | 205.76 | 162.45 | 173.09 | 158.56 | 116.33 | 136.84 |
| Pre-plant precipitation[b] | mm | 124.96 | 115.53 | 50.38 | 234.34 | 230.45 | 69.89 |
| Pre-plant temperature[b] | Celsius | -6.30 | -6.57 | 1.90 | -0.74 | -0.80 | 1.93 |
| Weighted land capacity[c] | - | 3.03 | 2.68 | 1.05 | 2.74 | 2.59 | 0.83 |
| Sections | | | 27,151 | | | 50,020 | |
| Observations | | | 298,661 | | | 550,220 | |

*Notes:* [a]Authors' calculations with the Cropland Data Layer, 2001-2011.

[b]Authors' calculations with Schlenker and Roberts (2009) weather data, 2001-2011.

[c]Authors' calculations with the Soil Survey Geographic (SSURGO) database. Larger values indicate poorer soil quality. See Section 4.4 for our calculation of weighted land capacity at the section level.

Table 1.2: Variation of Pre-Plant Precipitation under Various Sets of Fixed Effects

| | North Dakota | | | Iowa | | |
|---|---|---|---|---|---|---|
| | $R^2$ | $\sigma_e$ | \|e\| > 10mm | $R^2$ | $\sigma_e$ | \|e\| > 10mm |
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| No fixed effects (FE) | - | 50.4 mm | 85.1% | - | 69.9 mm | 91.7% |
| Section FE | 0.129 | 47.0 mm | 87.5% | 0.282 | 61.5 mm | 88.9% |
| Section FE + year FE | 0.844 | 19.9 mm | 54.4% | 0.828 | 27.6 mm | 73.3% |

*Notes:* This table summarizes regressions of pre-plant precipitation on various sets of fixed effects to assess how much variation is absorbed by the fixed effects. Columns (a) report the $R^2$ of the regressions. Columns (b) report the standard deviation of the residuals (remaining pre-plant precipitation variation) in millimeters. Columns (c) report the fraction of the observations having a residual larger than 10 mm.

Table 1.3: Estimation Results for Corn in North Dakota

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | -0.006** | -0.003 | -0.008*** | -0.008*** | -0.008** | -0.003 |
| | (0.003) | (0.003) | (0.002) | (0.001) | (0.003) | (0.003) |
| Pre-plant precipitation above threshold | -0.008*** | -0.006*** | -0.009*** | -0.008** | -0.008*** | -0.009*** |
| | (0.002) | (0.001) | (0.002) | (0.004) | (0.002) | (0.003) |
| Pre-plant precipitation below threshold | 0.003 | 0.005 | 0.004 | -0.013 | 0.003 | -0.008 |
| × after 2008 | (0.012) | (0.021) | (0.008) | (0.010) | (0.011) | (0.013) |
| Pre-plant precipitation above threshold | 0.011*** | 0.009*** | 0.010*** | 0.008** | 0.011*** | 0.010*** |
| × after 2008 | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| Pre-plant temperature | -0.264*** | -0.346*** | -0.161** | -0.198 | -0.300** | -0.203* |
| | (0.086) | (0.104) | (0.074) | (0.136) | (0.113) | (0.101) |
| Pre-plant precipitation × temperature | | | | | | -0.000 |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | -0.002 |
| | | | | | | (0.002) |
| Temperature from March 16 to May 31 | | | | | | -0.146 |
| | | | | | | (0.105) |
| Precipitation in the last growing season | | | | | | -0.001 |
| | | | | | | (0.001) |
| Observations | 298,661 | 185,746 | 92,323 | 20,592 | 271,510 | 298,661 |
| Number of sections | 27,151 | 16,886 | 8,393 | 1,872 | 27,151 | 27,151 |
| R-squared | 0.124 | 0.159 | 0.081 | 0.075 | 0.135 | 0.127 |
| Threshold of pre-plant precipitation | 110 | 110 | 110 | 110 | 110 | 110 |

*Notes*: Dependent variable in all regressions is the log of corn acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 1.4: Estimation Results for Soybeans in North Dakota

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | 0.051** | 0.070*** | 0.014 | -0.011 | 0.068*** | 0.045** |
| | (0.019) | (0.019) | (0.018) | (0.011) | (0.022) | (0.018) |
| Pre-plant precipitation above threshold | 0.005*** | 0.005** | 0.005*** | 0.009*** | 0.006*** | 0.009*** |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) | (0.003) |
| Pre-plant precipitation below threshold × after 2008 | | | | | | |
| Pre-plant precipitation above threshold | -0.007*** | -0.006*** | -0.008*** | -0.013*** | -0.007*** | -0.005** |
| × after 2008 | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Pre-plant temperature | -0.061 | -0.021 | -0.118 | -0.111 | -0.014 | -0.025 |
| | (0.108) | (0.110) | (0.106) | (0.170) | (0.133) | (0.134) |
| Pre-plant precipitation × temperature | | | | | | 0.001** |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | 0.002 |
| | | | | | | (0.001) |
| Temperature from March 16 to May 31 | | | | | | -0.109 |
| | | | | | | (0.119) |
| Precipitation in the last growing season | | | | | | -0.001 |
| | | | | | | (0.001) |
| Observations | 298,661 | 185,746 | 92,323 | 20,592 | 271,510 | 352,963 |
| Number of sections | 27,151 | 16,886 | 8,393 | 1,872 | 27,151 | 27,151 |
| R-squared | 0.139 | 0.154 | 0.138 | 0.145 | 0.157 | 0.137 |
| Threshold of pre-plant precipitation | 70 | 70 | 70 | 70 | 70 | 70 |

*Notes*: Dependent variable in all regressions is the log of soybeans acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 1.5: Estimation Results for Spring Wheat in North Dakota

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | -0.010*** | -0.013*** | -0.008** | -0.006* | -0.013*** | 0.008*** |
| | (0.003) | (0.004) | (0.003) | (0.003) | (0.004) | (0.003) |
| Pre-plant precipitation above threshold | 0.004*** | 0.004*** | 0.003 | -0.000 | 0.003* | -0.009*** |
| | (0.001) | (0.001) | (0.002) | (0.003) | (0.002) | (0.001) |
| Pre-plant precipitation below threshold | -0.067 | -0.033 | -0.518*** | | -0.096* | -0.042 |
| × after 2008 | (0.048) | (0.064) | (0.025) | | (0.054) | (0.058) |
| Pre-plant precipitation above threshold | -0.008*** | -0.010*** | -0.005** | -0.001 | -0.008*** | -0.012*** |
| × after 2008 | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| Pre-plant temperature | 0.366*** | 0.427*** | 0.322*** | 0.213*** | 0.383*** | 0.352*** |
| | (0.057) | (0.075) | (0.057) | (0.057) | (0.067) | (0.069) |
| Pre-plant precipitation × temperature | | | | | | -0.002*** |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | -0.001 |
| | | | | | | (0.002) |
| Temperature from March 16 to May 31 | | | | | | 0.158* |
| | | | | | | (0.082) |
| Precipitation in the last growing season | | | | | | -0.001 |
| | | | | | | (0.001) |
| Observations | 298,661 | 185,746 | 92,323 | 20,592 | 271,510 | 298,661 |
| Number of sections | 27,151 | 16,886 | 8,393 | 1,872 | 27,151 | 27,151 |
| R-squared | 0.112 | 0.104 | 0.130 | 0.233 | 0.118 | 0.121 |
| Threshold of pre-plant precipitation | 90 | 90 | 90 | 90 | 90 | 90 |

*Notes*: Dependent variable in all regressions is the log of spring wheat acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 1.6: Estimation Results for Grassland in North Dakota

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | 0.007*** | 0.005** | 0.004*** | 0.002*** | 0.004** | 0.003 |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| Pre-plant precipitation above threshold | 0.010*** | 0.009*** | 0.006*** | 0.003** | 0.008*** | 0.012*** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| Pre-plant precipitation below threshold | -0.009 | -0.013* | 0.001 | -0.002 | -0.011* | -0.009 |
| × after 2008 | (0.007) | (0.007) | (0.003) | (0.003) | (0.006) | (0.007) |
| Pre-plant precipitation above threshold | -0.017*** | -0.017*** | -0.008*** | -0.004* | -0.016*** | -0.014*** |
| × after 2008 | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) | (0.003) |
| Pre-plant temperature | -0.397*** | -0.542*** | -0.136*** | -0.066 | -0.616*** | -0.325*** |
| | (0.104) | (0.118) | (0.041) | (0.055) | (0.120) | (0.083) |
| Pre-plant precipitation × temperature | | | | | | 0.000 |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | -0.000 |
| | | | | | | (0.001) |
| Temperature from March 16 to May 31 | | | | | | -0.133*** |
| | | | | | | (0.045) |
| Precipitation in the last growing season | | | | | | 0.002** |
| | | | | | | (0.001) |
| Observations | 298,661 | 185,746 | 92,323 | 20,592 | 271,510 | 298,661 |
| Number of sections | 27,151 | 16,886 | 8,393 | 1,872 | 27,151 | 27,151 |
| R-squared | 0.331 | 0.441 | 0.152 | 0.059 | 0.345 | 0.337 |
| Threshold of pre-plant precipitation | 120 | 120 | 120 | 120 | 120 | 120 |

*Notes*: Dependent variable in all regressions is the log of grassland acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 1.7: Estimation Results for Corn in Iowa

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | 0.000** | -0.000 | 0.001* | -0.000 | 0.000 | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.002) | (0.000) | (0.000) |
| Pre-plant precipitation above threshold | -0.000 | 0.001*** | 0.001* | 0.018* | 0.024*** | -0.000 |
| | (0.001) | (0.000) | (0.001) | (0.009) | (0.003) | (0.001) |
| Pre-plant precipitation below threshold | -0.001*** | -0.001*** | -0.003*** | -0.006*** | -0.001*** | -0.001*** |
| × after 2008 | (0.000) | (0.000) | (0.000) | (0.002) | (0.000) | (0.000) |
| Pre-plant precipitation above threshold | 0.012*** | 0.008*** | 0.010*** | -0.021 | -0.011*** | 0.012*** |
| × after 2008 | (0.001) | (0.001) | (0.001) | (0.015) | (0.003) | (0.002) |
| Pre-plant temperature | -0.018 | -0.030** | -0.026 | -0.183** | -0.016 | -0.067* |
| | (0.023) | (0.013) | (0.028) | (0.076) | (0.023) | (0.037) |
| Pre-plant precipitation × temperature | | | | | | 0.000 |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | 0.000 |
| | | | | | | (0.000) |
| Temperature from March 16 to May 31 | | | | | | 0.079** |
| | | | | | | (0.037) |
| Precipitation in the last growing season | | | | | | 0.000 |
| | | | | | | (0.000) |
| Observations | 550,220 | 373,340 | 171,248 | 5,632 | 500,200 | 550,220 |
| Number of sections | 50,020 | 33,940 | 15,568 | 512 | 50,020 | 50,020 |
| R-squared | 0.031 | 0.014 | 0.121 | 0.353 | 0.030 | 0.032 |
| Threshold of pre-plant precipitation | 430 | 430 | 430 | 430 | 430 | 430 |

*Notes*: Dependent variable in all regressions is the log of corn acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 1.8: Estimation Results for Soybeans in Iowa

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | -0.000 | -0.001** | 0.005** | 0.007 | 0.000 | -0.001 |
| | (0.001) | (0.000) | (0.002) | (0.006) | (0.001) | (0.001) |
| Pre-plant precipitation above threshold | 0.000 | 0.000 | 0.001 | -0.001 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) |
| Pre-plant precipitation below threshold | -0.004** | 0.001 | -0.015*** | -0.016** | -0.004*** | -0.004*** |
| × after 2008 | (0.001) | (0.001) | (0.003) | (0.007) | (0.001) | (0.001) |
| Pre-plant precipitation above threshold | -0.001** | -0.000 | -0.002** | 0.002 | -0.001*** | -0.001** |
| × after 2008 | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) |
| Pre-plant temperature | 0.075*** | 0.043*** | 0.122*** | 0.047 | 0.090*** | -0.030 |
| | (0.016) | (0.014) | (0.030) | (0.094) | (0.016) | (0.048) |
| Pre-plant precipitation × temperature | | | | | | 0.000 |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | 0.000 |
| | | | | | | (0.000) |
| Temperature from March 16 to May 31 | | | | | | 0.167*** |
| | | | | | | (0.061) |
| Precipitation in the last growing season | | | | | | 0.000** |
| | | | | | | (0.000) |
| Observations | 550,220 | 373,340 | 171,248 | 5,632 | 500,200 | 550,220 |
| Number of sections | 50,020 | 33,940 | 15,568 | 512 | 50,020 | 50,020 |
| R-squared | 0.084 | 0.056 | 0.163 | 0.359 | 0.090 | 0.087 |
| Threshold of pre-plant precipitation | 180 | 180 | 180 | 180 | 180 | 180 |

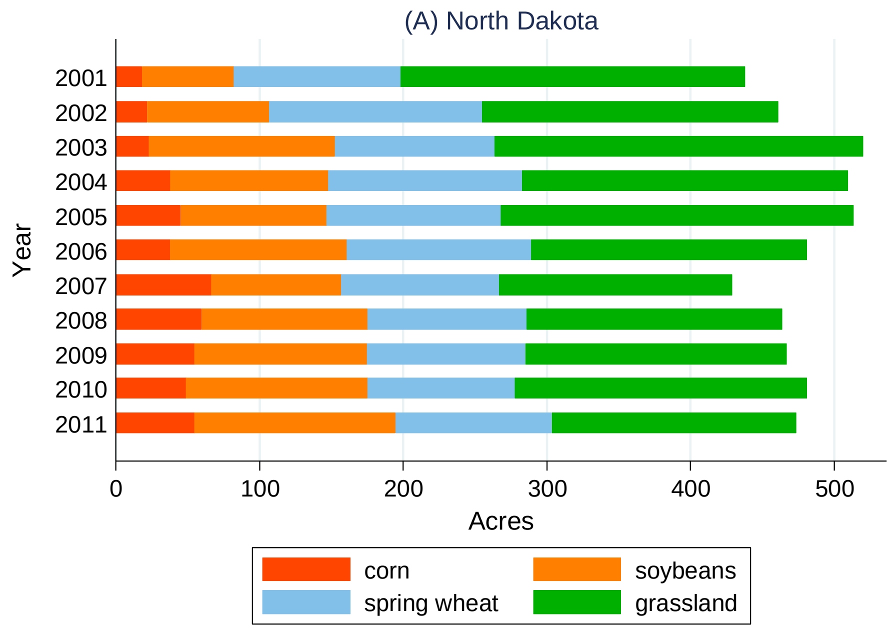
*Notes*: Dependent variable in all regressions is the log of soybeans acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

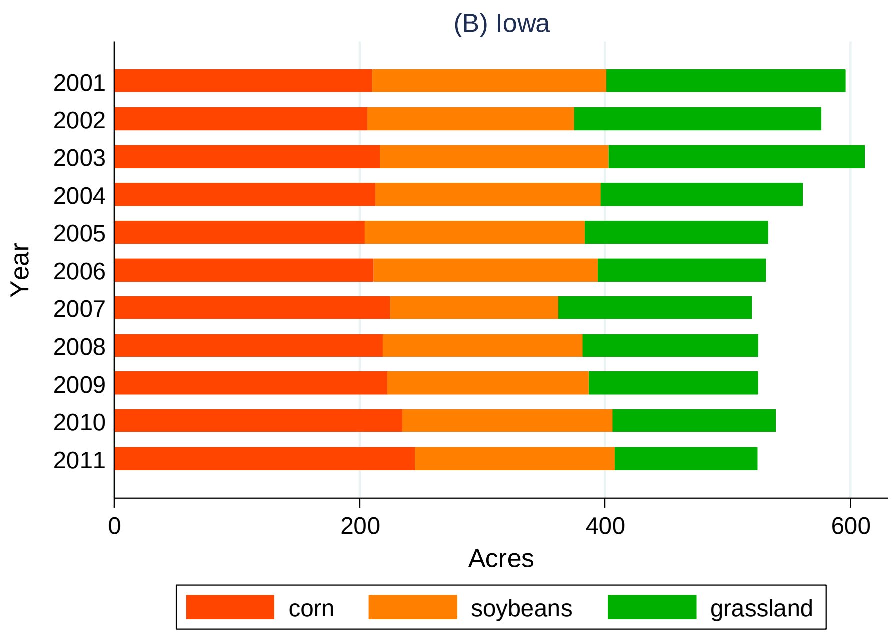
Table 1.9: Estimation Results for Grassland in Iowa

| | (1) Main | (2) Good quality soil | (3) Moderate quality soil | (4) Poor quality soil | (5) Skip 2008 | (6) Other controls |
|---|---|---|---|---|---|---|
| Pre-plant precipitation below threshold | 0.002*** | 0.002*** | 0.001*** | 0.002 | 0.002*** | 0.002*** |
| | (0.001) | (0.001) | (0.000) | (0.002) | (0.001) | (0.001) |
| Pre-plant precipitation above threshold | 0.001 | 0.000 | 0.000 | 0.002* | -0.001** | 0.001* |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) |
| Pre-plant precipitation below threshold | -0.001 | -0.001 | 0.001 | 0.005** | -0.000 | -0.000 |
| × after 2008 | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Pre-plant precipitation above threshold | -0.001** | -0.001*** | -0.001*** | -0.004* | 0.000 | -0.002*** |
| × after 2008 | (0.000) | (0.000) | (0.000) | (0.002) | (0.001) | (0.000) |
| Pre-plant temperature | 0.024 | 0.047 | -0.009 | -0.063 | 0.019 | 0.230*** |
| | (0.028) | (0.032) | (0.020) | (0.083) | (0.028) | (0.056) |
| Pre-plant precipitation × temperature | | | | | | -0.000** |
| | | | | | | (0.000) |
| Precipitation from March 16 to May 31 | | | | | | 0.000** |
| | | | | | | (0.000) |
| Temperature from March 16 to May 31 | | | | | | -0.317*** |
| | | | | | | (0.055) |
| Precipitation in the last growing season | | | | | | 0.000 |
| | | | | | | (0.000) |
| Observations | 550,220 | 373,340 | 171,248 | 5,632 | 500,200 | 550,220 |
| Number of sections | 50,020 | 33,940 | 15,568 | 512 | 50,020 | 50,020 |
| R-squared | 0.286 | 0.356 | 0.254 | 0.426 | 0.290 | 0.295 |
| Threshold of pre-plant precipitation | 240 | 240 | 240 | 240 | 240 | 240 |

*Notes*: Dependent variable in all regressions is the log of grassland acres. All columns include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regression (1) is our main result from equation (1) that includes pre-plant precipitation below and above the threshold, and the interactions of pre-plant precipitation variables with the policy change in 2008 as controls. Regressions (2)-(4) use subsamples by soil quality. Regression (5) drops the observations from 2008. Regression (6) includes potential endogenous controls. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

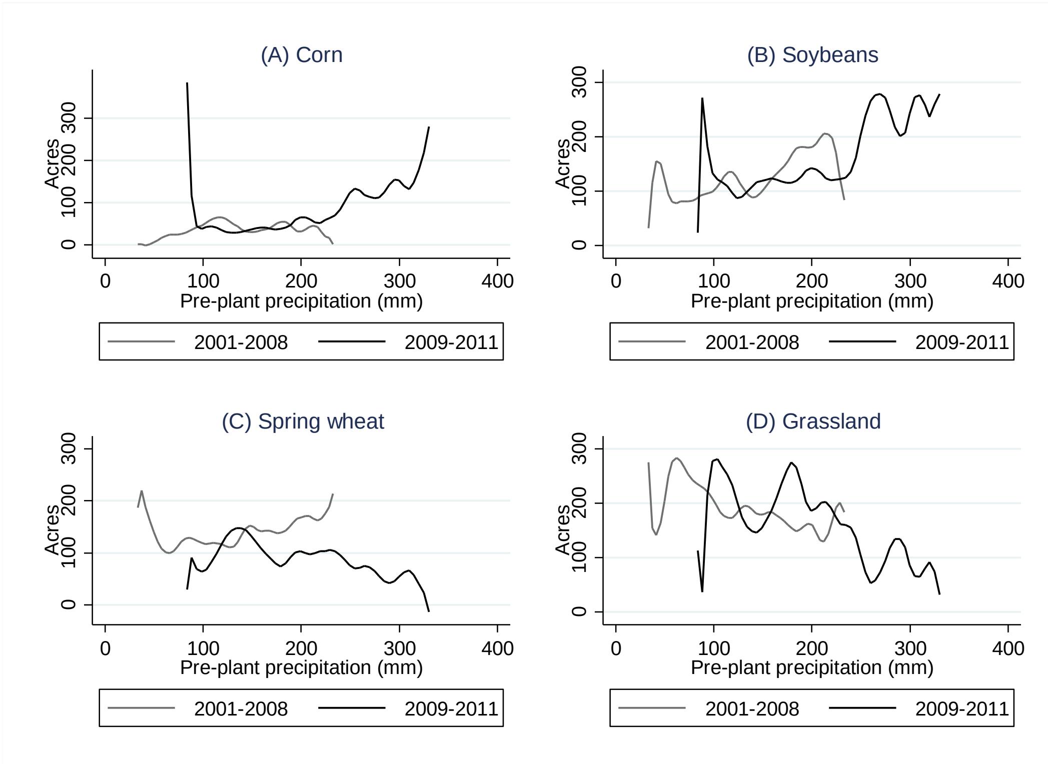
Figure 1.1: Average Cropland and Grassland Acreages at the Section Level



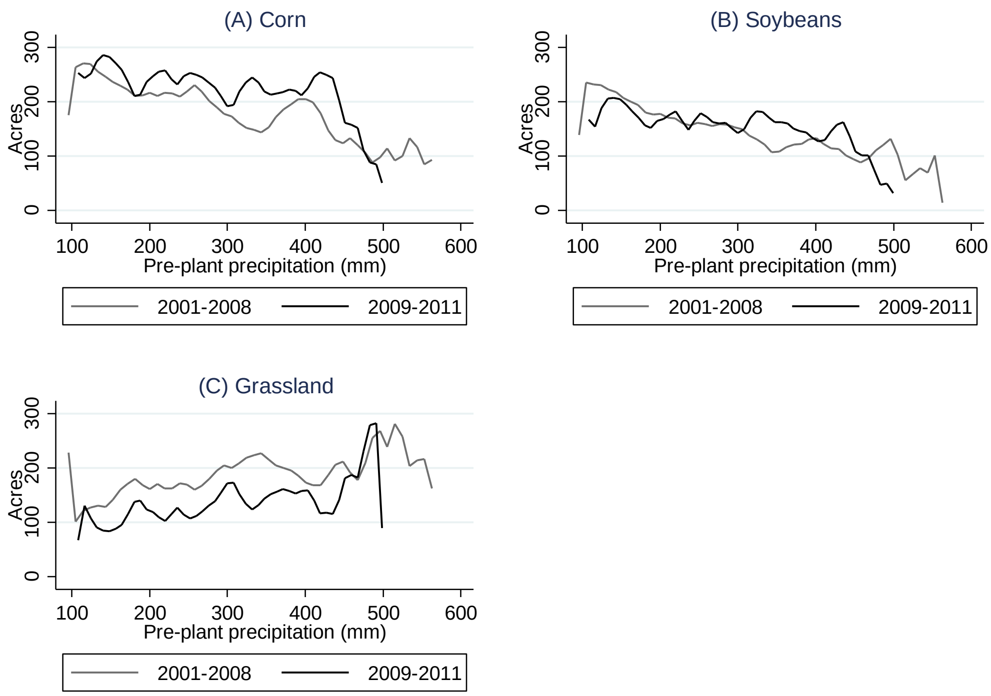

*Notes:* Figure displays acreages of major types of cropland use across years. Data at the section level is extracted from the Cropland Data Layer.

Figure 1.2: Relationship between Land Use and Pre-Plant Precipitation in North Dakota



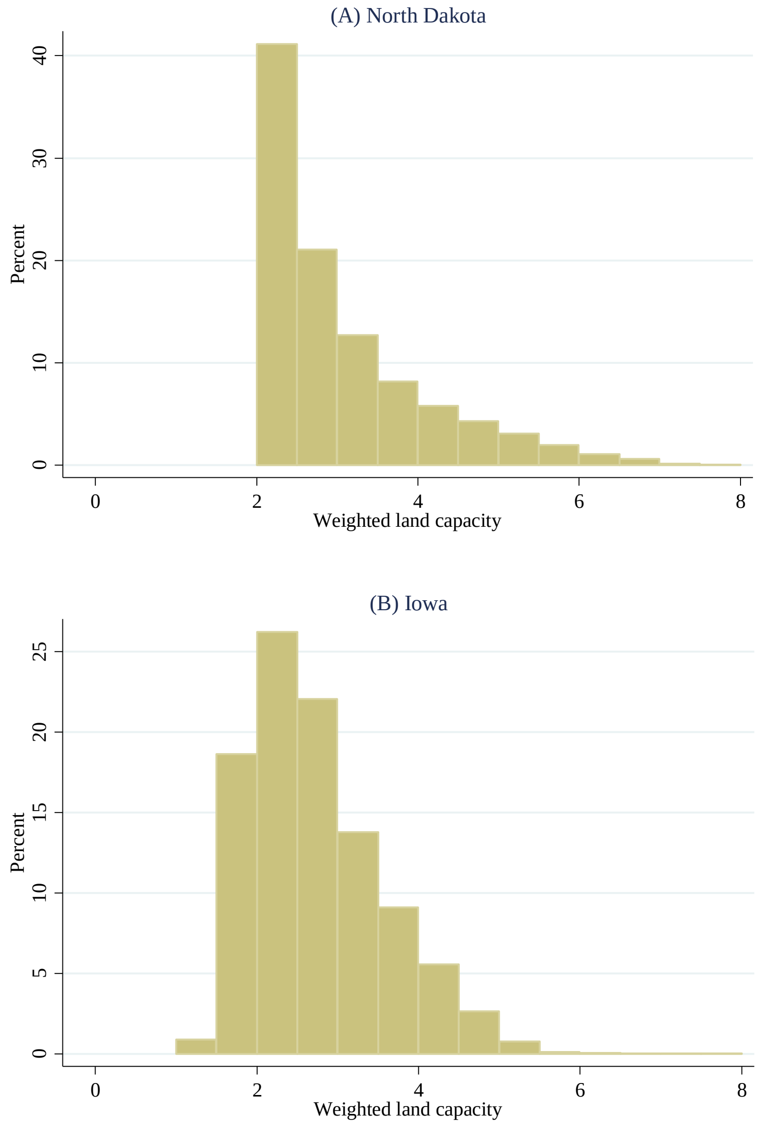

*Notes:* These plots are generated by the Kernel-weighted local polynomial smoothing with the settings: kernel = epan2, degree = 3, and bandwidth = 20. Data at the section level is extracted from the Cropland Data Layer and Schlenker and Roberts (2009) weather data.

Figure 1.3: Relationship between Land Use and Pre-Plant Precipitation in Iowa



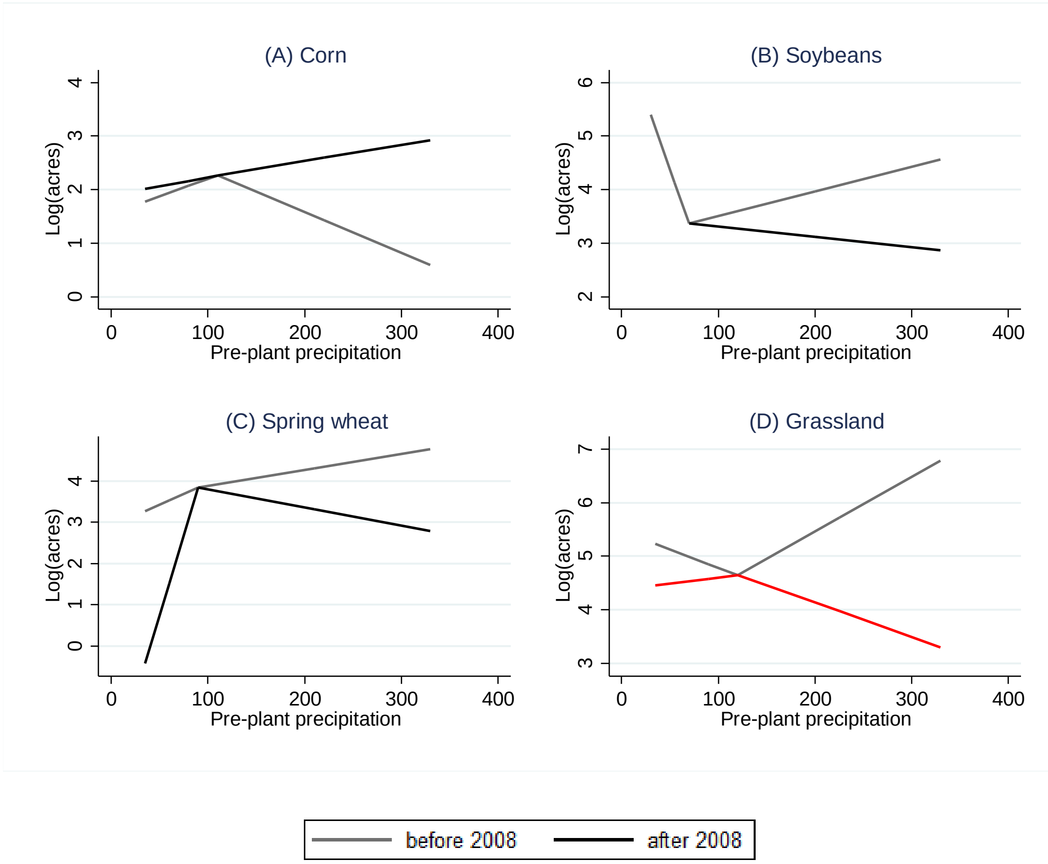

*Notes:* These plots are generated by the Kernel-weighted local polynomial smoothing with the settings: kernel = epan2, degree = 3, and bandwidth = 20. Data at the section level is extracted from the Cropland Data Layer and Schlenker and Roberts (2009) weather data.

Figure 1.4: Land Capacity Class by State



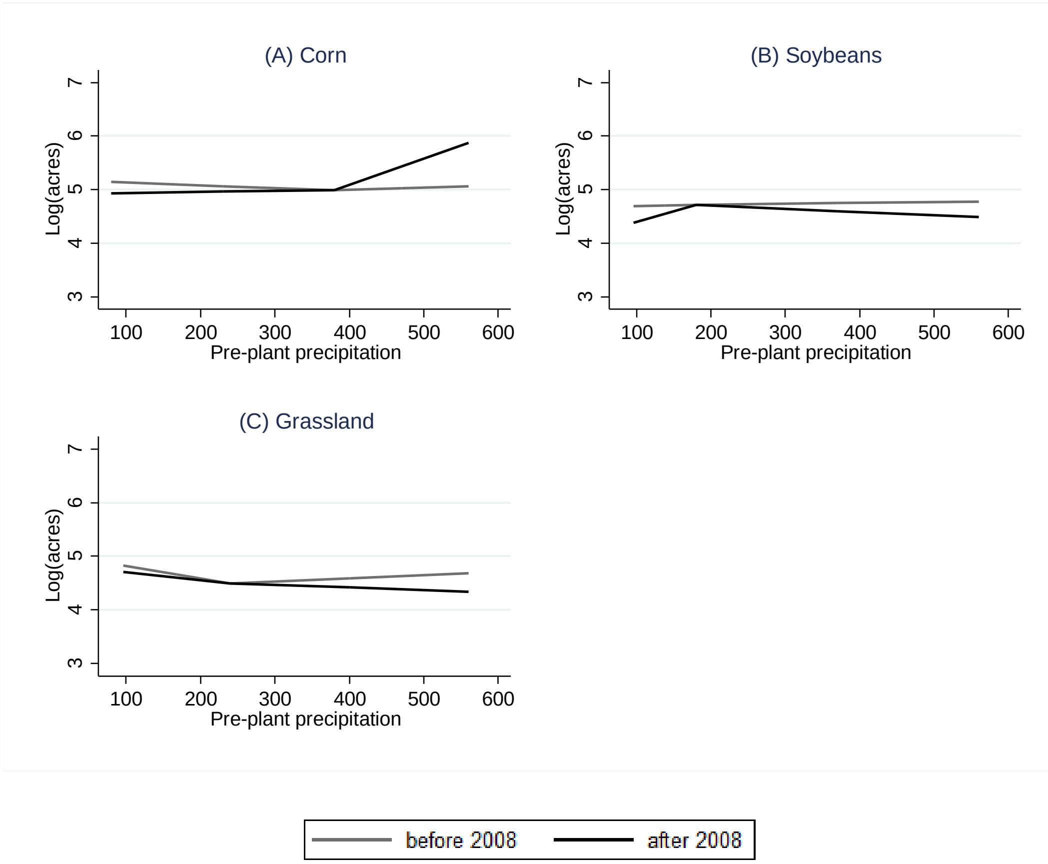

*Notes:* Figure displays the percentage of sections belonging to a class of weighted land capacity. Weighted land capacity is calculated by the authors with the Soil Survey Geographic (SSURGO) database. Larger values indicate poorer soil quality. See Section 4.4 for our calculation of weighted land capacity at the section level.

Figure 1.5: Predicted Effects of Pre-plant Precipitation and Policy Change in 2008 on Land Use in North Dakota




*Notes:* Figure displays the predicted means of log(acres) in the sections as a function of pre-plant precipitation. The threshold of pre-plant precipitation is 100 for corn, 60 for soybeans, 170 for spring wheat, and 130 for grassland.

Figure 1.6: Predicted Effects of Pre-plant Precipitation and Policy Change in 2008 on Land Use in Iowa




*Notes:* Figure displays the predicted means of log(acres) in the sections as a function of pre-plant precipitation. The threshold of pre-plant precipitation is 380 for corn, 270 for soybeans, and 240 for grassland.

# Chapter 2

# The Effect of Land-Use Change on Grassland Bird Species Richness in the Midwestern United States: A Dynamic Panel Analysis of the U.S. Biofuel Mandate

## 1 Introduction

Biodiversity loss is one of the major environmental changes underway on Earth (Cardinale et al., 2012). A key driver of biodiversity loss is natural habitat alteration and destruction through human activities (Millennium Ecosystem Assessment, 2005). Agricultural systems, with their vast use of land and freshwater resources, are a dominant force in this regard (Foley et al., 2011; Tilman et al., 2011), and the U.S. biofuel mandate is an important case in point (Roberts and Schlenker, 2013). The Energy Independence and Security Act of 2007 defines the mandate through annual biofuel production requirements through 2022. While several unanticipated environmental consequences of the mandate have been discovered (e.g., Hill et al., 2006, 2009; Fargione et al., 2008; Searchinger et al. 2008; McDonald et al., 2010; Mehaffey et al., 2012), biodiversity and wildlife are a significant concern because of their direct connection to biofuel-induced agricultural land-use change, especially in the Midwestern United States (Fargione et al., 2009; Fletcher et al., 2011; Meehan et al., 2010; Robertson et al., 2012). Against this backdrop, North American grassland birds have experienced more rapid population declines than any other avian group in North America (Brennan and Kuvleski, 2005). One of the top research priorities for conservation policy is to understand how different strategies for growing biofuel crops affect species like grassland birds (Fleishman et al., 2011). Despite the importance, little quantitative, causal evidence exists on the effect of land-use change on grassland bird species in the U.S. Midwest.

In this research, we develop and statistically estimate a dynamic framework for explaining the geographical variation in grassland bird species richness in the Midwest. Recent land-use changes in the region include cropland expansion from uncultivated land, expansion of monoculture cropland from rotational or diverse cropland, and intensified use of chemicals and fertilizers (Mehaffey et al., 2012; Wright and Wimberly, 2013). We estimate the causal effect on species richness of three major land uses: cropland, grassland, and developed land. The cropland category includes the region's dominant crops – corn and soybeans. Production of these crops is a high-input low-diversity land use, with significant inputs of fertilizer and pesticides along with relatively low plant diversity (Meehan et al., 2010). Grassland, in contrast, is a low-input high-diversity land use. For the analysis, we develop a unique geospatial panel dataset for ten states of the Midwest for 2006-2013. Observational data on bird abundance, land use, and weather are merged from three sources: North American Breeding Bird Survey (BBS), Cropland Data Layer (CDL), and the Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system.

Our research makes three advances in the empirical analysis of ecological-economic systems. First, we extend the analysis of species richness to include inherently intertemporal relationships in addition to spatial relationships. Last year's species richness at a site directly affects this year's species richness at the site due to birds' natal philopatry and breeding-site fidelity, which have been documented for several grassland bird species (e.g., Pearce, 2007; Ribic et al., 2009), in addition to the high correlation between species richness and abundance for birds (e.g. Bock et al. 2007). This is the *species richness state-dependent effect*, and it requires a regression model with a lagged dependent variable for species richness. A *habitat recruitment effect* operates through the (unobserved) effect of last year's land use on last year's breeding success. Lagged land-use variables capture the habitat recruitment effect; depending on these lagged variables, additional birds may return to the same site thereby producing higher species richness this year. Lastly, a *habitat attraction effect* reflects the extent to which land use in the current year attracts individuals searching for breeding habitat. Current-year land-use variables capture the habitat attraction effect in the model. We apply the Arellano-Bond dynamic panel data regression model (Arellano and Bond, 1991) to statistically estimate the intertemporal framework. The *Methods* section develops this in more detail.

Second, we characterize and address statistical concerns related to consistent estimation of parameters of regression models within the context of explaining variation in grassland bird species richness. The major concern of microeconometrics is endogeneity bias in parameter estimates, and three methods – instrumental variables, quasi-experiments, and randomized field experiments – are being applied to generate consistent estimates (Angrist and Pischke, 2008). The Arellano-Bond estimator uses an instrumental variables identification strategy. We compare our main results to results generated using cross-sectional data and related regression models, such as those applied in a recent study of bird species richness in the Midwest (Meehan et al., 2010).

Third, the main results are used for forecasting bird species richness under implementation of the biofuel mandate. The mandate exemplifies the potential for complex interrelationships among public policy, markets, human decision-making, and environmental change. By setting annual production requirements for renewable fuels such as corn ethanol, the mandate raised agricultural commodity prices by an estimated 30 percent and increased global agricultural production area by an estimated 2 percent (Roberts and Schlenker, 2013). This includes indirect land use change driven by the mandate, which can result in a net increase in carbon dioxide emissions (Searchinger et al., 2008). Here, we combine our regression estimates of the effects of land use on species richness with spatially explicit projections of Midwestern cropland and grassland use under the biofuel mandate (Mehaffey et al., 2012) to project changes in bird species richness until 2030.

The paper is structured as follows: Section 2 presents the model and our estimation method. In Section 3 we describe the database and our sample. The econometric and forecasting results are presented in Section 4. Section 5 discusses our results and concludes.

## 2 Dynamic panel model methodology

Here we describe the obstacles to identifying the effect of land-use change on grassland bird species richness. Then our econometric model will be introduced to overcome the obstacles.

### 2.1 Identification problems with traditional regression models

We start our econometric modeling with a standard cross-sectional species richness equation, which has been used extensively in related studies (e.g., Meehan et al., 2010, and Hamer et al., 2006).

$$y_i = \beta' X_i + \varepsilon_i \quad \text{with } \ i = 1, \dots, N \tag{1}$$

where $y_i$ denotes the grassland bird species richness along a BBS survey route $i$, $X$ is a $1 \times k$ vector of variables that determines the outcomes and includes for example land-use and weather variables, and $\varepsilon_i$ is an independently distributed error term with $E[\varepsilon_i] = 0$ for all $i$. The main advantage of cross-sectional estimation is better data availability for larger samples and sets of variables. However, cross-sectional estimation does not control for omitted or unmeasurable location-specific time-invariant effects and year-specific effects, and thus it results in inconsistent estimates.

Panel estimation provides an opportunity to control for unobserved effects. Consider the model

$$y_{i,t} = \beta_1' X_{i,t} + \gamma_i + \varphi_t + \varepsilon_{i,t} \quad \text{with } \ i = 1, \dots, N, \text{ and } t = 1, \dots, T \tag{2}$$

where $\varphi_t$ is an unobserved year-specific fixed effect for all locations at time $t$. $\gamma_i$ is an observed or unobserved route-specific or BBS-observer-specific time-invariant fixed effect. In this case, an endogeneity problem exists when $\gamma_i$ is correlated with the variables in $X$, variables such as land quality or the ability of farmers to react to natural or policy shocks. It is fairly common to reject the assumption of no correlation between local-specific fixed effects and land use decisions (e.g., Timmins, 2006, Ferraro and Pattanayak, 2006, and Roberts and Schlenker, 2012). Our Hausman test results also suggest rejecting this assumption. Conventional ordinary-least-square (OLS), random-effect, or mixed-effect panel data estimators result in inconsistent estimates when the assumption is rejected.

### 2.2 A dynamic model

In order to capture the temporal spillovers and the delayed response to land-use change of bird species richness, we estimate a dynamic model, equation (3), which adds the lags of the dependent and independent variables to equation (2):

$$y_{i,t} = \beta_1 y_{i,t-1} + \beta_2' A_{i,t} + \beta_3' A_{i,t-1} + \beta_4' W_{i,t} + \gamma_i + \varphi_t + \varepsilon_{i,t} \tag{3}$$

where $y_{i,t-1}$ is the lagged dependent variable that denotes the last year's grassland bird species richness of route $i$ in year $t-1$, $A_{i,t}$ is a vector of variables representing areas for three different land uses, including cropland, grassland, and developed land. $A_{i,t-1}$ is a vector of lagged independent variables for the three land uses. $W_{i,t}$ is a vector of weather variables, including the total precipitation from April to June in the vicinity of the BBS survey routes and the temperature, sky, and wind conditions at the time of the BBS survey itself. $\beta_1$ measures the spillover effect from last year's species richness, hence modeling the short-run dynamics of grassland bird species richness. $\beta_2$ is a vector of parameters that measure the habitat attraction effects from the alternative land uses this year. $\beta_3$ is a vector of parameters that measure the habitat recruitment effects provided by the three land uses in the last year. $\beta_4$ is a vector of parameters that measure the effects of the local weather conditions, and the area covered by water.

In this dynamic model, the lagged dependent variable is determined prior to the current period and so is a predetermined variable correlated with the past error term. Inclusion of the lagged dependent variable (i.e., lagged grassland bird species richness) in the presence of route-specific fixed effects, $\mathrm{\gamma_i}$, will lead to a upward bias of the estimated parameter of the lagged dependent variable, $y_{i,t-1}$ (e.g. see Hsiao, 2014). To eliminate the route-specific fixed effects, $\mathrm{\gamma_i}$, the standard approach is to use the fixed-effects estimator. This estimation strategy uses the demeaned estimation equation. After demeaning the equation, $(\mathrm{y_{i,t-1}} - \bar{\mathrm{y}}_{\mathrm{i,t-1}})$, where $\bar{\mathrm{y}}_{\mathrm{i,t-1}} = \frac{1}{(\mathrm{T}-1)} \sum_{\mathrm{t}=2}^{\mathrm{T}} \mathrm{y_{i,t-1}}$, is negatively correlated with the demeaned error term $(\varepsilon_{\mathrm{i,t}} - \bar{\varepsilon}_{\mathrm{i}})$. This leads to a downward bias of the estimated parameter of the lagged dependent variable, $y_{i,t-1}$ (see Nickell, 1981). To remedy this, the first-differenced equation can be used to eliminate the route-specific fixed effects, as in equation (4).

$$\Delta y_{i,t} = \beta_1 \Delta y_{i,t-1} + \beta_2' \Delta A_{i,t} + \beta_3' \Delta A_{i,t-1} + \beta_4' \Delta W_{i,t} + \Delta \varphi_t + \Delta \varepsilon_{i,t} \tag{4}$$

where $\Delta y_{i,t} = \Delta y_{i,t} - \Delta y_{i,t-1}$ and all other variables are defined as before. However, the OLS estimates of the differenced model are still inconsistent because the differenced residual is necessarily correlated with the lagged dependent variable, as both are a function of $\varepsilon_{\mathrm{i,t-1}}$. Our study attempts to address misspecification error and potential sources of endogeneity problem to obtain consistent estimation with predetermined (including lagged) and/or endogenous variables in regression models, and thus the consistent effect of land-use change on bird species richness can be identified.

## 2.3 Dynamic panel estimation

Instrumental variable (IV) approaches have been used extensively in empirical economics for estimating cross-sectional models and panel data models with an endogeneity problem. With cross-sectional models, endogenous variables are instrumented by variables that are not in the equation of interest, though finding suitable instruments is very difficult.[1] With panel models, the extra periods of data may provide additional instruments and additional moment conditions that lead to identification or overidentification of parameters.[2] Exogenous variables, including regressors in the equation of interest in periods prior to the current period, may be valid instruments for endogenous variables in the current period in a panel setting. Using a dynamic panel data estimator originally proposed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), we exploit the time series dimension of the bird and land data to create a rich structure of lags as instrumental variables.

The estimator starts from the first-difference equation (4). Following Arellano and Bond (1991), who introduced a Generalized Method of Moments (GMM) estimator for use in a short panel, further lagged levels of the grassland bird species richness are valid instruments for the differenced lagged dependent variable $\Delta y_{i,t-1}$ under the assumption of no serial correlation in $\varepsilon$. For instance, the second-lagged level $y_{i,t-2}$ is not correlated with $\varepsilon_{i,t}$ or $\varepsilon_{i,t-1}$ but is correlated with $\Delta y_{i,t-1}$. Further lagged levels available can be included as instruments to improve efficiency. These instruments enter separately for each year. In our case, the matrix of GMM instruments for the endogenous $\Delta y_{i,t-1}$ for each year is

[1] See Angrist and Pischke (2008) chapter 4 for the detail of IV estimation. In literature of empirical economics, instrumental variable estimators have been used to address endogeneity problems. For instance, Timmins (2006) exploits the variation of agricultural research stock over different regions in Brazil to instrument for land-use share, which is correlated to the determinants of land value when estimating the impact of climate change on land value. Schlenker and Roberts (2012) also have good instruments for crop yields in order to estimating the elasticity of crop supply. Other related studies highlighting the problem of endogenous land use are evaluations of farm policy or land conservation policy, such as Andam et al. (2008).

[2] See Cameron and Trivedi (2005) chapter 16 for an introduction to the use of lags to instrument for endogenous variables in dynamic panel models.

$$Z_y = \begin{bmatrix} y_{i0} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i0} & y_{i1} & \dots & 0 & \dots & 0 \\ \vdots & & & \ddots & \vdots & & \vdots \\ 0 & 0 & 0 & \dots & y_{i0} & \cdots & y_{iT-2} \end{bmatrix}$$

where the first row includes instruments for $\mathrm{t} = 2$, the second for $\mathrm{t} = 3$,and so on. The Arellano-Bond estimator uses the moment conditions $E(y_{i,s}\Delta\varepsilon_{i,t}) = 0$ for $s \leq t - 2$ so that the lags $y_{i,t-2,}$, $y_{i,t-3}$, … can be used as instruments for $\Delta y_{i,t-1}$ in the first-differenced equation (4).

Likewise, lagged levels of land-use variables are valid instruments for the differenced land-use variables if land use is endogenous. For instance, $A_{i,t-2}$ and further lags are valid instruments for $\Delta A_{i,t}$ and $\Delta A_{i,t-1}$. This requires an additional assumption that $A_{i,t}$ is uncorrelated with $\varepsilon_{i,t+1}$ for all $t$. This should be the case for our study. First, random shocks to future bird species richness should not affect farmers' current land use decisions. Second, unobserved time-varying shocks to $A_{i,t}$, such as precipitation in early spring, only affect $y_{i,t+1}$ through the effects of $A_{i,t}$ and $y_{i,t}$ as described in equation (3). Identification of equation (4) also requires that land-use changes are predicted by their lagged levels. That is, if $A_{i,t}$ is endogenous, $A_{i,t-2}$ should be correlated with $\Delta A_{i,t}$. If $A_{i,t}$ is predetermined, which means $A_{i,t}$ is correlated with $\varepsilon_{i,t-1}$ but not $\varepsilon_{i,t}$, $A_{i,t-1}$ would also be a valid instrument for $\Delta A_{i,t}$. Our tests for the assumptions will be described later.

However, the Arellano-Bond estimator behaves poorly in small samples when $\beta_1$ approaches unity (Blundell and Bond, 1998). Given the slow nature of changes in species richness in general, grassland bird species richness might be persistent over time. As a result, lagged levels are weak instruments for the first-differenced variables, and the Arellano-Bond estimates are considerably biased. We address this problem by applying the system GMM estimator. As Bun and Windmeijer (2010) presented, the system GMM estimator consistently has the smallest bias of the dynamic GMM estimators, because it is a weighted average of the difference and levels equations with the weights on the levels equation moments increasing in the weakness of the difference equation instruments.

Therefore, we apply the system GMM estimator for addressing endogeneity problems. With the additional moment conditions $E(\Delta A_{i,t}(\gamma_i + \varepsilon_{i,t})) = 0$, lagged differences $\Delta y_{i,t-2}$, $\Delta y_{i,t-3}$, … can be used as instruments for the endogenous $y_{i,t-1}$ in the level equation (3).

Likewise, lagged differences $\Delta A_{i,t-1}$, $\Delta A_{i,t-2}$, … can be used as instruments for an endogenous $A_{i,t}$. If $A_{i,t}$ is predetermined, the contemporaneous $\Delta A_{i,t}$ is also valid.[3] The moment conditions are estimated in Stata using XTABOND2.[4] We use the option for two-step robust estimation, which can be more efficient than one-step robust estimation (Roodman, 2009a). It has been shown that the two-step estimates of the GMM system standard errors are downward biased in finite samples, so we apply the finite-sample correction for the asymptotic variance of the two-step GMM estimator (Windmeijer 2005).

The main goal of our empirical strategy is to minimize the bias caused by the endogeneity problem in the dynamic panel data model, so that the causal effect of land use change on grassland bird species richness can be identified. Thus, from section 2.3.1 to section 2.3.4, we discuss several tests for the assumptions and other potential problems to be aware of when applying the system GMM estimator.

### 2.3.1 The tests of assumptions

A basic assumption of the system GMM estimator is that all lags are valid instruments if the errors are serially independent, as mentioned above. The Arellano-Bond test is used for testing zero autocorrelation in first-differenced errors. Regressions based on equation (4) are AR(1) by design because both $\Delta\varepsilon_{i,t}$ and $\Delta\varepsilon_{i,t-1}$ contain $\varepsilon_{i,t}$. If there is serial correlation in ε, equation (4) will be at least AR(2). The results of the tests will be presented with the regression results below.

Like other IV estimators, the system GMM estimator's instruments must satisfy the exclusion restriction that the set of instruments are not correlated with the unobserved error terms in the both the level equation (3) and the differenced equation (4). The Hansen test of overidentifying restrictions is used to test the joint validity of all moment conditions. The difference-in-Hansen test is also used to consider the validity of a subset of specified instruments, such as the instruments for the level equation, the lags of bird species richness used as instruments and, or the lags of land use variables used as instruments if land use variables are treated as predetermined or endogenous. See *Appendix 1* for the detailed test results.

[3] If $A_{i,t}$ is predetermined, $\Delta A_{i,t}$ is also a valid instrument because $E\left(\Delta A_{i,t}(\gamma_i + \varepsilon_{i,t})\right) = E\left(\Delta A_{i,t}\gamma_i\right) + E\left(A_{i,t}\varepsilon_{it}\right) - E\left(A_{i,t-1}\varepsilon_{it}\right) = 0 + 0 - 0$.

[4] See Roodman (2009a) for documentation.

### 2.3.2 Weak instruments

The system GMM estimator's instruments must also satisfy the inclusion condition that the set of instruments are correlated with the endogenous variable. While we have mentioned that the study could suffer from weak instrument biases with the difference GMM estimator, recent studies (e.g., Bun and Windmeijer, 2010, and Bazzi and Clemens, 2013) show that the system GMM estimator can suffer from the same problem. That is, differenced lagged variables may be valid but weak instruments for the level equation. No formal test had been developed for weak instruments in the dynamic GMM estimator until Bazzi and Clemens (2013) developed tests for underidentification (Kleibergen-Papp LM test) and weak instruments (Cragg-Donald and Kleibergen-Paap Wald tests). As presented in *Appendix 1*, we follow their test procedures and show that we do suffer from a weak instruments problem with the difference GMM estimator, but that the instruments are strong with the system GMM estimator in the presence of the lagged grassland bird species richness.

### 2.3.3 The number of instruments

The GMM estimator quickly produces a large number of instruments in the dynamic panel case, though we only use the first lags of endogenous variables as instruments in our preferred model, instead of including other available lags. Having many instruments can overfit the endogenous variables and thus bias estimates towards OLS and weaken overidentification tests. Roodman (2009b) recommends analyzing the sensitivity of dynamic panel data estimates to reductions in the number of instruments and reporting the number of instruments used in each regression. We follow Roodman's recommendations and, as showed later, the sensitivity analysis shows that restricting lags has little effect on the estimates of our variables of interest.

### 2.3.4 Spatial correlation

Due to the high mobility of birds, it is possible that spatial spillovers exist, i.e., that bird populations in neighboring locations affect each other. If spatial correlation exists and is not accounted for, there is cross section dependence in error terms. Typically, the literature of difference and system GMM estimators assumes that the disturbances are cross-sectionally independent. In empirical applications, time dummies are used to control for the common cross section dependence across locations. But if there is heterogeneous cross sectional dependence, these GMM estimators will not be consistent (Sarafidis and Robertson, 2009).

We follow the test procedure proposed by Sarafidis et al. (2009) for error cross sectional dependence after estimating a linear dynamic panel data model with the GMM estimators. This test procedure includes the Arellano-Bond test mentioned above and Sargan's difference test. Our test results, shown in *Appendix 1*, suggest no heterogeneous error cross section dependence in our model. This likely is due to the substantial distances between routes in the bird survey, namely the routes should be far enough apart to avoid spatial interactions.

## 3 Data

### 3.1 Bird data

Data on bird species richness is compiled from the North American Breeding Bird Survey (BBS) of the U.S. Geological Survey's Patuxent Wildlife Research Center. The BBS is a roadside survey, with trained observers gathering data along standardized survey routes on a single morning during early to mid-June each year. Each route is 40 km long with 50 designated stops, 0.8 km apart. Birds seen or heard within a 400 m radius of each stop are counted over a 3-minute period.

Corresponding to the 400 m survey radius, we created a buffer zone along each route with a radius of 400 m as our unit of analysis. Each route buffer represents the habitat quantity and quality available for birds within the landscape. We only used routes that met BBS data quality standards. In addition, we only used routes that were surveyed by the same observer for each route over our study period 2006-2013 in order to avoid unobserved heterogeneity from observers when using our statistical method.

Our main dependent variable, grassland bird species richness, is computed as the sum of the species observed at all stops along a given route among the 30 grassland bird species listed by Peterjohn and Sauer (1993). This measure of species richness is likely underestimated due to the limited duration of the survey; however, as long as this measurement error in the dependent variable is uncorrelated with the regressors, only the intercept will be confounded in regression models. If it is correlated with the regressors, the estimation method we use allows us to address the transient measurement error problem, while any permanent additive measurement errors are absorbed into time-invariant route-specific fixed effects (Bond et al. 2001).

### 3.2 Land cover data

The National Agricultural Statistics Service's Cropland Data Layer (CDL) program of the US Department of Agriculture (USDA) provides comprehensive, raster-formatted, geo-referenced, crop-specific land cover data during the growing season for the United States. The CDL's land cover classifications include over 50 crops and come with a spatial resolution of 30 m or 56 m. The CDL program started producing the annual land cover data for some states in 1997 and has covered the entire United States since 2008.

We constructed a balanced panel of land cover outcomes within the bird route buffers using the CDL data for 2006-2013 with our Python programs. We exclude CDL data before 2006 because it is less reliable and covers smaller states. Our cropland classifications include corn and soybeans, both of which are affected by increasing demand for biofuel (Mehaffey et al. 2012) and are measured at a high accuracy level (>90%) as calculated by the CDL program. The non-cropland classifications for grassland and developed land in this study are reclassified from the original CDL classifications. Because the CDL data is limited to distinguishing among unmanaged grassland, pasture, and hay, these land uses are combined into the "grassland" land cover category. Likewise, open space, low-developed, medium-developed, and high-developed land uses are combined into a "developed land" variable. This variable assumes that the CDL consistently distinguishes among these categories across years.

### 3.3 Weather data

In order to exploit the smaller scale variation in weather, we calculated the accumulated precipitation from April, May and June at the route-buffer level from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system, which generates monthly estimates of precipitation at 4-by-4 kilometer grid cells for the entire United States. Using our Python programs, these precipitation data cells are intersected with route buffer zones. The spring precipitation at the route-buffer level is then computed by averaging the intersected cells' precipitation values for each route buffer zone.

### 3.4 Soil data

We obtain several soil characteristics from USDA's Soil Survey Geographic (SSURGO) Database. This spatially high-resolution database provides 10-by-10 meter grid cells for the entire United States. We extract the soil characteristics within each route buffers using our Python programs. The soil characteristics of the interests are associated with both grassland bird species richness and people's land use decisions. We first obtain data on land capacity class that measures the limitation and requirement of conservation practices for cropping. Class 1 and Class 2 are good quality soil for cropping. Class 3 and Class 4 are moderate quality soil that have severe limitations for cropping and/or require careful conservation practices. Poor quality soil in Class 6, Class7, and Class8 has very severe limitations that make them generally unsuited to cultivation. We also obtain drainage data that identifies the frequency and duration of wet periods, as wells as data on flooding frequency that measures the annual probability of a flood event. The time-invariant soil data set is used for highlighting the potential bias due to unobserved heterogeneity among the route buffers.

### 3.5 Forecasting data

Biofuel-mandate projections are drawn from Mehaffey et al. (2012), who project Midwestern U.S. land-use change in 2020 driven by the U.S. biofuel mandate with a spatial resolution of 30 m. Based on the National Land Cover Database (NLCD) 2001, their cropland classifications are expanded to 18 classes by using the CDL dataset. These include corn, soybeans, wheat, cotton, alfalfa hay, fallow field, and other crops. The crops are designated as planted in monoculture, such as monoculture corn, or as a two-crop rotation, such as rotation between soybeans and fallow field. Similarly, their non-cropland classifications are down-scaled from the NLCD 2001 and include 155 classes of natural cover.

In order to make Mehaffey et al.'s land cover classifications in 2020 comparable to our classifications, we first upscale their 155 natural cover classes by intersecting their data with NLCD 2001 data using ArcGIS 10.0. We then reclassify the upscaled data to our land cover classifications with a simple assumption on rotational cropland. The assumption is, for each rotational-cropland grid cell, two crops would uniformly share the grid cell area. We then produce the projected land cover outcomes in 2020 at the route-buffer level for our forecasting inputs using our Python programs. Finally, to provide projected land cover outcomes for dynamic forecasting using our dynamic panel data model, we assume that each land cover class changes linearly each year between 2013 (observed) to 2020 (projected). We execute a linear interpolation to generate the land cover inputs at the route-buffer level and at county level for 2013-2019. After 2020, we assume the biofuel mandate's corn-based biofuel production standard for 2020 will apply for the years until 2030.

### 3.6 The estimation sample

The extracted datasets mentioned above are merged by each route buffer for our analysis. Our panel dataset is balanced and consists of 129 routes over 2006 to 2013 in the 11 Midwestern states, including North Dakota, South Dakota, Nebraska, Minnesota, Iowa, Kansas, Wisconsin, Illinois, Missouri, Indiana, and Ohio.

Table 2.1 presents basic summary statistics for our sample. The average grassland bird species richness is 7.32, ranging from 2 to 18. The average planting area of corn and soybeans is 1,345 hectares, and the average grassland area is 978 hectares. On average, total area of corn, soybeans, and grassland is 2,323 hectares, or about two-thirds of the average route buffer area. Figure 2.1 presents that the trend of the average grassland bird species richness is decreasing over the route buffers in the 11 states during the study period, while the trend of average grassland area is decreasing and the trend of the average corn and soybeans planting area is increasing.

## 4 Results

### 4.1 Land covers vary with predictors of grassland bird species richness and unobserved exogeneity, resulting in inconsistent estimates with conventional regression models.

Species-area regression models rely on the assumption that the land-use variables are orthogonal to the unobserved determinants of grassland bird species richness. First, we indirectly investigate the assumption by examining equality of observable characteristics that affect both land-use decisions and grassland bird species richness across the quartiles of grassland or cropland areas. If the observables are balanced across the quartiles, the unobservables may be more likely to be balanced so that valid estimates of the effects of land-use changes can be obtained (Altonji, Elder, and Taber, 2005).

Table 2.2 shows that the observables among the four quartiles of both grassland and cropland are markedly imbalanced. The entries of the table are, by quartile of the grassland area in our initial year 2006, the means of time-invariant soil characteristics, open water area and spring precipitation normal, in addition to time-varying developed land area and grassland bird richness at the route-buffer level. The means are calculated with pooled data from 2006 to 2013 but are adjusted for year effects. Quartile 1 refers to the route buffers with the smallest grassland area.  The last column reports F-statistics from tests of the null hypothesis of equality of means across the quartiles.  An F-statistics value larger than 3.34 indicates that the null hypothesis can be rejected at the 1-percent level.  As can be seen in Table 2.2, all of the F-statistics reject the null hypothesis and suggest that the cross-sectional analysis of area-species relationship may be biased due to specification error and potentially due to unobserved factors.

Table 2.3 further shows evidence of inconsistency of the estimated effects of grassland and cropland changes on grassland bird species richness.  The columns of (1) and (2) correspond to the conventional specification and more-predictors specification, respectively.  The added predictors in column (2) include acreage of high quality land, acreage of moderate quality land, average flooding frequency, average duration of wet periods, and normal spring precipitation.  Panel (A) of the table shows a huge variation of the year-specific estimates of grassland change.  It also shows the estimated results are not robust to the added control variables, suggesting potential confounders with the cross-sectional regression models.

While cross-sectional regression models are vulnerable to specification error and unobserved confounders, we are able to control for year-specific fixed effects, and to control for unobserved time-invariant variables in different ways using panel estimation models.  With an inclusion of year-specific fixed effects in pooled data models, Panel (B) of Table 2.3 shows that after controlling for unobserved time-invariant variables, the estimated coefficient of grassland change is decreased substantially from 0.486 to -0.149 by using a mixed-effect estimator, or to -0.421by using a fixed-effect estimator.  It is worth noting that the mixed-effect estimator, which is a random-effect estimator, has been applied regularly in ecological research.  However, our Hausman test result of chi-square statistics 413.88 markedly suggests random-effect estimators are not consistent.  It is expected because unobserved exogeneity is very likely to be correlated with land-use variables among route buffers, which violates the assumption of strict exogeneity for using random-effect models.  Hence, fixed-effect estimators would be preferred than random-effect estimators to control for unobserved exogeneity, though it still fails to control for time-varying latent variables.

Furthermore, using the pooled data we are able to investigate potential specification error from the temporal spillover of grassland bird species richness and the delayed effect of land-use changes with our dynamic model equation (3).  Table 2.4 shows that the estimated coefficients of lagged grassland bird species richness variable are statistically significant with all estimators except the fixed-effect model, which implies there is a species richness state-dependent effect. Table 2.4 also shows that there is delayed habitat recruitment effect of grassland on grassland bird species richness with all estimators except the fixed-effect model.

Overall, the findings above suggest that conventional cross-sectional and panel data estimators may be unable to produce a credible estimate of the effect of land use on grassland bird species richness in the presence of the temporal spillover of grassland bird species richness and delayed habitat recruitment effect. Because of the importance of the question, it is worth considering alternative methods to obtain a consistent estimate with the dynamic model setting.

### 4.2 The dynamic panel data model uses valid and strong instruments to control for biases without violating the assumptions of serially and spatially uncorrelated errors.

Not only does the system GMM estimator control for time-invariant variables like fixed-effect estimators, but it also can control for endogenous biases from the lagged grassland bird species richness and variables in the error term that are not orthogonal to route-buffer-specific fixed effects or our land-use variables. Our preferred specification is supported by several important tests of assumptions mentioned in the *Methods* section. The detailed test statistics are reported in *Appendix 1*. Overall, the test results suggest a few important findings. First, AR(2) test does not reject the null hypothesis of no second-order serial correlation in the first-differenced residuals. Second, there is no spatial correlation with our model, as Sargan's difference test does not reject the null hypothesis that there is no heterogeneous error cross section dependence. Third, our instruments are valid, as the Hansen test of overidentification and the difference-in-Hansen tests do not reject the null hypothesis that our instruments are proper. Forth, our instruments are not weak for the level equation. The results of the Kleibergen-Paap LM test and the Kleibergen-Paap Wald tests suggest that the identification is not weak to conduct meaningful hypothesis tests. Together, these findings allow us to use the system GMM estimator to address potential identification problems with the dynamic model and obtain a consistent estimate of the effect of land-use changes on grassland bird species richness.

### 4.3 Land use has an enduring effect on grassland bird species richness that operates through the temporal spillover of lagged grassland bird species richness.

Column 1 in Table 2.4 presents the estimated result of equation (4) using our preferred SGMM estimator. The coefficient on lagged grassland bird species richness means, on average, a decline of a unit of grassland bird species richness this year would reduce 0.19 unit of grassland bird species richness next year, holding other control variables fixed. The estimated coefficient is much lower than the estimate by using an OLS estimator and larger than the estimate by using a fixed effect estimator. Although the statistically significant temporal spillover effect does not show strong persistence of grassland bird species richness, it highlights a change in grassland acreage would influence the grassland bird species richness through years.

### 4.4 Grassland has a delayed positive effect on grassland bird species richness through the habitat recruitment effect, whereas developed land has a substantial negative attraction effect.

Positive habitat recruitment effect from grassland is statically significant, as can be seen in Table 2.4. The result suggests that one percent decrease in grassland hectares would result in a decrease of 0.71 units in grassland bird species richness next year. In addition, we find no evidence of habitat attraction effect from grassland. The estimated results for grassland indicate the importance of grassland habitat for breeding success and reproduction of grassland bird community.

With respect to cropland, though we find no evidence of attraction effect or recruitment effect, the coefficient shows much less recruitment effect from cropland. Unlike grassland and cropland, developed land has a statistically-significant negative attraction effect on grassland bird species richness. One percent increase in developed land hectares would result in a decrease of 1.6 units in grassland bird species richness due to the poor attraction effect of developed land. Yet, the recruitment effect is much lower than that from grassland habitat. Open water area also has a positive attraction effect, as it provides some wetland habitat. Spring precipitation also shows an inverted-U relationship with grassland bird species richness, as expected, as presented in *Appendix 1*. The pattern of effects of land use on grassland bird species richness is robust to the number of instruments and potentially endogenous variables, as presented in *Appendix 2*.

### 4.5 Under the US biofuel mandate (the baseline scenario), the average grassland bird species richness is predicted to decrease 22% and 13% in 2030 from 2013 and 2006 levels, respectively.

Panel A of Figure 2.2 presents our forecasting results of grassland bird species richness in the Midwest from 2013 to 2030. The results show the effects of intertemporal adjustments in grassland, cropland and developed land variables, while holding other predictors fixed at their average observed values over the study period, and holding year fixed effects for our prediction period fixed at the average of estimated year fixed effects for the 2006-2013 period. Our three land-use scenarios for cropland and grassland, showed in Panel B and Panel C of Figure 2.2, respectively, are based on Mehaffey et al. (2012)'s projection on the remaining rotational land in 2020 and on our assumption on the remaining rotational land. The baseline scenario (black line) assumes that the projected remaining rotational land is evenly distributed among five land-use categories: grassland, corn, soybeans, wheat, and other crops. Then, for each route buffer we execute a linear interpolation to generate the land use inputs for 2013-2019 for our dynamic model, and assume the projected remaining rotational land for 2021-2030 is fixed as that in 2020 provided that corn-based biofuel production standard is unchanged during the period. The projected results using our dynamic model show that on average over the Midwest grassland bird species richness would decline about 13% from 2013 to 2030. After 2006 when the first biofuel mandate had been enacted, grassland bird species richness is predicted to decrease about 22 % in 2030. The driving force behind these predicted impacts is the increase in developed land and the decrease in rotational cropland that should have been rested with grass cover but instead is converted to monocultural cropland for corn and soybeans production.

Our second scenario assumes that the remaining rotational cropland in 2020 projected by Mehaffey et al. (2012) is totally converted to grassland for conservation. The third scenario assumes that the remaining rotational cropland is totally converted to continuous corn or soybean. We demonstrate that land conservation is able to stop the declining trend of grassland bird species richness even the developed land is projected to be increasing. It is worth nothing that our projected results can be conservative, as Mehaffey et al. (2012) assumes that the increase in cropland area as a result of the biofuel mandate is only from intensive margin. That is, cropland expansion is from less rotational cropland and more monocultural cropland.

### 4.6 County-level forecasts demonstrate heterogeneous impacts and help to identify conservation hotspots.

The new dynamic panel model allows regional heterogeneity caused by time-invariant unobserved variables. We recover route fixed effects and generate county fixed effects in order to predict at the county level and look for conservation hotspots. We assume a county fixed effect is the average over the route fixed effects of the route buffers that are intersected within the county boundary. If a county does not intersect with a route buffer, its county fixed effect is generated by averaging the county fixed effects in the adjacent counties. Initial values for county-level grassland bird species richness in 2013 and fixed values for county-level inputs of the independent variables, except land-use variables, are generated in the same manner. County-level land-use projections are calculated from Mehaffey et al. (2012) under same assumptions about remaining rotational land with the baseline scenario mentioned in Section 4.5.

Panel A of Figure 2.3 present our projected spatial-heterogeneous impacts on grassland bird species richness under spatial patterns in grassland (Panel B) and cropland (Panel C) in 2030. Conservation hotspots according to projected impacts, as can be seen in Panel A of Figure 2.3, can include northwestern counties in North Dakota, southeastern counties in Minnesota, northwestern and mid-northern counties in Iowa, mid-western counties in Missouri, southwestern and northeastern counties in Illinois, southwestern and southeastern counties in Wisconsin, southwestern counties in Indiana, and mid-northern and southern counties in Ohio. These hotsopts are sensitive to the changes in grassland and cropland.

It is worth noting that some counties do not show a negative impact on grassland bird species richness given that grassland is projected to be decreasing in 2030. In those cases, the predicted outcomes are dominated by the county fixed effect (such as in mid-central and northeastern Iowa) or the initial value of lagged grassland bird species richness for our dynamic panel prediction model is low, less than 3 (such as in northwestern Minnesota). It implies that unobserved heterogeneity substantially influences grassland bird species richness in the counties, as we have argued. On the other hand, our model may not perform well to predict the immediately short-term effect for the counties with extremely low grassland bird species richness. However, we argue that this model should by far perform best to predict the impact of land use on grassland bird species richness, supported by the evidence below.

### 4.7 Out-of-sample model predictions are more accurate than those from standard regression models.

The new dynamic regression model is compared with other specifications in the literature by using the root-mean-squared error (RMSE) of out-of-sample predictions. Each model is estimated 100 times, randomly sampling 119 routes of our 129 routes from 2006 to 2012 as the calibration sample. The 129 routes in 2013 and the remaining 10 routes from 2006 to 2012 are treaded as the validation sample, about 19 % of the whole data sample. We compare the results between the preferred dynamic GMM model, seven single-year models, and panel data models with and without lagged dependent and independent variables. One-step-ahead forecasts are produced for models with lagged variables. The results show that the RMSEs of out-of-sample predictions of the seven cross-sectional models are from 2.2 to 2.8, as can be seen in Table 2.5. Besides, panel data models without lagged variables do not reduce the RMSEs, not matter fixed effect or mixed effect models are adopted. Our dynamic panel data model clearly outperforms those conventional models in terms of forecasting, reducing RMSE at least by 36%, from 2.2 to 1.4.

## 5 Discussion and conclusion

Many studies in the field of conservation biology have used statistical models to link large-scale land use and land cover to bird species richness. Most of the studies are constrained by availability of land data and temporal consistency of the available land data. As a result, studies frequently use cross-sectional land data, such as Meehan et al., 2010 and Hamer et al., 2006. The overarching concern with the cross-sectional model is omitted variables bias. Land-use variables and other variables, such as soil quality and climate variables (e.g., average temperature), are spatially correlated. If critical variables correlated with land-use variables are omitted from the regression model, a land-use variable will include effects of variables besides land use, leading to biased estimates and predictions. Indeed, in Section 4.1, our work shows the wide discrepancy between cross-sectional and panel data estimates of the effect of grassland and cropland changes on grassland bird species richness.

The panel data model has recently been used for addressing unobserved heterogeneity. Rittenhouse et al. (2012) use two-years of NLCD land data to control for time-invariant unobserved variables when using a mixed effects model. However, mixed-effects models rely on the assumption of strict exogeneity, namely, land-use variables are independent of unobserved route-specific fixed effects. Our work shows that this is not the case. Evans and Potts (2014) construct a panel dataset from 2006 to 2012 from the databases we use, and adopted OLS, random effect, and fixed effect models to estimate the impact of land use on bird species abundance. They find wide variation in parameter estimates based on the choice of a panel estimator, and suggest that controlling for unobserved route-level heterogeneity may be critical to estimating an abundance model. We are not aware of any existing study that has relaxed the strong assumption of strict exogeneity between land-use variables and location-specific fixed effects for a species richness model in a large-scale ecological impact study.

Our study aims to identify the causal effect of land use on grassland bird species richness. We use fine-scale land cover and weather panel data and combine it with dynamic models. We focus on species richness rather than abundance. The lack of precision in estimating the impact of land use on bird abundance is discussed in Evans and Potts (2014), and we cannot address the problem by using our dynamic panel models for explaining grassland bird species abundance. However, for grassland bird species richness, by using the system GMM estimator, we control for time-invariant unobserved heterogeneity and relax the assumption of strict exogeneity. By using the system GMM estimator, we further control for other time-varying sources of omitted-variables bias that previous studies have not addressed. The sources of bias may include the breeding philopatry effect and habitat recruitment effect.

We address the bias by extending the analysis of bird species richness to include inherently intertemporal relationships, namely, the breeding philopatry effect and habitat recruitment effect. The estimated results of our dynamic model are consistent with prior work showing that grassland generally is positively associated with bird species richness (e.g. Meehan et al. 2010; Rittenhouse et al. 2012). However, we demonstrate that it takes time for the effect of grassland to appear through both the breeding philopatry effect and habitat recruitment effect. When bird species richness is influenced by last year's bird species richness and by last year's habitat quality's effect on breeding success, policy makers would expect lagged impacts of grassland conversion or grassland conservation.

Our study, at the same time, finds no statistically significant evidence on the immediate attraction effect of grassland this year after controlling for the lagged species richness variable, lagged land-use variables, and weather variables. Estimates of the effect of grassland this year from previous studies may be confounded by the effect of breeding-site fidelity, the habitat recruitment effect, and other systematically unobserved factors. We also find no evidence that cropland affects grassland bird species richness. As our estimates of cropland are imprecise, we cannot rule out the potential attraction and recruitment effects from cropland. In addition, it is useful to note that although our results suggest that the effect of grassland is not only through cropland and developed land, grassland conversion for cropland or developed use would substantially affect grassland bird species richness. Our estimated results with the land-use variables could be a useful tool to developing conservation strategies for grassland bird species richness by setting a simple standard on grassland density within a route buffer zone or a county in the Midwest.

Other time-varying unobservables in the error term could be systematically related to land-use variables in our study, observables such as landscape configuration (e.g. Lewis and Plantinga 2007; Polasky et al. 2005). We cannot account for landscape configuration because of alternative spatial resolutions of land cover data layers over the study period, which preclude us from generating comparable landscape configuration variables across years. However, landscape configuration variables may be bad controls in our regression model, given that landscape configuration is generally the outcome of a land-use decision.[5] A landscape configuration variable, if such data were available, would still be useful for examining whether the effects of land use on grassland bird species richness are not only through landscape configuration.

The simulation demonstrates how our prediction model can project spatially-explicit outcomes, as well as how explicitly including lagged grassland bird species richness and land-use variables substantially improves prediction accuracy. A weakness of this prediction model is the prediction accuracy would be lower if the model is applied to regions outside our study area. In this case, the prediction model cannot be adjusted by a region-specific fixed effect. We suggest the prediction model is best suited for our study area based on the fact that the model outperforms other models used in prior studies.

[5] See Angrist and Pischke (2008) for more about bad controls.

Table 2.1 Summary statistics of the estimation sample

| | Mean | Std. Dev. | Min | Max | Unit |
|---|---|---|---|---|---|
| Grassland bird species richness | 7.32 | 2.57 | 2 | 18 | Number |
| Cropland | 1344.51 | 882.37 | 0 | 3227.94 | Hectares |
| Grassland | 978.30 | 730.28 | 44.84 | 3427.33 | Hectares |
| Developed land | 346.70 | 226.03 | 8.78 | 2295.36 | Hectares |
| Open water | 35.26 | 50.49 | 0 | 386.36 | Hectares |
| Spring precipitation | 3.04 | 1.13 | 0.79 | 7.11 | 100 mm |

*Notes:* The sample for this table includes all observations that are used for estimation. There are 1,032 observations for 129 route buffers.

Table 2.2 Sample means by quartiles of grassland and cropland

| | Grassland | | | | | Cropland | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Quartile | 1 | 2 | 3 | 4 | F-Stat | 1 | 2 | 3 | 4 | F-Stat |
| *Soil quality* | | | | | | | | | | |
| Drainage | 1612.1 | 1270.4 | 849.6 | 919.6 | 47.07 | 927.1 | 893.1 | 1183.8 | 1647.8 | 46.12 |
| Flooding Frequency | 84.55 | 147.76 | 142.23 | 65.3 | 33.71 | 84.59 | 125.21 | 120.66 | 109.38 | 6.13 |
| High quality soil | 1681.6 | 1423.6 | 971.6 | 856.5 | 65.5 | 649.8 | 956.0 | 1246.5 | 2081.0 | 220.88 |
| Moderate quality soil | 433.0 | 771.7 | 866.2 | 1657.4 | 214.2 | 1307.6 | 1050.4 | 808.2 | 562.0 | 61.78 |
| Poor quality soil | 512.28 | 395.21 | 595.84 | 663.02 | 9.95 | 647.17 | 511.91 | 586.39 | 420.87 | 7.07 |
| *Climate and weather* | | | | | | | | | | |
| Normal rainfall | 294.30 | 290.22 | 278.68 | 268.18 | 15.71 | 271.00 | 283.36 | 276.38 | 300.62 | 18.87 |
| Realized rainfall | 239.50 | 240.97 | 221.22 | 204.76 | 52.72 | 211.93 | 222.36 | 225.43 | 246.74 | 51.42 |
| *Other land covers* | | | | | | | | | | |
| Open water area | 13.69 | 29.31 | 41.56 | 38.95 | 7.38 | 48.34 | 29.37 | 34.52 | 11.3 | 11.15 |
| Developed land | 252.90 | 314.99 | 340.69 | 220.23 | 19.80 | 273.06 | 301.62 | 289.97 | 264.15 | 11.41 |
| *Outcome variable* | | | | | | | | | | |
| Grassland bird species richness | 7.00 | 7.14 | 7.75 | 8.66 | 11.16 | 8.06 | 7.87 | 7.58 | 7.05 | 4.44 |

*Notes:* A F-statistics value larger than 3.34 indicates that the null hypothesis that the means across quartiles are equal can be rejected at the 1-percent level.

Table 2.3 Estimated results of static models

| | ln(grassland) | | ln(cropland) | |
|---|---|---|---|---|
| Specification | (1) | (2) | (1) | (2) |
| *(A) Single-year data model* | | | | |
| 2006 | 0.034 | -0.123 | 0.061* | 0.460** |
| 2007 | 0.221 | 0.108 | 0.065* | 0.292 |
| 2008 | 0.482 | 0.485 | 0.096*** | 0.216 |
| 2009 | 0.673** | 0.629* | 0.106*** | 0.454** |
| 2010 | 0.615* | 0.550 | 0.053** | 0.239 |
| 2011 | -0.049 | -0.074 | 0.056 | 0.045 |
| 2012 | 0.927** | 0.811** | 0.063*** | 0.489* |
| 2013 | 0.614* | 0.638* | | 0.459* |
| *(B) Pooled data (2006-2013) model* | | | | |
| OLS | 0.486* | 0.384 | -0.082 | 0.295* |
| Mixed effects | -0.149 | -0.220 | -0.359** | -0.059 |
| Fixed effects | -0.421* | -0.421* | -0.192 | -0.192 |
| More control variables | No | Yes | No | Yes |

*Notes:* ** p<0.01, * p <0.05 . Robust standard errors in parenthesis. The dependent variable in all specifications is the level of grassland bird species richness. There are 129 observations for a single-year regression. There are 903 observations for 129 routes for the pooled-data models. Year effects included in all pooled-data models.

Table 2.4 Estimation results of dynamic models

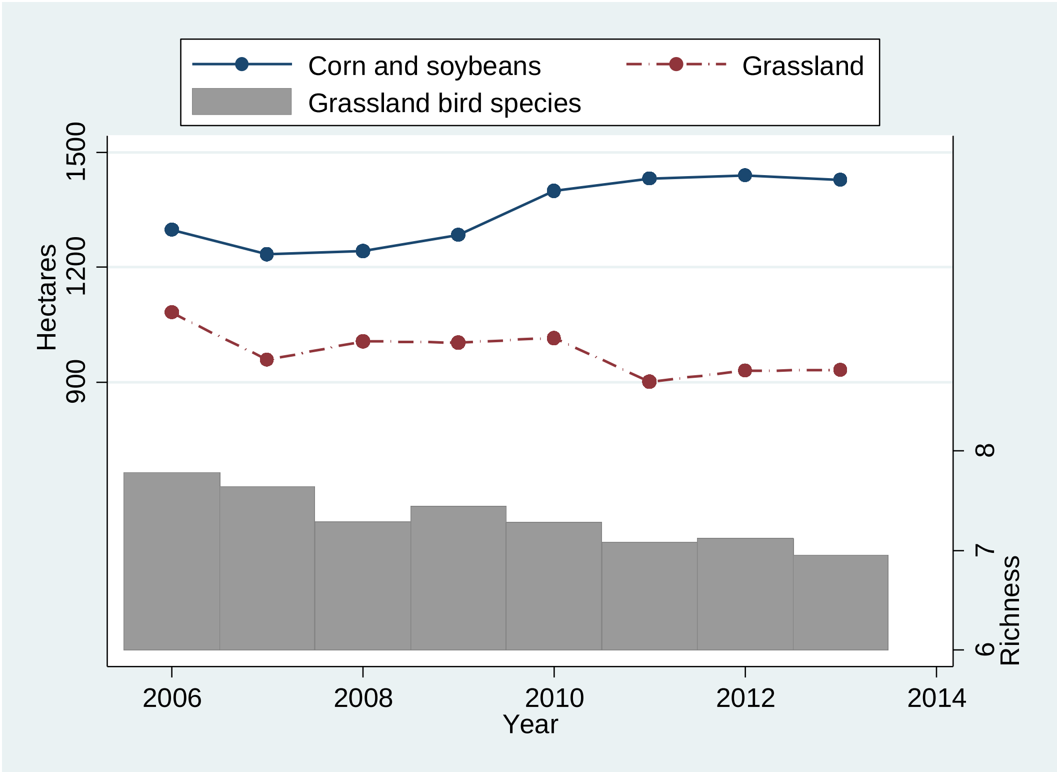
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | SGMM | OLS | ME | FE |
| Lagged grassland bird species richness | 0.191** | 0.767** | 0.884** | -0.031 |
| | (0.062) | (0.029) | (0.016) | (0.031) |
| ln(grassland) | -0.258 | -0.504* | -0.474* | -0.503* |
| | (0.216) | (0.199) | (0.185) | (0.211) |
| Lagged ln(grassland) | 0.710** | 0.682** | 0.597** | 0.224 |
| | (0.185) | (0.195) | (0.187) | (0.220) |
| ln(cropland) | -0.280 | -0.391* | -0.328* | -0.372* |
| | (0.255) | (0.189) | (0.136) | (0.149) |
| Lagged ln(cropland) | 0.323 | 0.388* | 0.326* | 0.246 |
| | (0.200) | (0.178) | (0.132) | (0.134) |
| ln(developed land) | -1.601** | -0.499** | -0.296* | -0.197 |
| | (0.366) | (0.182) | (0.142) | (0.515) |
| Lagged ln(developed land) | 0.235 | 0.103 | 0.064 | 0.118 |
| | (0.137) | (0.157) | (0.118) | (0.112) |

*Notes:* * $p < 0.05$, ** $p < 0.01$. Heteroskedasticity-robust standard errors in parentheses in column 1. Robust standard errors in parentheses in columns 2, 3, and 4. The dependent variable in all specifications is the level of grassland bird species richness. Year effects included in all specifications. There are 903 observations for 129 routes. Column 1 uses the system GMM estimator. Column 2 uses the ordinary least squares estimator. Column 3 uses the mixed effect estimator. Column 4 uses the fixed effect estimator. See Appendix 1 for the estimates of other controls.

Table 2.5  Out-of-sample prediction comparison for various model specifications

| Model | Root-mean-squared prediction error (RMSE) |
|---|---|
| Dynamic panel, SGMM | 1.35 |
| Cross section 2006 | 2.58 |
| Cross section 2007 | 2.33 |
| Cross section 2008 | 2.21 |
| Cross section 2009 | 2.28 |
| Cross section 2010 | 2.70 |
| Cross section 2011 | 2.45 |
| Cross section 2012 | 2.32 |
| Panel, OLS | 2.27 |
| Panel, mixed effect | 2.64 |
| Panel, fixed effect | 2.80 |

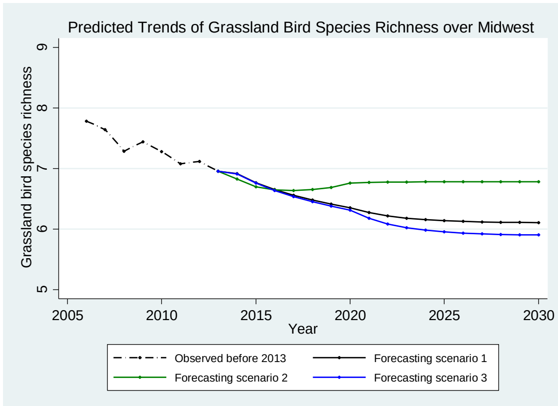
Figure 2.1  Average land use and grassland bird species richness



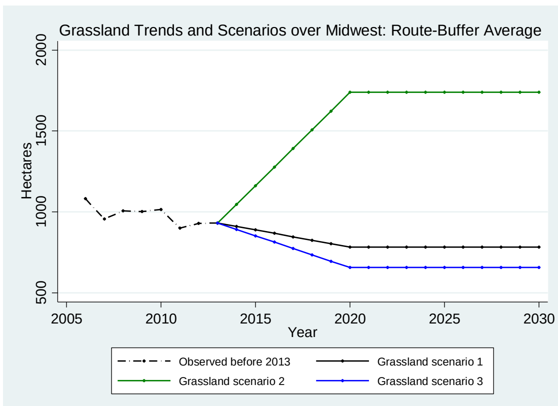

*Notes:* Figure displays the average grassland bird species richness, average cropland and grassland use in 2006-2013 over the estimation sample.

Figure 2.2 Forecasting results over the Midwest and the three land-use scenarios

A




B




C

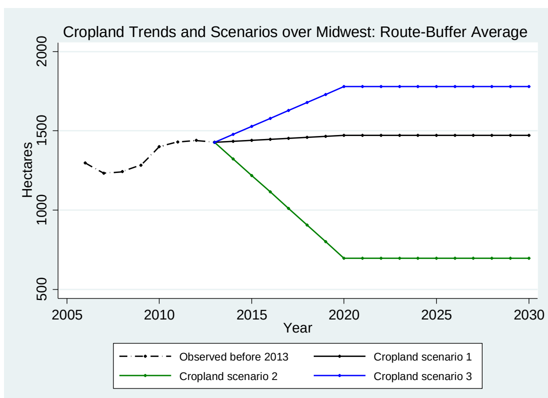
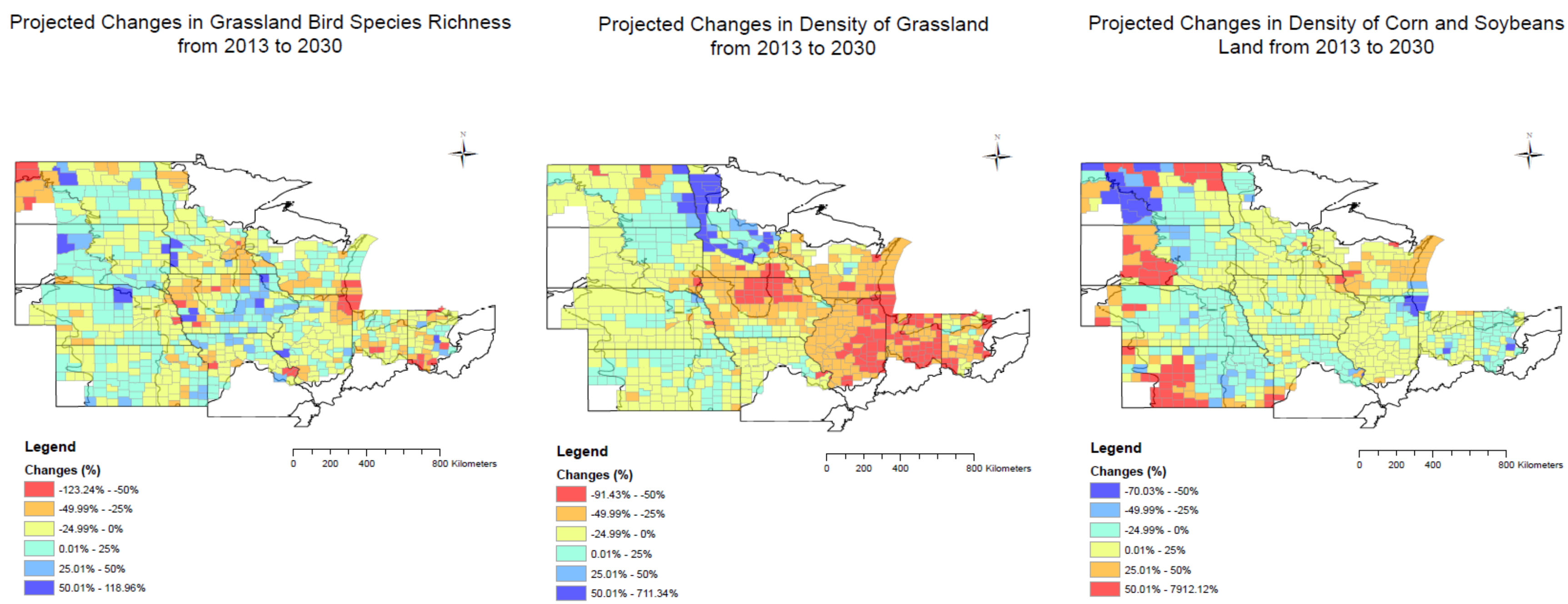


Figure 2.3  Spatially heterogeneous impacts on grassland bird species richness

A B C



**References**


Altonji GA, Elder TE, Taber CR (2005) Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy* 113:151-184.

Andam KS et al. (2008) Measuring the effectiveness of protected area networks in reducing deforestation. *Proc Natl Acad Sci USA* 105:16089-16094.

Anderson T, Hsiao C (1982) Formulation and estimation of dynamic models using panel data. *Journal of Econometrics* 18:47-82.

Angrist J and Pischke J (2008) *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press, Princeton).

Arellano M and Bond SR (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58:277-297.

Arellano M and Bover O (1995) Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics* 68:29-51.

Armsworth PR, Gaston KJ, Hanley ND and Ruffell RJ (2009) Contrasting approaches to statistical regression in ecology and economics. *Journal of Applied Ecology* 46:265-268.

Bazzi S, Clemens MA (2013) Blunt instruments: Avoiding common pitfalls in identifying the causes of economic growth. *American Economic Journal: Macroeconomics* 5:152-186.

Blundell R, Bond SR (1998) Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87:115-143.

Blundell R, Bond SR (2000) GMM estimation with persistent panel data: An application to production functions. *Econometric Reviews* 19:321-340.

Bock CE, Jones ZF, Bock JH (2007) Relationships between species richness, evenness, and abundance in a southwestern savanna. *Ecology* 88(5):1322-1327.

Brennan LA, Kuvlesky Jr. WP (2005) North American grassland birds: An unfolding conservation crisis. *Journal of Wildlife Management* 69:1–13.

Bun MJG, Windmeijer F (2010) The weak instrument problem of the system GMM estimator in dynamic panel data models. *Econometrics Journal* 13:95-126.

Cameron A, Trivedi P (2005) *Microeconometrics: Methods and Applications* (Cambridge University Press, Cambridge).

Cardinale BJ et al. (2012) Biodiversity loss and its impact on humanity. *Nature* 486:59-67.

Evans SG, Potts MD (2014) Effect of agricultural commodity prices on species abundance of US grassland birds. *Environmental and Resource Economics*: 1-17.

Fargione JE, Hill J, Tilman D, Polasky S, Hawthorne P (2008) Land clearing and the biofuel carbon debt. *Science* 319:1235-1238.

Fargione JE et al. (2009) Bioenergy and wildlife: Threats and opportunities for grassland conservation. *BioScience* 59:767–77.

Ferraro P, Pattanayak S (2006) Money for nothing? A call for empirical evaluation of biodiversity conservation investments. *PLoS Biol* 4:e105.

Fleishman E et al. (2011) Top 40 priorities for science to inform US conservation and management policy. *BioScience* 61:290-300.

Fletcher, RJ et al. (2011) Biodiversity conservation in the era of biofuels: risks and opportunities. *Frontiers in Ecology and the Environment* 9:161-168.

Foley JA et al (2011) Solutions for a cultivated planet. *Nature* 478:337-342.

Hamer TL, Flather CH, Noon BR (2006) Factors associated with grassland bird species richness: The relative roles of grassland area, landscape structure, and prey. *Landscape Ecology* 21:569-583.

Hill J et al. (2006) Environmental, economic, and energetic costs and benefits of biodiesel and ethanol biofuels. *Proc Natl Acad Sci USA* 103:11206-11210.

Hill J et al. (2009) Climate change and health costs of air emissions from biofuels and gasoline. *Proc Natl Acad Sci USA* 106:2077-2082.

Hsiao C (2014) *Analysis of Panel Data* (Cambridge University Press, Cambridge).

Lewis DJ, Plantinga AJ (2007) Policies for habitat fragmentation: combining econometrics with GIS-based landscape simulations. *Land Economics* 83:109-127.

McDonald RI, Fargione J, Kiesecker J, Miller WM, Powell J (2009) Energy sprawl or energy efficiency: Climate policy impacts on natural habitat for the United States of America. *PLoS ONE* 4:e6802.

Millennium Ecosystem Assessment (2005) *Ecosystems and Human Well-Being: Policy Responses* (Island Press, Washington, DC).

Meehan TD, Hurlbert AH, Gratton C (2010) Bird communities in future bioenergy landscapes of the Upper Midwest. *Proc Natl Acad Sci USA* 107:18533-18538.

Mehaffey M, Smith E, Van Remortel R (2012) Midwest U.S. landscape change to 2020 driven by biofuel mandates. *Ecological Applications* 22(1):8-19.

Mehaffey M, Van Remortel R, Smith E, Bruins R (2011) Developing a dataset to assess ecosystem services in the Midwest, United States. *International Journal of Geographic Information Services* 25:681-695.

Pearce JM (2007) Philopatry: A return to origins. *Auk* 124:1085-1087.

Peterjohn BG, Sauer JR (1993) North American Breeding Bird Survey Annual Summary 1990-1991. *Bird Populations* 1:1-15.

Polasky S et al. (2005) Conserving species in a working landscape: land use with biological and economic objectives. *Ecological Applications* 15:1387-1401.

Ribic CA et al. (2009) Area sensitivity in North American grassland birds: Patterns and processes. *Auk* 126(2):233-244.

Rittenhouse CD et al. (2012) Land-cover change and avian diversity in the conterminous United States. *Conservation Biology* 26(5): 821-829.

Roberts MJ, Schlenker W (2013) Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate. *American Economic Review* 103:2265-2295.

Robertson BA et al. (2012) Are agrofuels a conservation threat or opportunity for grassland birds in the United States? *Condor* 114:679-688.

Roodman D (2009a) How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, 9:86-136.

Roodman D (2009b) A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71:135-158.

Sarafidis V, Yamagata T, Robertson D (2009) A test of cross section dependence for a linear dynamic panel model with regressors. *Journal of Econometrics* 148:149-161.

Sarafidis V, Robertson D (2009) On the impact of error cross-sectional dependence in short dynamic panel estimation. *Econometrics Journal* 12:62-81.

Searchinger T et al. (2008) Use of U.S. croplands for Biofuels increases greenhouse gases through emissions from land-use change. *Science* 319:1238-1240.

Sissne F. (2007) *Energy Independence and Security Act of 2007: A Summary of Major Provisions* (Congressional Research Service, Washington, DC).

Suttle KB et al. (2007) Species interactions revere grassland responses to changing climate. *Science* 315:640-642.

Timmins C. (2006). Endogenous land use and the Ricardian valuation of climate change. *Environmental and Resource Economics* 33:119-142.

Tilman D et al. (2011) Global food demand and the sustainable intensification of agriculture. *Proc Natl Acad Sci USA* 108:20260-20264.

Wiens J, Fargione J, Hill J (2011) Biofuels and biodiversity. *Ecological Applications* 20(4): 1085-1095.

Wiser R, Barbose G (2008) *Renewables Portfolio Standards in the United States: A Status Report with Data through 2007* (Lawrence Berkeley National Lab, Berkeley)

Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics* 126:25-51.

Wright CK, Wimberly MC (2013) Recent land use change in the Western Corn Belt threatens grasslands and wetlands. *Proc Natl Acad Sci USA* 110:4134-4139.

# Chapter 3

# Economic Impacts of Extreme Weather:

# Evidence from a Quasi-Experiment with Great Lakes Lake Levels

## 1 Introduction

The economic effects of extreme weather events vary, yet may be severe in some cases. Weather disasters – hurricanes, tornados, and typhoons – occur when an extreme event strikes a population center or destroys a substantial physical infrastructure. These cause severe effects by the very definition of disaster. Agriculture is particularly sensitive to extreme weather, such that agricultural producers in the United States can receive government "disaster payments" after freezes, droughts, heat waves, and floods. In other cases, fluctuating or extreme weather may affect broad economic sectors or especially vulnerable populations without a focus on a specific disaster. The response functions to weather variables may have nonlinearities that are important to understand.

A growing literature assesses the causal impacts of extreme weather events or weather fluctuations. Deschênes and Moretti (2009) study the effect of extreme temperature events on human mortality in the United States, and Deschênes and Greenstone (2011) study the effect of daily temperature fluctuations on annual human mortality rates and residential energy consumption in the United States. In the agricultural sector, Deschênes and Greenstone (2007) study the effect of random annual variation in temperature and precipitation on agricultural profits in the United States, while Schlenker and Roberts (2009) investigate the effect of daily temperature variation on yields of corn, soybeans, and cotton. An important theme in this literature is that the frequency of extreme weather events is projected to increase with future climate change, such that economic effects of extreme weather events should be evaluated as input to climate policy deliberations.

Lake levels of the Great Lakes are a large-scale ecosystem service, influenced by present-day weather fluctuations and subject to future climate change. Lake levels support economic activities on the five lakes and in the adjacent coastal areas along the 9,774 miles of Great Lakes shoreline.[1] The lakes and their levels are important to commercial shipping, hydropower generation, and outdoor recreation. Indeed, the Great Lakes and their connecting rivers and channels serve as an important shipping corridor along the U.S.-Canadian border heading east from Minnesota. In the coastal areas, Great Lakes lake levels affect municipal water supply, shoreline property development, and beach and related recreation. For context, recreation and tourism is a major sector in several Great Lakes states, largely due to the presence of (and access to) Lakes Erie, Huron, Michigan, Ontario and Superior along the states' long coastlines.

We study a multi-year drought beginning in 2000 that resulted in extremely low lake levels of Lake Michigan and Lake Huron (Sellinger, et al., 2008). Our research treats these low levels as a quasi-experiment when asking: did the extremely low levels of 2000-2006 result in economic impacts in the coastal counties surrounding Lake Michigan-Huron[2]? Since the early 1900's, outflows from Lake Superior have been regulated to maintain high levels of the lake for hydropower and commercial shipping (Clites and Quinn, 2003). This results in spatial competition for lake levels. As the downstream lake from Superior, Michigan-Huron levels are lower than they would be absent regulation. In particular, water storage in Superior negatively affects Michigan-Huron levels during periods of regional drought. This can be harmful to the native ecosystem and to downstream economic interests. The regulated water flow, along with the recent drought levels of Lake Michigan-Huron, precipitated the need for a five-year, $14.6 million study known as the International Upper Great Lakes Study.[3] This study is examining the physical causes and ecological and economic consequences of fluctuating levels of Lakes Superior, Michigan, and Huron. According to the study plans, however, causal evidence is not being developed to evaluate economic consequences. The study is due for completion in 2012.

[1]The five Great Lakes hold about 18% of the Earth's freshwater and combine for a surface area of over 94,000 square miles (Sellinger et al., 2008; and http://coastwatch.glerl.noaa.gov/statistic/physical.html).
[2] We follow the practice of scientists, who note that Lake Michigan and Lake Huron behave hydraulically as one lake and thus refer to it as Lake Michigan-Huron.
[3] See http://www.iugls.org/ for a detailed description of the study.

We focus on identifying impacts in the recreation and tourism sector in the coastal counties of Lake Michigan-Huron. The recreation and tourism sector has the second highest number of job of any sector in these counties. Previous research and expert opinion, moreover, have identified the sector as vulnerable to Great Lakes levels. Low levels of the lakes appear especially harmful to recreational boating and marinas (e.g., Connelly et al., 2007; Michigan State University, 2001). More generally, the background report for the Upper Great Lake study concluded that extremely high or low levels negatively affect tourism in coastal areas, and that low levels in particular reduce demand for waterfront facilities, such as beaches.[4] The empirical hypothesis guiding our research, consequently, is that the extremely low levels of Michigan-Huron resulted in negative economic impacts.

We estimate average treatment effects of the 2000-2006 episode of extremely low levels of Lake Michigan-Huron using the difference-in-difference-in-differences (DDD) estimator. The coastal counties of Michigan-Huron serve as the treatment group in the research design. Two control groups are formed. One group is the coastal counties of Lakes Superior, Erie, and Ontario. These lakes did not experience extremely low levels during this period, in part due to the regulated outflows of Superior and Ontario for hydropower generation. A second control group is the inland counties adjacent to the coastal counties of the Great Lakes. In addition to the conventional type of control group, we develop county pairs, where each pair consists of a coastal county and the adjacent inland county for the Great Lakes. County-pair fixed effects are a final control that we investigate (as in Dube, Lester, and Reich, 2010; Kahn and Mansur, 2011).

Four outcome variables from the recreation and tourism sector are considered in the regressions: number of business enterprises, employment, real earnings, and real earnings per worker.[5] We compile a panel dataset for 1990-2006 using county-level data from the Quarterly Census of Employment & Wages (QCEW) database from the Bureau of Labor Statistics. We examine the two NAICS sectors that encompass recreation and tourism: Arts, Entertainment, &

[4] The report's authors write, "Outdoor recreation and water-related tourism is likewise greatly affected by variations in water levels …When extreme high or low water levels occur, tourism in the coastal communities throughout the Great Lakes suffers (Upper Lakes Plan of Study Revision Team, 2005, p. 53). And, "…effects could also include impacts on businesses in small waterfont communities during low water periods that make their marina inaccessible or reduce the attractiveness of waterfront facilities, such as beaches, for visitors and customers" (ibid, p. 54).

[5] While we would ideally use direct measures of recreation and tourist activities, sources for such data do not exist for constructing a panel data set over an area spanning portions of eight states.

Recreation (Sector 71) and Accommodations & Food Services (Sector 72). These data sources and variables are being applied to develop causal estimates of economic impacts (e.g., Black et al., 2005; Kahn and Mansur, 2011; Michaels, 2008).

The paper continues with a background section that describes the policy setting for regulation of the Upper Great Lakes, the recreation and tourism sector in the Great Lakes states, and previous research on the impact of fluctuating lake levels. Section 3 develops the empirical framework and data, including preliminary results in support of the DDD approach. Section 4 presents the main results. Section 5 offers concluding remarks. Average levels of the Great Lakes are predicted to change in the event of future climate change, and our results shed light on this topic.

# 2 Background

This section discusses: aspects of Great Lakes levels; the recreation and tourism sector in the Great Lakes states; and previous research on the effects of relatively low and high lake levels.

## 2.1 Levels of the Great Lakes

Annual average water levels of the Great Lakes are subject to weather-based natural fluctuations and human regulation.[6] Lake Michigan-Huron, for example, experienced extended periods of above-average levels during the 1970's and 1980's, yet is currently experiencing a prolonged drought period of extremely low levels beginning in 2000 (Figure 3.1). In terms of human regulation, water levels and outflows are regulated for hydropower generation at two points. A hydropower project controls flows from Lake Superior to Lake Michigan-Huron, and a similar project controls flows from Lake Ontario into the St. Lawrence River. Official regulation plans govern operation of these projects in terms of outflow rates under various lake-level conditions.

The International Joint Commission[7] (IJC) sets policy on Great Lakes regulation. The IJC mandated in the mid-1970's that levels of Lake Michigan-Huron must be considered when controlling outflows from Lake Superior. This spatial interaction previously had been ignored;

[6] Precipitation and evaporation are the main factors of annual stochastic variation. Levels of the Great Lakes also experience cyclic variation within a year, with higher levels after spring rains and snowmelt, and lower levels after summer evaporation.
[7] The IJC was created under the Boundary Waters Treaty of 1909, which pertains to the transboundary lakes and rivers of Canada and the United States. The IJC is led by six commissioners, three from each country. Twenty boards have been organized under the IJC to assist in the implementation of its responsibilities.

when managing outflows for hydropower, a higher level of Lake Superior results in greater hydraulic head and thus greater power generation. A regulation plan, Plan 1977, was implemented in 1979 to achieve this new goal of managing across lakes, with additional modifications made in 1990 in Plan 1977-A.[8] Plan 1977-A adopts the goal of managing Lake Superior outflow rates such that the levels of Superior and Michigan-Huron are in the same position relative to their long-term means (Clites and Quinn, 2003). Nevertheless, Clites and Quinn conclude that the regulation plan favors the maintenance of high levels on Lake Superior.[9]

Figures 3.1 and 3.2 illustrate these ideas. Lake levels of Lake Michigan-Huron had much greater variation than levels of Lake Superior during 1960-2007 (Figure 3.1). This pattern has held since the early 1900's when Superior's outflows were first controlled. Second, Lake Superior's regulated levels have been substantially higher than the simulated (counterfactual) natural levels for most of the period 1910-2000 (Figure 3.2). This came at the expense of levels in the downstream unregulated lakes, Michigan-Huron and Erie. In particular, Lake Superior's levels were maintained at above-natural levels during the two periods when Lake Michigan-Huron experienced its lowest levels, 1931-34 and 1963-64.

Lake levels and regulated outflows have generated controversy over the last decade in light of the extremely low levels of Lake Michigan-Huron. Spurred by these concerns, the IJC decided to revisit the topic of regulation of Lake Superior outflows and Lake Michigan-Huron levels, and it organized the International Upper Great Lakes Study to do so.[10] Among the study objectives are: (1) to understand how the existing regulation of lake levels and outflows affect economic and environmental outcomes on and around the regulated lake (Superior) and around the downstream lakes (Michigan-Huron and Erie); and (2) to recommend alternative regulation plans based on the outcomes projected under various regulation scenarios.

## 2.2 Recreation and Tourism Sector

[8] Under the IJC's policy guidance, the International Lake Superior Board of Control forms and implements these specific plans.

[9] Clites and Quinn (2003, p. 169) conclude that, despite Plan 1977 and Plan 1977-A, "…the management strategy has not deviated from the early 1900's, when the control of Lake Superior's outlet was clearly for the purpose of maintaining high levels on the lake for navigation and hydropower."

[10] A few years earlier, the IJC had organized the International Lake Ontario-St. Lawrence River Study was a five-year, $20 million study completed in 2006 (International Lake Ontario-St. Lawrence River Study Board, 2006). The Study Board recommended three alternative regulations for Lake Ontario, to be considered by the International Joint Commission and the federal governments of Canada and the United States. A new regulation plan has not been finalized.

The recreation and tourism sector is the second largest sector, in terms of employment, in the coastal counties of the Great Lakes states (Vaccaro and Read, 2011).[11] We define the overall sector as NAICS 71—Arts, Entertainment, and Recreation and NAICS 72—Accommodations and Food Services. Employment in sectors 71 and 72 was 265,960 jobs in 2001, or 8.1% of total employment in these counties (Panel A of Table 3.1). Personal income in the sectors was $31.76 million, or 3.1% of total personal income. The data for 2001 are reported as a basis of comparison to a recent study of Great Lakes recreational boating (U.S. Army Corps of Engineers (USACE), 2008).

Policymakers have focused attention on the recreation and tourism sector as important to the Great Lakes region and, as well, vulnerable to fluctuating levels of the Great Lakes. The International Upper Great Lakes Study identifies recreational boating and tourism as one of the four sectors for study (along with commercial navigation, consumptive water uses, and hydropower). Preliminary results from the study are reported below in section 2.3. The U.S. Congress similarly targeted the sector in a request to the USACE to study the economic impact of Great Lakes recreational boating. The USACE study adopted an input-output methodology to assess the regional economic footprint of Great Lakes boating (USACE, 2008). It distinguished expenditures on recreational boating trips (such as spending on lodging, restaurants, and fuel) from expenditures on recreational boats (such as spending on repairs, annual slip fees at marinas, and offseason storage). A sampling of the computed impacts of these expenditures on employment and personal income is reported in Panels B and C of Table 3.1. Panel D of Table 3.1 then reports economy-wide totals for the region. In total, expenditures on boating trips are calculated to generate 38,289 jobs and $1.023 billion in personal income in the Great Lakes counties in 2001. [12] Similarly, expenditures on boats is calculated to generate 21,979 jobs and $0.744 billion in personal income. Combined, the 60,268 jobs "created" by recreational boating constitute 1.7% of employment in Great Lakes coastal counties in 2001.

---

[11] Vaccaro and Read (2011) estimated that more than 1.5 million jobs in 2009 are directly related to the Great Lakes. The two largest sectors are manufacturing, with almost 1 million jobs, and recreation and tourism, with over 200,000 jobs. Most of the calculations are based on employment in coastal counties bordering the Great Lakes. The National Ocean Economics Program (http://www.oceaneconomics.org/) provides similar data through a state- and county-based searchable database. These two efforts do not pose the counterfactual question of what would employment in these counties be if they did not border the Great Lakes.

[12] Following the standard methodology in regional input-output analysis, the figures on employment and personal income incorporate both direct and indirect impacts throughout all sectors of the economy.

## 2.3 Previous Research

Previous research on the effect of Great Lakes levels on the recreation and tourism sector is limited to studies of marina operators and recreational boaters. All of the prior studies used survey research methods. None of them developed a basis for causal inference about the economic effects of fluctuating lake levels.

In a survey of 105 marina operators conducted in 1991, Bergmann-Baker et al. (1995) found that, qualitatively, low lake levels resulted solely in negative effects (e.g., problems with access to marina slips and boat ramps), while high water levels had a mix of negative and positive effects (e.g., better access to shallow channels).[13] Estimated lost revenues from unusable slips during low levels ranged from $250 to $48,000 per operator, and estimated costs of adapting to low levels through dredging ranged from $1,000 to $600,000 per operator. The revenues and costs were taken from operator recollections of their cumulative experience over a ten-year period prior to 1991.

The recent International Upper Great Lakes Study included a study team focused on recreational boating (the "Recreational Boating, Tourism & Cruise Ships Technical Working Group," or TWG for short). The TWG reported on a survey of 78 marina operators about the effects of low lake levels on marina revenues from slip rentals (TWG, 2011). The survey instrument inquired about three hypothetical decreases in lake levels: one-foot, two-foot, and three-foot decreases relative to the levels at the time of the survey, 2009. The TWG report used the survey results to extrapolate to totals for the upper Great Lakes region (excluding Canadian portions) for reduced revenues from marina slips due to the low levels. The projected reductions are: $3.9 million per year for a one-foot decrease; $9.7 million per year for a two-foot decrease; and $30.7 million per year for a three-foot decrease (TWG, 2011, p. 14). The projected revenue reductions are nonlinear in lake-level decreases. The projections are not made based on the standard method of using a random sample to reach various conclusions about a population. Moreover, they are based on hypothetical rather than actual behavior.

Marina operators also were surveyed in a smaller study of five counties adjacent to Lake Michigan (Michigan State University, 2001). Thirty-one operators were interviewed, with 23

[13] The Bergmann-Baker et al. study was commissioned by the IJC to provide information about the effects of fluctuating lake levels on marinas and recreational boating. The IJC was responding to public concern about the relatively high levels of the Great Lakes in the mid-1980's.

representing marinas from two Michigan counties and 8 representing marinas from three Wisconsin counties. The survey was conducted near the end of the recreational boating season in 2000, which was a year of extremely low levels of Lake Michigan-Huron. The results indicated that 33% of the marinas had unusable slips that year due to the low levels, with lost revenue ranging from about $8,000 to over $40,000 per marina. In Michigan, 20% of the operators reported dredging to adapt to low water, at an average cost exceeding $43,000 per marina. According to the report, some marinas went out of business due to the low levels, with the perception of operators that more would close if the low levels persisted.[14]

The MSU study also interviewed a random sample of 451 recreational boaters in the same five-county region in late 2000. "Low water levels" was cited most frequently (29% of all respondents) as the boaters' main problem. For comparison, in second place, 11% of respondents cited "jet ski noise" as the main problem. Among boaters who used their boats less frequently in 2000, "lower water levels" were cited as the main reason by 19% of this group. And 33% of all respondents stated that declining water levels had already imposed significant economic impacts on boating, marinas, and boating-related tourism.

Connelly et al. (2007) conducted a mail survey of recreational boaters in New York who had boated on Lake Ontario or the St. Lawrence River in 2002.[15,16] With 2,388 respondents, the survey collected data on boaters' use rates of the lake and river during the 2002 boating season, expenditures per boating day, and maximum willingness-to-pay in excess of expenditures per boating day (consumer's surplus). (The wtp question was asked as a hypothetical contingent-valuation question using an open-ended format.) Boaters were sampled based in part on geographic location of their activity. These same geographic locations were assessed in terms of depth of water at marinas and boating ramps, and the related vulnerability of the various locations to relatively low and high lake levels. Researchers then derived a functional relationship between loss of boating days and changes in levels of Lake Ontario, and a second,

[14] According to the report, "The phone contacts proved to be a painful experience for both surveyors and marina operators. Many operators reported being out of business due to low water and did not want to talk about the economic impacts of low water." (Michigan State University, 2001, p. 20).
[15] This study was commissioned as part of the International Lake Ontario-St. Lawrence River Study (see footnote 10).
[16] The researchers initially screened, via telephone, a random sample of 10,382 boaters with boats registered in the eight New York counties adjacent to Lake Ontario and the St. Lawrence River to assess whether they boated on the lake or river in 2002. This sample was stratified to obtain geographic diversity within the region. Boaters that had used the lake or river were then included in the mail survey, with 3,412 surveys mailed.

related functional relationship between loss of consumer's surplus and changes in lake levels. Two main results were developed. First, the aggregate consumer's surplus for New York residents was estimated at $178 million for recreational boating on Lake Ontario and the St. Lawrence River in 2002. Second, loss of consumer's surplus due to reduced boating is relatively small in a three-foot range of lake levels, from 245 to 248 feet of water-level elevation.[17] Loss of surplus increases substantially for levels below 245 feet, but loss of surplus does not increase substantially for levels above 248 feet.

# 3 Empirical Framework

This section discusses: the conceptual motivation for the study; data and data sources; preliminary results that guide the research design; and estimation setup.

## 3.1 Conceptual Motivation

The water level of Lake Michigan-Huron is provided as a pure public good to consumers and firms in the coastal areas surrounding the lake. Summer lake levels are affected by weather in the watershed over the prior winter and spring, along with the level from the previous year. IJC regulations can also be binding when levels are extreme; they serve to smooth levels across years or between lakes. In general, though, the extremely low levels of the lake are a weather-related shock that persists for the duration of the summer recreation season. These low levels are exogenous to consumers and firms in the recreation and tourism sector of Lake Michigan-Huron.

The setting of extremely low lake levels contrasts with other quasi-experimental settings of random weather or exogenous policy. First, most extreme weather events, such as a heat wave, are relatively short in duration. Extreme lake levels are relatively long in duration, however, lasting the entire summer recreation season. Second, a treatment imposed as a public policy, such as a minimum wage, is typically designed to last for several years. Levels of Lake Michigan-Huron, in contrast, are considered independent across years since annual weather is an independent stochastic event. Thus, although the recent extreme levels of Lake Michigan-Huron

[17] The elevation numbers are used with reference to the International Great Lakes Datum, 1985, which is the elevation reference system for water levels within the Great Lakes-St. Lawrence River system.

have persisted for several years, decision-makers expected the lake level to rise toward its long-term average when ending a season of low levels.[18]

In this research, we consider lake level as an argument of consumer demand for recreational and tourist activities. Such activities include recreational boating, beach activities, and aesthetic enjoyment of the waterfront. As a shock, an extremely low lake level decreases recreational demand. Equilibrium output in the sector also decreases (holding supply fixed). In addition, an extremely low lake level reduces supply of marina slips and docks, as boats do not have sufficient clearance above the lake bottom. Again, this reduces output in this industry. These negative output effects also spillover into the restaurant and lodging industries, with demand and output decreasing for these services.

We examine the impact of the lake-level shock on the labor market in the recreation and tourism sector. Demand for labor decreases given the reductions in output just described. We expect equilibrium employment, earnings, and earnings per worker to decrease.

We also examine establishments in the recreation and tourism sector as a fourth outcome variable. With the hypothesized decrease in demand and output in the sector, establishments might exit the industry, particularly in light of the prolonged period of extremely low lake levels.

### 3.2 Data Sources

We use lake-level monitoring data from the US Army Corps of Engineers (USACE)[19] in order to construct average water levels from April to September for each lake by year. The data measured at Mean Low Water Datum consist of lake-specific monthly-average lake levels, which are simply the average of daily recorded elevations over several monitoring stations around each Great Lake. The dataset represents lake-level water levels, e.g., we do not observe spatially finer data, such as data at the county level. This is unfortunate, because an interesting check of the validity of our research design would be to test whether coastal water depths are equal in treated and control counties during non-extreme weather periods.

[18] Over time, people might alter their perception of the occurrence of extreme water levels and alter their responses to expected lake-level shocks given their experience with, or expert information about, extreme water levels.

[19] The data on lake levels is at http://www.lre.usace.army.mil/greatlakes/hh/greatlakeswaterlevels/historicdata/.

The variables for lake levels are not used directly. Instead, we use them (1) to define control and treatment periods on Lake Michigan-Huron and (2) to verify that levels of Lakes Superior, Erie, and Ontario do not fluctuate much.

To conduct the economic impact analysis, we collect county-by-sector data on employment (number of employees), earnings (dollars), and establishments (number of firms) for 1990-2006. The data are from the Quarterly Census of Employment and Wages (QCEW), provided by the Bureau of Labor Statistics (BLS). We use two two-digit NAICS sectors: 71, Arts, Entertainment, and Recreation, and 72, Accommodation and Food Services.[20] The two sectors' economic outcomes account for most Great-Lakes-related recreational and tourist activities. Although the two sectors cover other non-recreational or non-Great-Lakes-related activities, these should be controlled for by the research design. For each sector, we sum outcomes in the second quarter (April to June) and the third quarter (July to September) to reflect the fact that recreational and tourist activities – especially those potentially affected by lake levels – generally occur in these two quarters. Four outcome variables are generated: employment, earnings, earnings per worker, and establishments.

Other explanatory variables include county-level demographic and economic characteristics, i.e., total employment, population, and personal income. The county-level data are from the Regional Economic Information System (REIS) provided by the Bureau of Economic Analysis (BEA, US Department of Commerce 1990-2006). In addition, county-level weather information (based on National Climatic Data Center's TD-3200 data series) includes monthly average, minimum, and maximum in temperature and accumulated precipitation. We create seasonal weather variables by averaging the monthly weather conditions and interacting seasonal temperature with seasonal precipitation.

### 3.3 Research Design: Summary Statistics

Since only coastal counties are subject to the risks of lake-level variation in a given year, it is instructive to understand the degree to which these sources of variation are orthogonal to county observables. If significant differences occur across counties associated with observed differences prior to the treated years, then the nature of these differences should motivate the

[20] Data at a finer scale (more digits than the two-digit NAICS level) would have allowed us to examine within-sector industries more precisely. However, many of our sample counties are rural areas, and their data are frequently withheld at the finer scale due to BLS disclosure policy.

choice of a suitable empirical specification. Here we contrast two groups: (1) the treatment group consisting of the coastal counties of Lake Michigan-Huron (M-H) and (2) a potential control group consisting of the coastal counties of Lakes Superior, Erie, and Ontario (S-E-O).

Table 3.2 reports mean values of the four outcome variables and several socioeconomic variables, stratified by the treatment group and the potential control group. The values pertain to the pre-treatment period, 1990-99, and they are organized by NAICS sectors 71 and 72. Columns (1) and (2) show the mean values for the each of the two groups in sector 71, while Column (3) shows the *t*-statistics for a test of equal means. The results for sector 71 show that the differences between the two groups are statistically significant in general, with exceptions for the variable for earnings per worker. The mean for the four outcome variables is smaller for the treatment group than for the control group. In contrast, the mean for the changes in the four outcome variables and for the socioeconomic variables are larger for the treatment group than the control group. The results for sector 72, as presented in columns (4), (5), and (6), are similar to results for Sector 71. The main idea from Table 3.2 is that counties in the treatment group may be systematically different than counties in the control group.

It is also worth noting again that, although the occurrence of an extremely low lake level in a given year is a random weather shock, the extreme weather will likely trigger lake-level regulations by the IJC. This implies that the samples are not well balanced, that is, the treated counties are spatially and perfectly sorted to counties connecting to Lake Michigan-Huron.

Due to the economic and spatial sorting just described, relying solely on cross-sectional variation might confound lake-level variation with other sources of heterogeneity across counties. Likewise, relying solely on time-series variation in treated counties is suspect given that, for example, a public policy might be implemented simultaneously to an extremely low lake level in a treated year. Failing to account for these differences might lead to a confounding of the effect of extremely low lake levels with the effects of other county characteristics. Credible identification requires accounting for all these sources of observed and unobserved confounders.

## 3.4 Research Design: Graphical Results and Common Trends Tests

Preliminary results, from above and also summarized here in Section 3.4, suggest the need for a second control group. We developed a control group based on inland counties adjacent to the Great Lakes coastal counties. Figure 3.3 shows our sample counties and three groups: (1) the treatment group of Lake Michigan-Huron coastal counties, (2) a control group of Lakes Superior, Erie, and Ontario coastal counties; and (3) a control group of inland counties adjacent to the coastal counties.

Comparing these treatment and control groups is instructive for validating the empirical strategy. We develop graphical results that compare Lake Michigan and Huron (M-H, hereafter) coastal counties; Lake Superior, Lake Erie, and Lake Ontario (S-E-O, hereafter) coastal counties; M-H inland counties; and S-E-O inland counties. For instance, Figure 3.4A and 3.4B depict a similar analysis of NAICS sector 71 and sector 72, respectively. We also test a common trends hypothesis that growth in an outcome variable in treatment counties and control counties was the same prior to when the extremely low lake levels began in 2000. To conduct the test, we regress the change in log outcomes over the period 1990-99 against an indicator of whether the county is in a treatment group, year dummies, county socioeconomic characteristics, and county weather variables. [21]

First, employment trends in sector 71 for the M-H coastal counties and the S-E-O coastal counties are not similar before 2000 (Figure 3.4A and 3.4B), indicating that other factors unrelated to lake-level shocks are affecting the trends for each group and should be controlled for. The result is also consistent to our common trend test, which shows a statistically significant difference in the trends of the two groups (Table 3.3, Panel A, column (1)). Moreover, mean earnings of sector 71 (Figure 3.5A) and mean establishments of sector 71 (Figure 3.6A) show similar results as described for the employment trends and fail to pass the common trends tests (Table 3.3, Panel A, columns (2) and (4), respectively). The results highlight the need to control for the differences of the trends of our outcome variables.

Comparisons of the M-H coastal counties and their inland counties, along with comparisons of the S-E-O coastal counties and their inland counties, show more similarity (Figures 3.4, 3.5, and 3.6). Employment, earnings, and establishments tend to have similar trends prior to 1998. The results of the common trends tests also show no statistically significant

[21] County socioeconomic characteristics include log county population (for all regressions), log county employment (for sector-level employment and earnings per worker regressions), and log county income (for sector-level earnings, earnings per worker and establishments regressions). County weather variables include monthly average precipitation over April to September and its square term, monthly average maximum temperature over April to September and its square term, and the interaction term between monthly average precipitation and monthly average maximum temperature.

differences between the trends of the coastal counties and inland counties (Table 3.4, Panel A), with earnings per worker the only exception. These results imply inland counties might be a good control.

For sector 72, the employment trends for M-H coastal counties and S-E-O coastal counties before 2000 are similar before 2000 (Figure 3.4B) and pass the common trend test (Table 3.4, Panel B). Comparisons of trends of earnings and establishments between the two groups also show similar trends (Figures 3.5B and 3.6B). However, other unobserved and time-varying local or regional characteristics might still be affecting our outcome variables. The outcome variables show similar trends between the M-H coastal counties and the M-H inland counties, along with similar trends between the S-E-O coastal counties and the S-E-O inland counties (Figures 3.4B, 3.5B and 3.6B). The common trends tests confirm these results (Table 3.4, Panel B).

To further support our identification strategy, we compare trends in employment ratios across M-H and S-E-O coastal counties to trends in employment ratios across M-H and S-E-O inland counties (Figure 3.7). The trends in these ratios are similar, except in some years such as in 1998 when Lake Michigan-Huron suffered extremely high lake levels and in 1999 when Lake Ontario suffered low lake levels. That is, the regional-specific labor demand shocks that are unrelated to lake levels tend to be persistent over the coastal and inland counties in the years before 2000. This evidence of regional shocks having similar employment effects on M-H coastal and inland counties supports our identification strategy, which relies on observations from inland counties adjacent to the coastal counties. Moreover, after 2000, the employment trend of ratio between the M-H counties and S-E-O counties in coastal counties is clearly less than that in inland counties, especially in sector 71.

Similar evidence is developed for earnings and establishments, that is, comparisons of the ratio between M-H and S-E-O mean earnings across coastal and inland counties (Figure 3.8) and the ratio between M-H and S-E-O mean establishments across coastal and inland counties (Figure 3.9). The results are similar to the employment ratios just described. Although the evidence supports our identification strategy, we will drop the observations in 1998 and 1999 as a robustness check, given that there might be some unobserved lake-level-related shocks on our sample counties during these two years and that these shocks would confound our estimates.

## 3.5 Estimation Setup

We use the DDD estimator to identify average treatment effects of extremely low lake levels on outcomes in the recreation and tourism sector. The treatment group consists of coastal counties of Lake Michigan-Huron, which experienced extremely low lake levels from 2000 to 2006. Coastal counties of Lakes Superior, Erie, and Ontario are used as a control group to separate out confounders that affect all Great Lakes coastal counties, as well as confounders that operate on a national level. Inland counties adjacent to the coastal counties are used as a control group to separate out regional variation that is unrelated to being a coastal county. The identification assumption is that the treatment counties would have changed at the same rate as the control counties if there had been no extremely low levels of Lake Michigan-Huron. We apply the DDD estimator as

$$\begin{aligned}\ln y_{cijt} = {} & \beta_1 LowLake_i + \beta_2 Coastal_j + \beta_3 Post_t + \beta_4 LowLake_i Coastal_j + \beta_5 LowLake_i Post_t + \\ & \beta_6 Coastal_j Post_t + \beta_7 LowLake_i Coastal_j Post_t + \sum \phi_k X_{kct} + \alpha_c + \psi_t + \varepsilon_{cijt}\end{aligned} \quad (1)$$

where $c$ indexes counties, $t$ indexes years, $y_{cijt}$ is the outcome variable (employment, earnings, earning per worker, or establishments), $LowLake_i$ is an identifier for treatment counties, $Coastal_j$ is an identifier for coastal counties, $Post_t$ is an identifier for treatment years (2000-06), $X_{kct}$ is a vector of a county's weather and socioeconomic characteristics, in order to control for recreational demand and supply shifters that are unrelated to lake levels; $\alpha_c$ is a county fixed effect, $\psi_t$ is a year fixed effect, and $\varepsilon_{cijt}$ is the idiosyncratic error term. The time-invariant terms fall out, of course, when we apply the fixed-effects (FE) model estimator to equation (1).

The parameter of interest is $\beta_7$, which gives the average treatment effect of extremely low lake levels. It provides an estimate of the semi-elasticity of employment, earnings, earnings per worker, or enterprises with regard to changes in the status of extremely low lake levels.

A second specification substitutes county-pair fixed effects for the county fixed effects:

$$\begin{aligned}\ln y_{cijtp} = {} & \beta_1 LowLake_i + \beta_2 Coastal_j + \beta_3 Post_t + \beta_4 LowLake_i Coastal_j + \beta_5 LowLake_i Post_t + \\ & \beta_6 Coastal_j Post_t + \beta_7 LowLake_i Coastal_j Post_t + \sum \phi_k X_{kct} + \alpha_p + \psi_t + \varepsilon_{cijtp}\end{aligned}$$

(2)

where $p$ indexes county-pairs. The key feature of the specification is the county-pair fixed effect $\alpha_p$, which soaks up spatial variation in local labor market conditions, proximity to intermediate input providers and final consumers, and climate and topographical amenities.

# 4 Results

We estimated equations (1) and (2) to assess the effect of extremely low levels of Lake Michigan-Huron on the recreation and tourism sector. The sector is represented by two NAICS sectors: 71—Arts, Entertainment, and Recreation, and 72—Accommodations and Food Services. Results are organized by Sector 71 (Table 3.5) and Sector 72 (Table 3.6). The main focus of the results is the estimated average treatment effect, $\beta_7$.

Overall, the estimated treatment effects are quite small and statistically insignificant. This generalization applies across the four outcome variables, four alternative specifications, and two sectors. The only exception is with earnings per worker in Sector 71, in which two of the four specifications are positive and statistically significant.

For Sector 71, the estimated employment effects and enterprise effects are uniformly negative (Table 3.5). This sector would reflect adjustments in enterprises directly related to beach recreation, marinas, recreational boating, and recreational fishing. Conventional wisdom, as reflected in the discussion in Section 2, suggests that these enterprises would be especially vulnerable to low lake levels. Yet, although the estimates are negative, the standard errors are actually larger in absolute value than the estimates, such that the statistical evidence does not support a finding of negative effects.

The estimated establishment effects in Sector 72 are uniformly negative (Table 3.6). The standard errors are relatively large, however, as above with Sector 71. Here, we might expect that low lake levels would not drive a motel or restaurant out of business, i.e., a finding of no effect is plausible. At the same time, reducing the workforce when business is slow is more plausible. The estimated employment effects, though, are statistically insignificant regardless of specification.

The two alternative specifications of fixed effects – county fixed effects versus county-pair fixed effects – generated different results. Most notably, $R^2$'s increased substantially in some cases with the county-pair fixed effects. We nevertheless prefer the results with county fixed effects as they capture unobservables that could vary substantially for coastal counties. For example, characteristics such as length of coastline, gradient of beach, and aesthetic quality of the coast would be captured in coastal county fixed effects. These would be lost with the county-pair fixed effects, which would capture phenomenon in a small regional economy that were common to both a coastal county and its adjacent inland county. (In fact, beginning with Holmes (1998), the idea of paired fixed effects is to join together spatial units that can be viewed as "twins." We are not following this convention with the county-pair fixed effects.)

Finally, removing observations from 1998 and 1999 did not substantially alter the results from the perspective that coefficient estimates remained statistically insignificant.

# 5 Conclusions

Lake Michigan-Huron experienced a protracted period of extremely low lake levels from 2000 through 2006. Previous analysis of the low levels, largely based on survey studies and input-output methods, showed dramatic employment and personal income impacts on recreational boating associated with the lakes. A body of expert opinion, similarly, suggested that the low levels negatively affected the recreation and tourism sector of the coastal counties around these lakes. Reacting to the widespread concern, the IJC funded a ~$15 million study to investigate causes and consequences of fluctuating lake levels in the Upper Great Lakes. Despite the attention, no research has generated causal statistical evidence on the impact of the extremely low lake levels.

Our DDD analysis found no statistically significant effects on employment outcomes of the extremely low lake levels of Lake Michigan-Huron. Since our estimated coefficients are imprecise, we cannot rule out that the 2000-06 episode resulted in substantial negative effects in the labor market or a net exit of enterprises in the recreation and tourism sector, as previous studies found for the boating-related tourism sector (e.g., TWG, 2011). Our study is an initial step toward causally estimating the average treatment effects of the 2000-06 episode of low levels. Adjustments of consumers and producers to extreme weather might play a role in explaining the result of no statistically significant effects. Future research includes investigating adjustments to extremely low lake levels and assessing the long-run effect of extremely low lake levels.

Our study is constrained by data availability. First, data for studying output effects, such as profits and the number of visits in the recreation and tourism sector, does not exist for use in econometric analysis. Second, data for studying 4-digit or 6-digit NAICS industries is not available, as BLS disclosure rules impede this. This is a limitation of studying rural counties.

The average levels of the Great Lakes are projected to decrease under most scenarios of climate change. Our results suggest that attention should be focused on other potential consequences of low lake levels, such as ecological impacts and impacts in other economic sectors, including the electricity generation sector.

## References


Bergmann-Baker, U., J. Brotton, and G. Wall. 1995. “Socio-economic Impacts of Fluctuating Water Levels on Recreational Boating in the Great Lakes.” *Canadian Water Resources Journal*, 20(3): 185-194.

Black, D. A., T. McKinnish and S. Sanders. 2005. “The Economic Impact of the Coal Boom and Bust,” *Economic Journal*,115(502): 449-476.

Clites, A. H., and F. H. Quinn. 2003. “The History of Lake Superior Regulation: Implications for the Future,” *Journal of Great Lakes Research*, 29(1): 157-171.

Connelly, N.A., T. L. Brown, and J. W. Brown. 2007. “Measuring the Net Economic Value of Recreational Boating as Water Levels Fluctuate,” *Journal of the American Water Resources Association*, 43(4): 1016-1023.

Deschênes, O., and M. Greenstone. 2007. “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather,” *American Economic Review*, 97(1): 354-385.

Deschênes, O., and M. Greenstone. 2011. “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US,” *American Economic Journal: Applied Economics*, 3(4): 152-185.

Deschênes, O., and E. Moretti. 2009. “Extreme Weather Events, Mortality, and Migration,” *Review of Economics and Statistics*, 91(4): 659-681.

Dube, Arindrajit, T. William Lester, and Michael Reich. 2010. “Minimum Wage Effects Across State Borders: Estimates Using Contiguous Counties,” *Review of Economics and Statistics*, 92(4): 945-964.

Gruber, J. 1994. “The Incidence of Mandated Maternity Benefits.” *American Economic Review* 84(3): 622-641.

Kahn, M. E. and E. T. Mansur. 2011. “Do Local Energy Prices and Regulation Affect the Geographic Concentration of Employment? A Border Pairs Approach,” Dartmouth mimeo, June.

Kellogg, R., and H. Wolff. 2008. “Daylight Time and Energy: Evidence from an Australian Experiment,” *Journal of Environmental Economics and Management*, 56: 207-220

Michaels, G. 2008. “The Effect of Trade on the Demand for Skill: Evidence from the Interstate Highway System,” *Review of Economics and Statistics*, 90(4): 683-701

MSU -- Michigan State University, Department of Park, Recreation and Tourism Resoiurces; Planning and Zoning Center, Inc.; and EPIC MRA. 2001. “Economic Impact of Lake Michigan Levels on Recreational Boating and Charter Fishing in Five Counties.” Final Report submitted to the U.S. Army Corps of Engineers, March.

Schlenker, W., and M. J. Roberts. 2009. “Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change,” *Proceedings of the National Academy of Sciences*, 106(37): 15594-15598.

Sellinger, C. E., C. A. Stow, E. C. Lamon, and S. S. Qian. 2008. “Recent Water Level Declines in the Lake Michigan-Huron System,” *Environmental Science and Technology*, 42(2): 367-373.

TWG --Recreational Boating, Tourism & Cruise Ships Technical Working Group. 2011. "Economic Impacts of Water Levels on the Upper Great Lakes," Peer Review Submission to the International Upper Great Lakes Study, January.

U.S. Army Corps of Engineers (USACE). 2008. "Great Lakes Recreational Boating." Main Report in response to Public Law 106-53, Water Resoiurces Development Act of 1999. December.

Vaccaro, L., and J. Read. 2011. "Great Lakes Jobs: 2011 Report." Michigan Sea Grant College Program, http://www.miseagrant.umich.edu/downloads/economy/11-203-Great-Lakes-Jobs-report.pdf, February.

**Table 3.1: Employment and personal income by sector/activity in Great Lakes coastal counties, 2001**

| | Employment (number of jobs) | Personal Income ($ millions) |
|---|---|---|
| **Panel A: QCEW data** | | |
| Arts, Entertainment, and Recreation | 40,470 | 8,140 |
| (NAICS Sector 71) | [1.1%] | [0.6%] |
| Accommodations and Food Services | 225,490 | 23,620 |
| (NAICS Sector 72) | [7.0%] | [2.5%] |
| Sum | 265,960 | 31,760 |
| | [8.1%] | [3.1%] |
| **Panel B: Economic impact of spending on recreational boating trips, by selected activity:** | | |
| Marina Services | 1,294 | 36 |
| Recreation and Entertainment | 969 | 27 |
| Lodging | 3,551 | 97 |
| Restaurants | 10,524 | 173 |
| Sum | 16,338 | 333 |
| **Panel C: Economic impact of spending on recreational boats, by selected activity:** | | |
| Slip Fees | 2,361 | 66 |
| Yacht Dues | 523 | 15 |
| Off-season Storage | 703 | 20 |
| Put-in and Haul-out | 747 | 21 |
| Repairs | 2,912 | 78 |
| Sum | 7,246 | 200 |
| **Panel D: Total economic impact (direct and indirect) across all sectors and activities:** | | |
| Spending on recreational boating trips | 38,289 | 1,023 |
| Spending on recreational boats | 21,979 | 744 |
| Sum | 60,268 | 1,767 |

*Notes*: Panel A data are compiled by the authors from the Quarterly Census of Employment and Wages. Numbers in brackets represent the percentage of economy-wide totals for Sector 71 and Sector 72. Numbers in Panel B represent the Direct Effects of trip-related spending on Employment and Personal Income in comparable activities to the sectors in Panel A. The numbers are from an input-output modeling study reported in U.S. Army Corps of Engineers (USACE, 2008), which uses economic data from 2001. Panel C represents the Direct Effects of boat-related spending, using number from USACE (2008). Panel D represents Direct and Indirect Effects summed over all sectors, using numbers from USACE (2008).

## Table 3.2: Group means for pre-treatment years, 1990-99

| | Sector 71 | | | Sector 72 | | |
|---|---|---|---|---|---|---|
| | Lake M-H coastal counties | Lake S-E-O coastal counties | t-Statistic (Col. 1 - Col. 2) | Lake M-H coastal counties | Lake S-E-O coastal counties | t-Statistic (Col. 4 - Col. 5) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| (1) Log of levels of outcome variables | | | | | | |
| Log (employment) | 5.790 | 6.306 | -4.97 | 7.512 | 7.977 | -5.53 |
| Log (total earnings) | 13.990 | 14.516 | -4.65 | 15.370 | 15.853 | -5.34 |
| Log (earnings/worker) | 6.405 | 6.417 | -0.55 | 6.062 | 6.082 | -1.48 |
| Log (establishments) | 3.299 | 3.828 | -7.52 | 4.845 | 5.382 | -7.85 |
| (2) Log of trends in outcome variables | | | | | | |
| Log (annual change in employment) | 0.038 | -0.015 | 3.17 | 0.029 | 0.022 | 1.13 |
| Log (annual change in total earnings) | 0.044 | -0.006 | 3.09 | 0.045 | 0.029 | 2.03 |
| Log (annual change in earnings/worker) | 0.007 | 0.009 | -0.30 | 0.016 | 0.007 | 1.75 |
| Log (annual change in establishments) | 0.020 | 0.003 | 2.74 | 0.021 | 0.011 | 2.75 |
| (3) Log of socioeconomic variables | | | | | | |
| Log (annual change in employment) | 0.021 | 0.010 | 4.88 | 0.020 | 0.011 | 4.66 |
| Log (annual change in personal income) | 0.020 | 0.014 | 3.02 | 0.020 | 0.015 | 2.97 |
| Log (annual change in total income) | 0.031 | 0.016 | 7.10 | 0.031 | 0.017 | 7.26 |
| Log (annual change in population) | 0.011 | 0.002 | 8.11 | 0.011 | 0.002 | 8.51 |
| No. of counties | 30 | 23 | | 32 | 25 | |
| Sample size | 300 | 230 | | 320 | 250 | |

*Note*: Samples use data from April-September each year.

## Table 3.3: Common trends tests: Michigan-Huron counties vs. Superior-Erie-Ontario counties

| | Log (annual change in employment) | Log (annual change in total earnings) | Log (annual change in earnings/worker) | Log (annual change in establishments) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Sector 71* | | | | |
| Michigan-Huron | 0.059*** | 0.055*** | -0.003 | 0.014** |
| counties (=1) | (0.016) | (0.014) | (0.006) | (0.007) |
| R-sq | 0.06 | 0.04 | 0.05 | 0.03 |
| Sample size | 477 | 477 | 477 | 477 |
| County no. | 53 | 53 | 53 | 53 |
| *Panel B: Sector 72* | | | | |
| Michigan-Huron | 0.002 | 0.010 | 0.008* | 0.006 |
| counties (=1) | (0.006) | (0.010) | (0.004) | (0.004) |
| R-sq | 0.06 | 0.03 | 0.13 | 0.14 |
| Sample size | 513 | 513 | 513 | 513 |
| County no. | 57 | 57 | 57 | 57 |

*Notes*: The table reports coefficient estimates on the variables for the group identifier. Dependent variables are the change in log outcome variables. Regressions include controls for year dummies and county socioeconomic and weather variables, described in detail in the text. Samples use data from April-September each year. Standard errors clustered by county are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

## Table 3.4: Common trends tests: Coastal counties vs. border inland counties

| | Log (annual change in employment) | Log (annual change in total earnings) | Log (annual change in earnings/worker) | Log (annual change in establishments) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Sector 71* | | | | |
| Coastal counties | -0.020 | -0.026 | -0.008* | -0.001 |
| (=1) | (0.015) | (0.018) | (0.005) | (0.006) |
| R-sq | 0.05 | 0.10 | 0.03 | 0.02 |
| Sample size | 828 | 828 | 828 | 828 |
| County no. | 92 | 92 | 92 | 92 |
| *Panel B: Sector 72* | | | | |
| Coastal counties | 0.003 | 0.006 | 0.005 | -0.002 |
| (=1) | (0.006) | (0.008) | (0.004) | (0.003) |
| R-sq | 0.05 | 0.03 | 0.10 | 0.10 |
| Sample size | 873 | 873 | 873 | 873 |
| County no. | 97 | 97 | 97 | 97 |

*Notes*: The table reports coefficient estimates on the variables for the group identifier. Dependent variables are the change in log outcome variables. Regressions include controls for year dummies and county socioeconomic and weather variables, described in detail in the text. Samples use data from April-September each year. Standard errors clustered by county are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

**Table 3.5: DDD regression results for Sector 71: Average treatment effects of extremely low levels of Lake Michigan-Huron**

| Treatment effect on outcome variable | Log(employm'nt) | Log(earnings) | Log(earnings per worker) | Log(establish-ments) | County no. | Sample size |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Regression (A): with county fixed effects | -0.082<br>(0.107) | -0.031<br>(0.136) | 0.052<br>(0.056) | -0.018<br>(0.059) | 92 | 1564 |
| Regression (B): with county-pair fixed effects | -0.022<br>(0.085) | 0.092<br>(0.105) | 0.064*<br>(0.033) | -0.043<br>(0.048) | 87 | 1479 |
| Regression (C): with county fixed effects without samples 98-99 | -0.050<br>(0.112) | 0.015<br>(0.138) | 0.066<br>(0.060) | -0.011<br>(0.065) | 92 | 1380 |
| Regression (D): with county-pair fixed effects without samples 98-99 | -0.006<br>(0.090) | 0.132<br>(0.110) | 0.079**<br>(0.035) | -0.039<br>(0.051) | 87 | 1305 |
| | | | | | | |
| R-sq of regression (A) | 0.64 | 0.64 | 0.09 | 0.84 | | |
| R-sq of regression (B) | 0.90 | 0.87 | 0.68 | 0.93 | | |
| R-sq of regression (C) | 0.65 | 0.64 | 0.09 | 0.84 | | |
| R-sq of regression (D) | 0.90 | 0.87 | 0.67 | 0.94 | | |

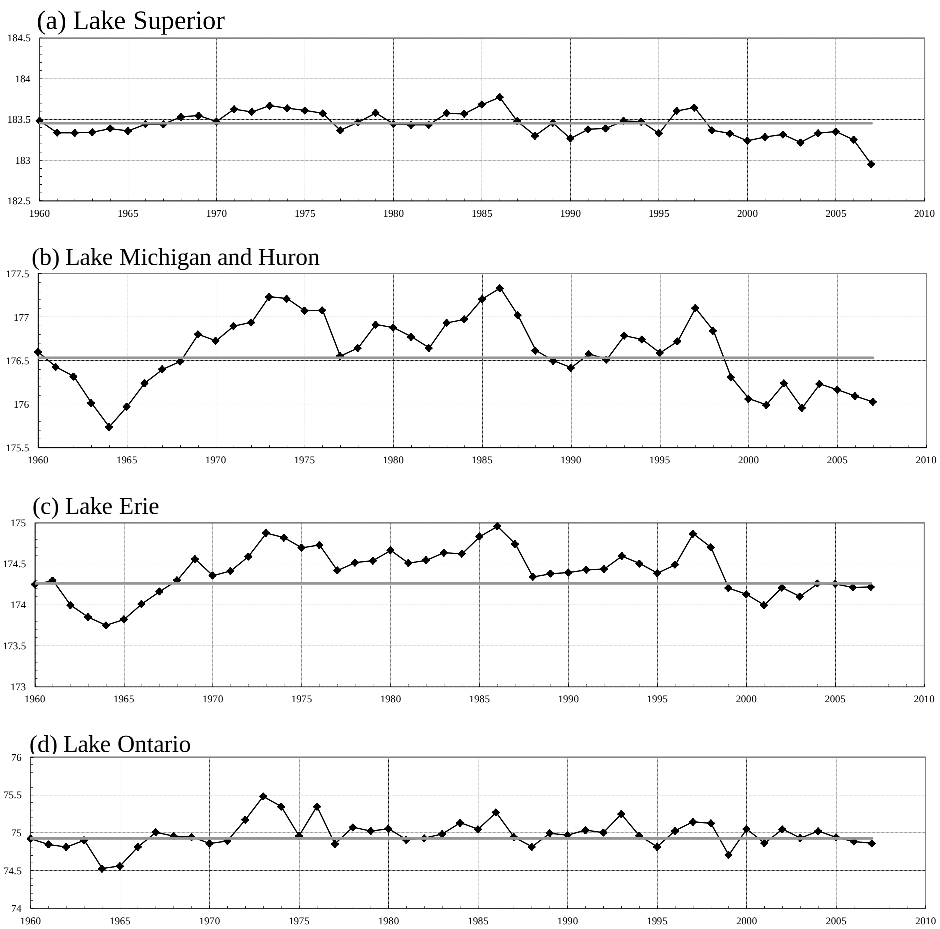
*Notes*: The table reports DDD estimates. Dependent variables are log outcome variables. Regressions include controls for year dummies and county socioeconomic and weather characteristics, described in detail in the text. Regression (A) and regression (B) use observations from 1990-2006. Regression (C) and regression (D) drop observations from 1998-99. Samples use data from April-September each year. Standard errors clustered by county are in parentheses for regression (A) and regression (C). The Eicker-White standard errors are in parentheses for regression (B) and regression (D). * significant at 10%; ** significant at 5%; *** significant at 1%

**Table 3.6: DDD regression results for Sector 72: Average treatment effects of extremely low levels of Lake Michigan-Huron**

| Treatment effect on outcome variable | Log(employm'nt) | Log(earnings) | Log(earnings per worker) | Log(establish-ments) | County no. | Sample size |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Regression (A): with county fixed effects | 0.024<br>(0.051) | 0.025<br>(0.063) | -0.001<br>(0.023) | -0.002<br>(0.036) | 97 | 1649 |
| Regression (B): with county-pair fixed effects | -0.003<br>(0.031) | 0.014<br>(0.055) | 0.004<br>(0.017) | -0.007<br>(0.031) | 92 | 1564 |
| Regression (C): with county fixed effects without samples 98-99 | 0.027<br>(0.057) | 0.032<br>(0.069) | 0.003<br>(0.026) | -0.004<br>(0.040) | 97 | 1455 |
| Regression (D): with county-pair fixed effects without samples 98-99 | -0.004<br>(0.033) | 0.019<br>(0.057) | 0.006<br>(0.018) | -0.011<br>(0.032) | 92 | 1380 |
| | | | | | | |
| R-sq of regression (A) | 0.89 | 0.79 | 0.12 | 0.84 | | |
| R-sq of regression (B) | 0.98 | 0.94 | 0.74 | 0.97 | | |
| R-sq of regression (C) | 0.89 | 0.79 | 0.13 | 0.84 | | |
| R-sq of regression (D) | 0.98 | 0.94 | 0.74 | 0.97 | | |

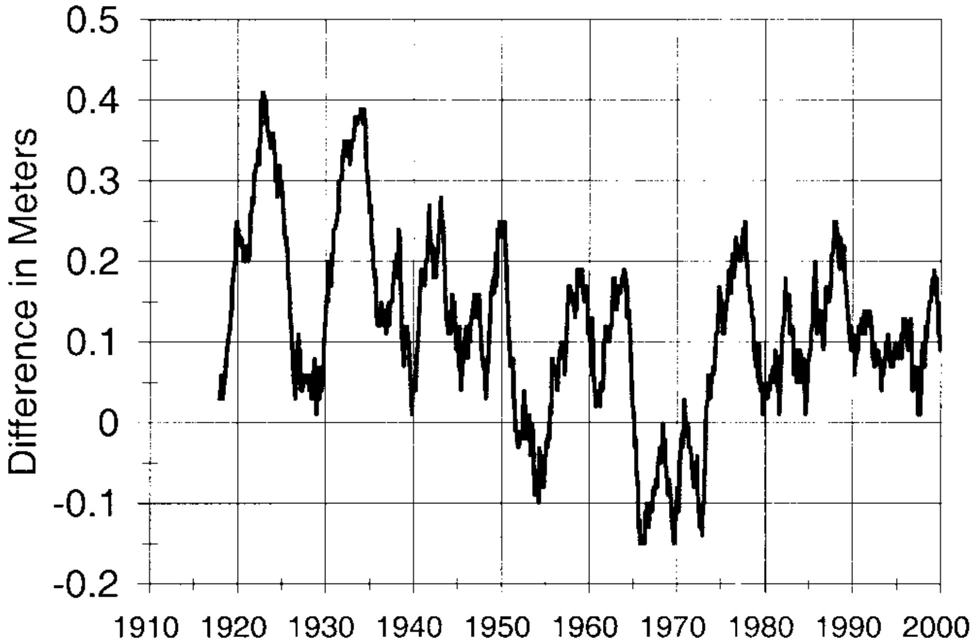
*Notes*: The table reports DDD estimates. Dependent variables are log outcome variables. Regressions include controls for year dummies and county socioeconomic and weather variables, described in detail in the text. Regression (A) and regression (B) use observations from 1990-2006. Regression (C) and regression (D) drop observations from 1998-99. Samples use data from April-September each year. Standard errors clustered by county are in parentheses for regression (A) and regression (C). The Eicker-White standard errors are in parentheses for regression (B) and regression (D). * significant at 10%; ** significant at 5%; *** significant at 1%

**Figure 3.1: Great Lakes lake levels, 1960-2007**



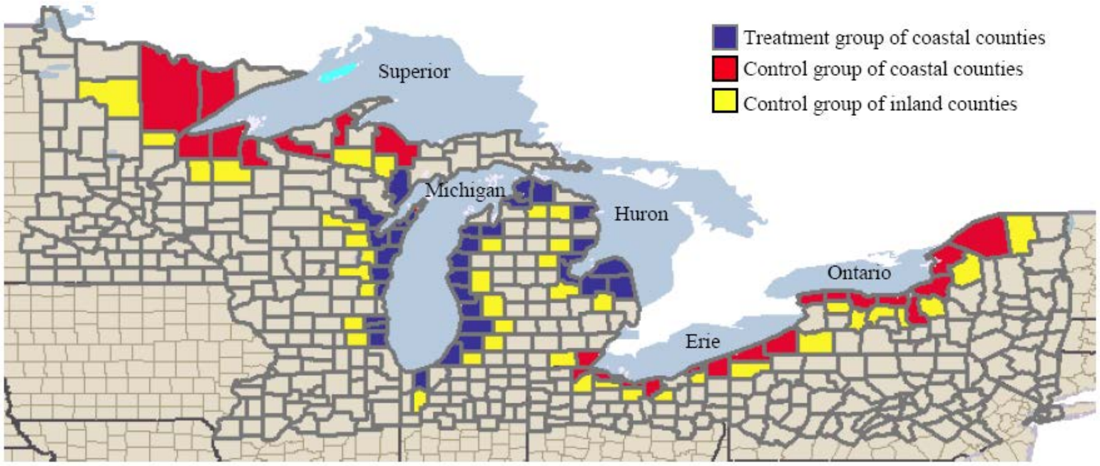

*Notes*: Lake levels for each lake are measured by the average of monthly lake levels over April to September each year. The vertical axis is the lake level in meters and the horizontal axis is year. The gray line is the long-term average for each lake.

**Figure 3.2: Water storage on Lake Superior increases its levels above natural levels**




From Clites and Quinn, 2003.

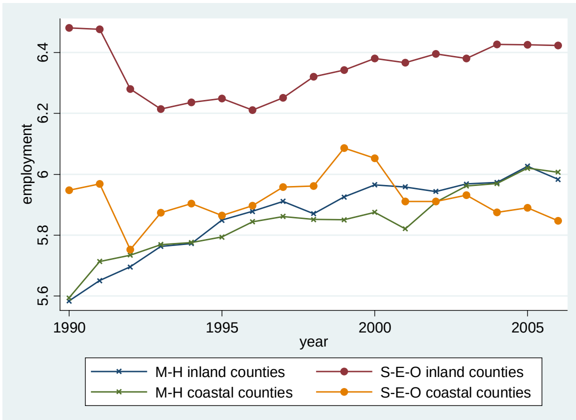
**Figure 3.3: Map of treatment and control counties for NAICS Sector 72**



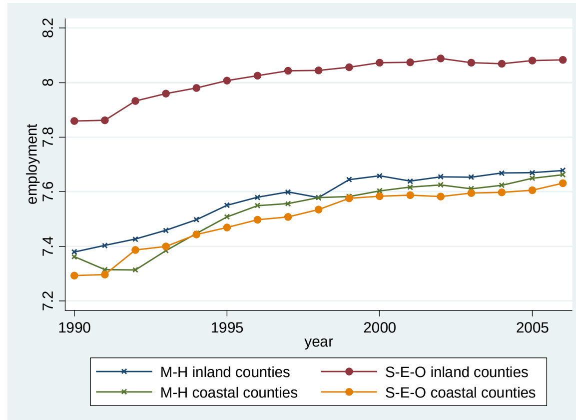

*Notes*: The map shows the counties used across the eight Great Lakes states for the analysis of NAICS Sector 72. Counties are dropped from the sample when: (1) data are withheld in a year by the Bureau of Labor Statistics' disclosure policy for the QCEW dataset; (2) the county connects to Lake St. Clair; (3) the county contains the major cities of Chicago, Milwaukee, Cleveland, or Buffalo. This map shows the 57 coastal counties and 44 inland counties for NAICS Sector 72. For NAICS Sector 71,using the same sample construction rule, the sample counties include 50 coastal counties and 42 inland counties.

## Figure 3.4: Mean employment from April to September, 1990-2006

(A) NAICS Sector 71



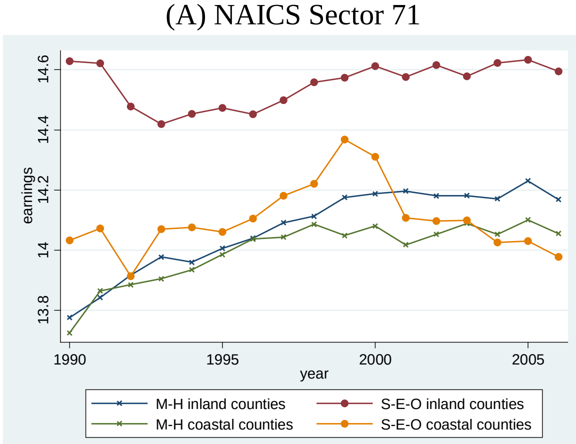

(B) NAICS Sector 72



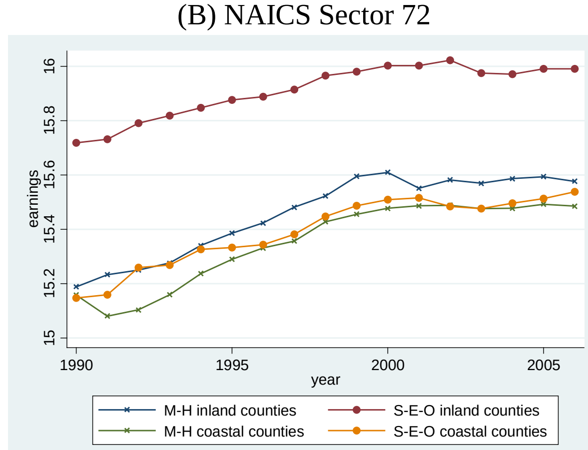

*Notes:* The figures plot log county mean employment for NAICS Sector 71 or NAICS Sector 72 by four groups: Lake Michigan-Huron (M-H) coastal counties, Lake Superior, Lake Erie and Lake Ontario (S-E-O) coastal counties, Lake Michigan-Huron (M-H) inland counties that are adjacent to the M-H coastal counties, and Lake Superior, Lake Erie and Lake Ontario (S-E-O) inland counties that are adjacent to the S-E-O coastal counties. Samples use data from April-September each year.

## Figure 3.5: Mean earnings from April to September, 1990-2006

(A) NAICS Sector 71



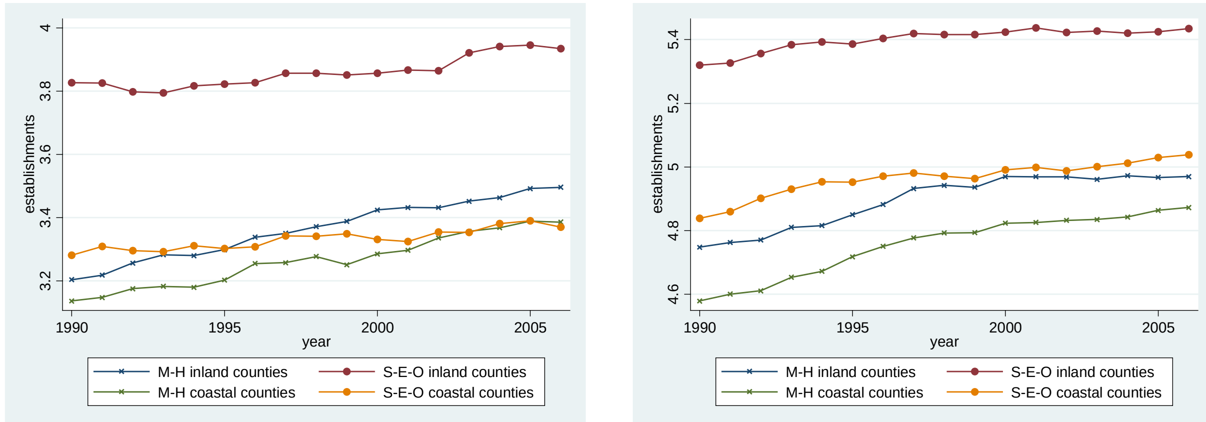

(B) NAICS Sector 72




*Notes*: The figures plot log county mean earnings for NAICS Sector 71 or NAICS Sector 72 by four groups: Lake Michigan-Huron (M-H) coastal counties, Lake Superior, Lake Erie and Lake Ontario (S-E-O) coastal counties, Lake Michigan-Huron (M-H) inland counties that are adjacent to the M-H coastal counties, and Lake Superior, Lake Erie and Lake Ontario (S-E-O) inland counties that are adjacent to the S-E-O coastal counties. Samples use data from April-September each year.

**Figure 3.6: Mean establishments from April to September, 1990-2006**

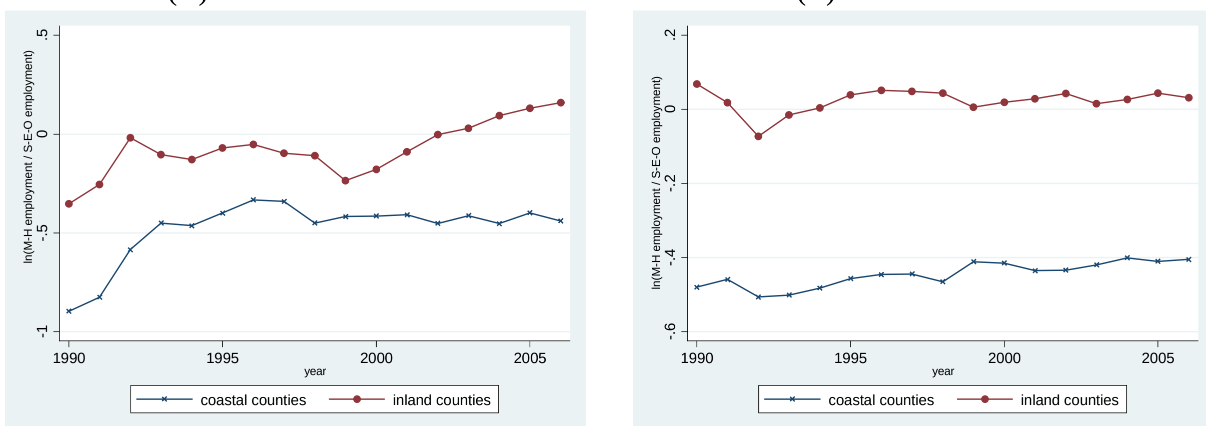
(A) NAICS Sector 71 (B) NAICS Sector 72




*Notes*: The figures plot log county mean establishments for NAICS Sector 71 or NAICS Sector 72 by four groups: Lake Michigan-Huron (M-H) coastal counties, Lake Superior, Lake Erie and Lake Ontario (S-E-O) coastal counties, Lake Michigan-Huron (M-H) inland counties that are adjacent to the M-H coastal counties, and Lake Superior, Lake Erie and Lake Ontario (S-E-O) inland counties that are adjacent to the S-E-O coastal counties. Samples use data from April-September each year.

**Figure 3.7: Mean employment ratios for M-H to S-E-O, coastal and inland, 1990-2006**

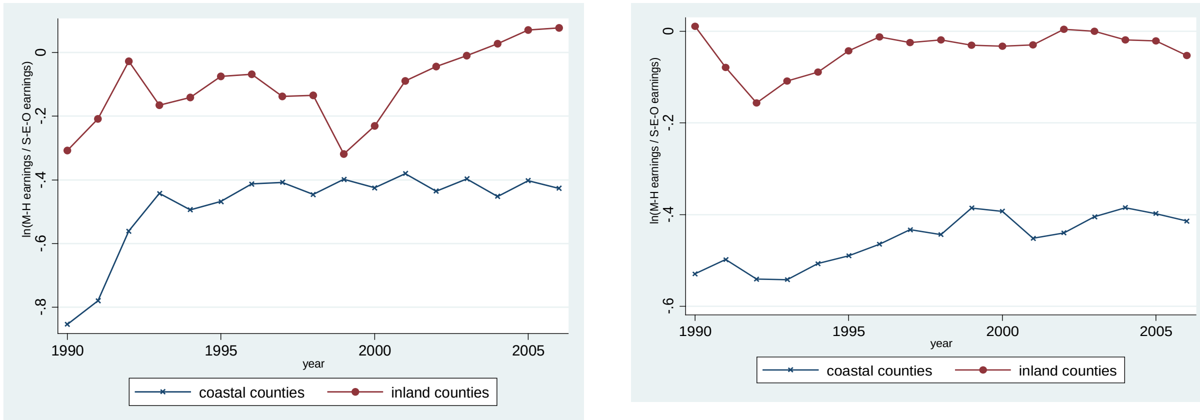
(A) NAICS Sector 71 (B) NAICS Sector 72




*Notes*: The figures plot the log of the ratio of mean employment in M-H counties to S-E-O counties, across coastal counties and adjacent inland counties, 1990-2006. Samples use data from April-September each year.

**Figure 3.8: Mean earnings ratio for M-H to S-E-O, coastal and inland, 1990-2006**

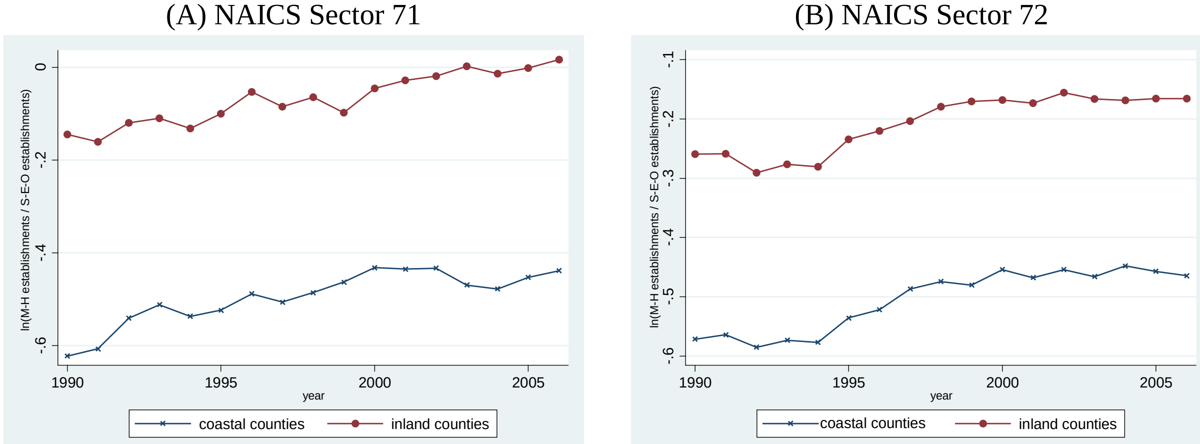
(A) NAICS Sector 71 (B) NAICS Sector 72




*Notes*: The figures plot the log of the ratio of mean earnings in M-H counties to S-E-O counties, across coastal counties and adjacent inland counties, 1990-2006. Samples use data from April-September each year.

**Figure 3.9: Mean establishment ratios for M-H to S-E-O, coastal and inland, 1990-2006**

(A) NAICS Sector 71 (B) NAICS Sector 72




*Notes*: The figures plot the log of the ratio of mean establishments in M-H counties to S-E-O counties, across coastal counties and adjacent inland counties, 1990-2006. Samples use data from April-September each year.

# Appendix 1

## Model Specifications and Detailed Estimation and Test Results

Our preferred model is supported by several important tests of assumptions mentioned in the *Methods* section. In this section, we present why we construct our empirical model specification with lagged variables, as well as why we prefer to use the system GMM estimator, along with detailed estimated results and test statistics.

### A1.1 Advantages and potential issues of the use of lagged dependent and independent variables

Our goal is to estimate the consistent impact of land use on grassland bird species richness. Existing studies have documented the existence of breeding-site fidelity, and its association with breeding-site quality (e.g. Schmidt 2004; Ribic et al. 2009). Literature related to breeding-site fidelity has focused on bird abundance for specific grassland bird species. However, given that bird species abundance is positively associated with bird species richness (e.g. Bock et al. 2007) grassland bird species richness could be positively associated with the effect of breeding philopatry. If breeding-site fidelity is omitted in a regression model, the estimated grassland effect would bias upward. Moreover, if land use has an enduring, long-run effect on species richness, the short-run effect of current land use would be confounded by the effect of the previous land use. Both the biased estimate and the ignorance of the enduring effect may misguide conservation policy makers. Thus, we prefer to include a lagged grassland bird species richness variable and lagged land-use variables in our regression model.

However, there are statistical issues that come with the inclusion of lagged dependent and independent variables and our attempt to control for unobserved heterogeneity. First, there is a collinearity concern, as our explanatory variables regarding land use include grassland, cropland (including corn and soybean), and developed land variables and their first lags. Second, the lagged dependent variable is necessarily correlated with the error term if we control for the fixed effect by a differenced regression model, as described in the *Methods* section.

Fortunately, with our short panel dataset that increases the sample size and uses the cross-sectional differences in route buffer characteristics, the problem of collinearity among the land use variables in a single time series can be reduced or avoided (e.g. Hsiao, 2014). Also, as the system GMM estimator uses a differenced regression model, we do not detect collinearity among the differenced current and lagged land use variables by using the variance inflation factor a simple diagnostic for collinearity. In addition, with our unique panel dataset, we are able to address the endogeneity problem by obtaining valid instrumental variables from the lagged information of the endogenous variable after accounting for the covariates. We conduct several statistical tests validating our empirical strategy and several robustness checks confirming our robust estimated results, as presented below.

### A1.2 Comparison of estimation results using alternative estimators

Table A1 shows detailed estimates by using different estimators. It is not surprising that the estimates of lagged grassland bird species richness and land use variables are so different across the alternative estimators. As described in the *Methods* and *Results* sections, using traditional panel data models, such as column 1, column, and column 3, the estimated results are not consistent due to the endogeneity problem.

We address the endogeneity problem from the lagged dependent variable by using the system GMM estimator. In Table A1, the estimate of lagged grassland bird species richness by using our preferred model (column 5) lies comfortably in between the estimates by using the ordinary least squares estimator (column 1) and the fixed effect estimator (column 3). However, we find that the first-differenced GMM estimate of lagged grassland bird species richness (0.009) is close to the fixed effect estimate (-0.031), so it seems likely that the GMM estimate is also biased downwards perhaps due to weak instruments (Bond et al. 2001). We use the test procedure for weak instruments provided by Bazzi and Clemens (2013) and also find that the first-differenced estimator suffers from a weak instruments problem, as using the third lagged grassland bird species richness (i.e. the nearest valid lags) as instruments fails the Kleibergen-Paap Wald test. Thus we exploit additional moment conditions by using a system GMM estimator, and the burden of strong identification in the system estimator would rely on these levels equation moments.

It is worth nothing that our preferred model also only uses the nearest valid (i.e. the first lagged differenced grassland bird species richness) lags as instruments for the level equation, because any attempts that include further lags as instruments, including the use of a collapsed instrument matrix, suffer from a weak instruments problem. In the followings, we will show the results that only use the nearest valid lags of the endogenous variable as instruments under alternative assumptions of model specifications related to the grassland, cropland, and developed land use variables.

### A1.3 Detailed estimation and test results using the system GMM estimator

In the presence of lagged grassland bird species richness, our empirical strategy is aimed at finding good instrumental variables (IV) in order to address the endogeneity problem and obtain the consistent estimate of the land use's impact. Several important tests results related to our selection of instruments are presented in Table A2 with the use of the system GMM estimator.

Column 1 in Table A2 presents the results of our preferred model, supported by several important tests of assumptions for the estimator mentioned in the *Methods* section. First, in column 1 when we treat all the land use variables are exogenous and only the lagged dependent variable is endogenous, the p-value of 0.81 for the AR(2) test does not reject the null hypothesis of no second-order serial correlation in the first-differenced residuals, suggesting that the errors are serially independent and the lags are valid instruments. The same conclusion obtained when we treat the grassland, cropland, and developed land variables as endogenous or predetermined, showed in columns 2 to 4. In column 5, when our outcome variable is total grassland bird abundance and only the lagged total grassland bird abundance variable is treated as endogenous, the test result also suggests that the errors are serially independent and we may use the lags as instruments.

Second, in column 1 the p-value of 0.37 for the Hansen (J statistics) test of the overidentifying restrictions provides evidence that the full set of instruments is valid. However, in column 3 when we treat grassland, cropland, and developed land variables as predetermined, the low p-value of 0.14 for the Hansen test may provide evidence against the null hypothesis that the full set of instruments is valid. Besides, the difference-in-Hansen test results also show that, in column 3, the subsets of (excluded) instruments are not valid. Thus, we turn to other specifications, even though column 3 shows that the set of instruments appears not weak. In contrast, if the grassland, cropland, and developed land variables are treated as endogenous, the Hansen tests and the differenced-in-Hansen tests suggest that the lags used as instruments are valid, as can be seen in column 2. However, the p-value of 0.395 for the Kleibergen-Paap Wald test suggests that these valid instruments are far too weak for instrumentation to remove a 30-percent portion of OLS bias, even the instruments pass the Kleibergen-Paap LM test for underidentification with the p-value of 0.004. These tests in column 2 and column 3 provide evidence of "the difficulties that arise when weak instruments are valid and strong instruments are invalid" argued by Bazzi and Clemens (2013).

Since the set of moment conditions in the model treating a grassland, cropland, or developed land variable as endogenous is a strict subset of the set of moment conditions in the model treating these land use variables as predetermined, using the difference-in-Hansen test, we specifically test for the validity of the additional instruments if any of these land use variables can be predetermined. The results show that, for the grassland and developed land variables, the difference-in-Hansen tests do not reject the null hypothesis that the additional instruments are valid. Thus, in column 4, we treat grassland and developed land variables as predetermined, but cropland as endogenous. The estimates between column 3 and 4 are similar. Yet, as can be seen in the result of the Kleibergen-Paap test, the set of the instruments is weak; even these instruments are valid and pass the Kleibergen-Paap LM test, as column 2.

Therefore, we select column 1 as our preferred model, in which we treat all land use variables as exogenous after controlling for unobserved heterogeneity, year effects, precipitation during spring season, and other controls. By using the estimator, we also address the endogeneity problem in the presence of the lagged dependent variable. Although there might be time-varying unobserved factors that are correlated with a land use variable, the lagged information of land use cannot provide both valid and strong instruments. Yet, the exogeneity of land use variables for birds' siting decision may be reasonable after accounting for unobserved heterogeneity, such as soil quality and climate, and conditioning on our controls. For instance, many unobserved manmade shocks, correlated with cropland or grassland, on birds can be captured in the developed land variables. Also, a local weather shock last year, such as severe drought, may affect bird sitting decision and farmers' land use decision simultaneously, a potential endogeneity problem. But our robustness checks presented later show similar estimated results of the land use variables as our preferred specification in column 1 if we include a control for the local weather in the past non-breeding season.

In column 5, we use the logged total grassland bird abundance as the outcome variable and also have its first lagged variable as a control due to breeding philopatry. By this model specification we provide a new analytical insight into identifying the species-area relationship. The estimates of grassland show that attraction effect and recruitment effect are both around 0.1 at 10% significance level, indicating that a 1% decrease in grassland this year will reduce 0.1 % of total grassland bird abundance this year via attraction effect and further reduce 0.1% of total grassland bird abundance next year via recruitment effect. Developed land also shows a negative attraction effect. But, the Hansen test and the weak instruments test show that the instruments may be invalid and not strong. Changing instruments or specifications cannot solve the issue, suggesting that identifying the causal impact land use on bird abundance is still an open question.

### A1.4 Spatial correlation test

We follow the test method proposed by Sarafidis et al. (2009) for error cross sectional dependence after estimating a linear dynamic panel data model with the GMM estimators. This test examines whether error cross section dependence is left after including time dummy variables in the regression using the AR(2) test (or m2 test in their paper) and the difference-in-Sargan test. First, all the AR(2) tests shown in Table A2 suggest that there is no evidence of error serial correlation and this implies possibly no heterogeneous error cross section dependence. This is confirmed by the fact that the p-value of 0.131 for the Sargan's difference test based on the system GMM estimator safely fail to reject the null hypothesis that the cross section dependence is homogeneous across pairs of cross section units. This is likely due to the substantial distances between routes in the bird survey or the inclusion of year fixed effects in the model has accounted for the universal time-related shocks in the error term.

# Appendix 2

## Sensitivity Analysis

In this section, we present that the estimation result using our preferred estimator is robust to several specifications regarding the use of land use variables and potentially endogenous variables, and the lags of instruments.

### A2.1 Robustness checks to specifications

There is a concern that the collinearity problem between cropland and grassland might not be avoided with the panel data model. If farmers decide to plant less corn or soybeans by setting aside some of their farmland, grassland acreage would increase. That is, grassland could be the outcome of cropland decision that also affects grassland bird species richness. Though our data does not show this perfect substitution, we drop one of these two variables in the regression and show that the estimates of grassland and cropland are similar, as can be seen in column 2 and column 3 in Table A3. It is worth noting that, with our preferred specification that includes both cropland and grassland, we are able to examine whether a decrease of grassland affects grassland bird species richness through mechanisms other than an increase of cropland. Our results suggest that the effect of grassland is not only through cropland, but finding no evidence about the effect of cropland in the regression does not mean that there is no effect of cropland.

There might be potential endogenous variables that are correlated with both grassland bird species richness and land use, especially provided that our preferred model assumes land use variables are exogenous. Column 4 and column 5 in Table A3 consider the robustness of the main results to adding controls for wetland and total precipitation in the non-breeding season, from September in the last year to March in the current year. The added variables are treated as exogenous. The results suggest that the estimates of lagged grassland bird species richness, grassland, cropland, and developed land variables are robust to the addition of the variables, though the difference-in-Hansen test result (p-value 0.020) rejects that the added instruments of non-breeding season precipitation are valid.

In column 6 of Table A3, we use a quadratic time trend that is common to all route buffers in the regression, instead of using year-fixed effects, to capture technological change about conservation and agricultural practices. The results show that the effects of land use variables are similar to our main results, but the temporal effect of lagged grassland bird species richness becomes statistically insignificant. Yet, the result of the Hansen test for overidentification , p-value 0.089, suggests that the set of instruments is not valid.

### A2.2 Robustness checks to the use of lags as instruments

Table A4 presents the estimates of land use variables are not sensitive to the number of the lags used as instruments, especially when we use a collapsed instrument matrix that restricts the number of instruments suggested by Roodman (2009b), as can be seen in column 5 and column 6. The estimate of lagged dependent variables appears somewhat sensitive to the number of lags. Yet, again, we select column 1 that only uses the nearest valid lags (and the exogenous variables) instrumenting for the endogenous variable as our preferred model, because only the nearest lags passes our weak IV tests. Any attempts that include further lags as instruments, including the use of a collapsed instrument matrix, suffer from the problem of weak instruments.

### A2.3 Results using different cropland variables

In Table A5 we use different cropland measures, while we have found no evidence on the effect of cropland using the preferred model. In column 2 we replace cropland variables by corn as the variable of interest for cropland. In column 3 the cropland variable is measured by total acreage of corn, soybeans, and wheat. In column 4 the cropland measure is the same as our preferred model in column 1, but wheat variables are added to the regression as wheat provides better habitat for birds than that provided by corn and soybean. In column 5 we replace cropland variables by three individual crops, namely, corn, soybeans, and wheat. The results show that the estimates of non-cropland controls are consistent, and we still have not found evidence on the effect of cropland on grassland bird species richness, unless through grassland and developed land.

Table A1 Comparison of estimation results using alternative estimators

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | OLS | ME | FE | DGMM | SGMM |
| Lagged grassland bird species richness | 0.767** | 0.884** | -0.031 | 0.009 | 0.191** |
| | (0.029) | (0.016) | (0.031) | (0.070) | (0.062) |
| ln(grassland) | -0.504* | -0.474* | -0.503* | -0.398 | -0.258 |
| | (0.199) | (0.185) | (0.211) | (0.251) | (0.216) |
| Lagged ln(grassland) | 0.682** | 0.597** | 0.224 | 0.347 | 0.710** |
| | (0.195) | (0.187) | (0.220) | (0.253) | (0.185) |
| ln(cropland) | -0.391* | -0.328* | -0.372* | -0.519* | -0.280 |
| | (0.189) | (0.136) | (0.149) | (0.220) | (0.255) |
| Lagged ln(cropland) | 0.388* | 0.326* | 0.246 | 0.061 | 0.323 |
| | (0.178) | (0.132) | (0.134) | (0.176) | (0.200) |
| ln(developed land) | -0.499** | -0.296* | -0.197 | -0.121 | -1.601** |
| | (0.182) | (0.142) | (0.515) | (0.399) | (0.366) |
| Lagged ln(developed land) | 0.103 | 0.064 | 0.118 | 0.165 | 0.235 |
| | (0.157) | (0.118) | (0.112) | (0.126) | (0.137) |
| temperature of BBS | -0.001 | 0.001 | 0.006 | 0.004 | -0.006 |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.006) |
| windy of BBS | 0.025 | 0.033 | -0.074 | -0.060 | 0.015 |
| | (0.053) | (0.044) | (0.049) | (0.060) | (0.074) |
| sky of BBS | -0.034 | -0.032 | -0.080 | -0.057 | -0.025 |
| | (0.055) | (0.041) | (0.052) | (0.061) | (0.059) |
| ln(open water) | 0.211* | 0.236* | 0.151 | 0.187 | 0.245** |
| | (0.090) | (0.113) | (0.126) | (0.132) | (0.091) |
| Lagged ln(open water) | -0.189* | -0.234* | -0.273** | -0.103 | -0.141 |
| | (0.095) | (0.113) | (0.094) | (0.111) | (0.101) |
| ln(spring precipitation) | 1.129 | 1.182* | 0.745 | 1.341* | 1.356* |
| | (0.635) | (0.481) | (0.444) | (0.641) | (0.603) |
| Lagged ln(spring precipitation) | 0.504 | 0.195 | 0.919 | 1.235 | 0.908 |
| | (0.500) | (0.453) | (0.532) | (0.640) | (0.680) |
| ln(square of spring precipitation) | -0.557 | -0.501* | -0.309 | -0.468 | -0.895** |
| | (0.308) | (0.235) | (0.220) | (0.308) | (0.297) |
| Lagged ln(square of spring precipitation) | -0.514* | -0.299 | -0.424 | -0.529 | -0.814* |
| | (0.234) | (0.223) | (0.260) | (0.298) | (0.312) |
| Constant | 2.192* | 0.571 | 10.226* | - | 10.535** |
| | (0.943) | (0.732) | (4.562) | - | (2.770) |
| Observations | 903 | 903 | 903 | 774 | 903 |

*Notes:* * $p < 0.05$, ** $p < 0.01$. Robust standard errors in parentheses. The dependent variable in all specifications is the level of grassland bird species richness. Year effects included in all models. Column 1 uses the ordinary least squares estimator. Column 2 uses the mixed effect estimator. Column 3 uses the fixed effect estimator. Column 4 uses the differenced GMM estimator. Column 5 uses the system GMM estimator.

Table A2 Estimation results using the SGMM estimator and test statistics

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Lagged grassland bird species richness | 0.191** | 0.258** | 0.271** | 0.252** | - |
| | (0.062) | (0.070) | (0.070) | (0.067) | - |
| Lagged ln( total grassland bird abundance) | - | - | - | - | 0.305** |
| | - | - | - | - | (0.067) |
| ln(grassland) | -0.258 | 1.496* | -0.245 | -0.153 | 0.101 |
| | (0.216) | (0.654) | (0.272) | (0.274) | (0.051) |
| Lagged ln(grassland) | 0.710** | -0.565 | 0.590* | 0.664** | 0.093 |
| | (0.185) | (0.493) | (0.240) | (0.242) | (0.055) |
| ln(cropland) | -0.280 | 0.339 | -0.166 | -0.224 | 0.051 |
| | (0.255) | (0.452) | (0.231) | (0.408) | (0.033) |
| Lagged ln(cropland) | 0.323 | -0.147 | 0.079 | 0.243 | -0.048 |
| | (0.200) | (0.367) | (0.190) | (0.367) | (0.027) |
| ln(developed land) | -1.601** | -0.794 | -0.907* | -0.965* | -0.493*** |
| | (0.366) | (0.425) | (0.417) | (0.408) | (0.128) |
| Lagged ln(developed land) | 0.235 | 0.192 | 0.383* | 0.359* | -0.019 |
| | (0.137) | (0.192) | (0.157) | (0.154) | (0.024) |
| temperature of BBS | -0.006 | -0.007 | -0.010 | -0.011 | 0.002 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.002) |
| windy of BBS | 0.015 | -0.000 | -0.019 | -0.021 | -0.018 |
| | (0.074) | (0.073) | (0.078) | (0.075) | (0.020) |
| sky of BBS | -0.025 | -0.021 | -0.013 | -0.033 | 0.009 |
| | (0.059) | (0.070) | (0.070) | (0.065) | (0.013) |
| ln(open water) | 0.245** | 0.260* | 0.172 | 0.195* | 0.058 |
| | (0.091) | (0.114) | (0.100) | (0.091) | (0.038) |
| Lagged ln(open water) | -0.141 | -0.236 | -0.127 | -0.141 | 0.058 |
| | (0.101) | (0.135) | (0.114) | (0.103) | (0.038) |
| ln(spring precipitation) | 1.356* | 0.986 | 0.693 | 0.665 | 0.213 |
| | (0.603) | (0.702) | (0.716) | (0.716) | (0.151) |
| Lagged ln(spring precipitation) | 0.908 | 0.436 | 0.533 | 0.350 | -0.167 |
| | (0.680) | (0.710) | (0.758) | (0.733) | (0.129) |
| ln(square of spring precipitation) | -0.895** | -0.725* | -0.594 | -0.606 | -0.140 |
| | (0.297) | (0.338) | (0.335) | (0.340) | (0.074) |
| Lagged ln(square of spring precipitation) | -0.814* | -0.596 | -0.630 | -0.557 | 0.032 |
| | (0.312) | (0.313) | (0.335) | (0.328) | (0.066) |
| Constant | 10.535** | 2.372 | 7.441* | 6.524* | 4.558*** |
| | (2.770) | (3.498) | (3.196) | (3.135) | (1.103) |
| AR(1): z-statistic [a] | -7.26 | -6.17 | -6.29 | -6.27 | -6.64 |
| p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(2): z-statistic [a] | 0.25 | 1.04 | 0.39 | 0.33 | -0.22 |
| p-value | 0.806 | 0.299 | 0.694 | 0.741 | 0.826 |
| Number of instruments | 34 | 64 | 67 | 66 | 34 |
| Hansen test all instruments (p-value) [b] | 0.370 | 0.423 | 0.143 | 0.543 | 0.150 |
| Hansen test excluding instruments for levels (p-value) [c] | 0.652 | 0.575 | 0.900 | 0.813 | 0.088 |
| Difference-in-Hansen test (p-value) [c] | 0.197 | 0.318 | 0.021 | 0.286 | 0.402 |
| Hansen test excluding instruments of lagged grassland bird species richness (p-value) [c] | - | 0.492 | 0.628 | 0.700 | - |
| Difference-in-Hansen test (p-value) [c] | - | 0.312 | 0.014 | 0.247 | - |
| Hansen test excluding instruments of lagged grassland, cropland, and developed land variables (p-value) [c] | - | 0.647 | 0.116 | 0.119 | - |
| Difference-in-Hansen test (p-value) [c] | - | 0.362 | 0.229 | 0.717 | - |
| Kleibergen-Paap LM test (p-value) [d] | 0 | 0.004 | 4.36e-5 | 2.62e-5 | 2.03e-6 |
| Kleibergen-Paap Wald statistics [e] | | | | | |
| $H_0$: relative OLS bias > 10 percent (p-value) | 3.80e-07 | 1 | 1 | 1 | 0.117 |
| $H_0$: relative OLS bias > 30 percent (p-value) | 6.09e-11 | 0.395 | 0.020 | 0.593 | 0.004 |
| Cragg-Donald Wald statistics [e] | | | | | |
| $H_0$: relative OLS bias > 10 percent (p-value) | 4.92e-06 | 1 | 1 | 1 | 0.102 |
| $H_0$: relative OLS bias > 30 percent (p-value) | 1.71e-09 | 0.424 | 0.097 | 0.069 | 0.003 |

*Notes:* [*] $p < 0.05$, [**] $p < 0.01$. Heteroskedasticity-robust standard errors in parentheses. The dependent variable in all specifications except column (5) is the level of grassland bird species richness. The dependent variable in column (5) is the natural log of total grassland bird abundance. Year effects included in all specifications. Lagged dependent variable is endogenous in all specifications. There are 903 observations for 129 routes. In Column 1, only lagged grassland bird species richness is endogenous. In column 2, grassland, cropland, and developed land are assumed to be endogenous. In column 3, grassland, cropland, and developed land are assumed to be weakly endogenous. In column 4, while grassland and developed land are assumed to be weakly endogenous, cropland is assumed to be endogenous. In Column 5, only lagged total grassland bird abundance is endogenous.

[a]AR(1) and AR(2) are the first-order and second-order serial correlation tests in the first-differenced residuals. If the first-differenced residuals are serially uncorrelated, we expect to reject the null hypothesis that there is zero autocorrelation in the first-differenced residuals at order 1 but not at higher orders.

[b]The null hypothesis of the Hansen test for overidentifying restrictions is that all the instruments, as a group, appear exogenous. The test is aimed at characterizing instrument (in)validity or examining whether the model is correctly specified.

[c]The null hypothesis of the difference-in-Hansen test is that the specified variables are proper instruments (See Hayashi 2000).

[d]The null hypothesis of the Kleibergen-Paap LM test is that the structural equation is underidentified, i.e., the rank condition fails. The test uses a procedure from Bazzi and Clemens (2013).

[e]The null hypothesis of the Cragg-Donald Wald test and Kleibergen-Paap Wald tests is that the bias of the estimates of the endogenous variables reported in the table are greater than 10 or 30 percent of the OLS bias. While Cragg-Donald test assumes homoscedastic error terms, Kleibergen-Paap test is robust to non-i.i.d. errors. The test uses a procedure from Bazzi and Clemens (2013). The weak IV tests provide evidence that even though the parameters might be identified, the instruments are weak.

Table A3 Robustness checks to specifications

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Lagged grassland bird species richness | 0.191** | 0.189** | 0.188** | 0.160** | 0.133* | 0.109 |
| | (0.062) | (0.064) | (0.063) | (0.057) | (0.063) | (0.064) |
| ln(grassland) | -0.258 | -0.213 | - | -0.292 | -0.357 | -0.226 |
| | (0.216) | (0.196) | - | (0.208) | (0.237) | (0.217) |
| Lagged ln(grassland) | 0.710** | 0.607** | - | 0.754** | 0.680** | 0.787** |
| | (0.185) | (0.180) | - | (0.193) | (0.190) | (0.191) |
| ln(cropland) | -0.280 | - | -0.269 | -0.233 | -0.138 | -0.184 |
| | (0.255) | - | (0.255) | (0.225) | (0.303) | (0.182) |
| Lagged ln(cropland) | 0.323 | - | 0.206 | 0.277 | 0.360 | 0.229 |
| | (0.200) | - | (0.209) | (0.175) | (0.238) | (0.154) |
| ln(developed land) | -1.601** | -1.522** | -1.477** | -1.311** | -1.185** | -1.413** |
| | (0.366) | (0.361) | (0.374) | (0.389) | (0.327) | (0.259) |
| Lagged ln(developed land) | 0.235 | 0.218 | 0.107 | 0.015 | 0.182 | 0.401** |
| | (0.137) | (0.139) | (0.128) | (0.147) | (0.147) | (0.124) |
| ln(open water) | 0.245** | 0.213* | 0.281** | 0.204* | 0.264** | 0.257** |
| | (0.091) | (0.086) | (0.098) | (0.095) | (0.095) | (0.094) |
| Lagged ln(open water) | -0.141 | -0.108 | -0.137 | -0.240* | -0.093 | -0.117 |
| | (0.101) | (0.099) | (0.105) | (0.097) | (0.112) | (0.107) |
| ln(spring precipitation) | 1.356* | 1.371* | 1.163 | 1.098 | 0.489 | 0.516 |
| | (0.603) | (0.622) | (0.601) | (0.605) | (0.761) | (0.640) |
| Lagged ln(spring precipitation) | 0.908 | 0.629 | 0.909 | 0.731 | 0.219 | 0.449 |
| | (0.680) | (0.620) | (0.729) | (0.643) | (0.798) | (0.645) |
| ln(square of spring precipitation) | -0.895** | -0.879** | -0.824** | -0.732* | -0.436 | -0.692* |
| | (0.297) | (0.300) | (0.295) | (0.305) | (0.354) | (0.323) |
| Lagged ln(square of spring precipitation) | -0.814* | -0.694* | -0.805* | -0.694* | -0.452 | -0.648* |
| | (0.312) | (0.291) | (0.329) | (0.301) | (0.358) | (0.315) |
| ln(wetland) | - | - | - | -0.012 | - | - |
| | - | - | - | (0.078) | - | - |
| Lagged ln(wetland) | - | - | - | 0.268** | - | - |
| | - | - | - | (0.090) | - | - |
| ln(non-breeding season precipitation) | - | - | - | - | -0.735* | - |
| | - | - | - | - | (0.359) | - |
| Lagged ln(non-breeding season precipitation) | - | - | - | - | -0.287 | - |
| | - | - | - | - | (0.174) | - |
| Year | - | - | - | - | - | 0.142** |
| | - | - | - | - | - | (0.031) |
| Year square | - | - | - | - | - | -0.000** |
| | - | - | - | - | - | (0.000) |

*Notes:* * $p < 0.05$, ** $p < 0.01$. Heteroskedasticity-robust standard errors in parentheses. The dependent variable in all specifications is the level of grassland bird species richness. Year effects included in all specifications, except column 6. Lagged dependent variable is endogenous in all specifications. There are 903 observations for 129 routes. . Column 1 is the results of our preferred model. Column 2 drops the cropland variables. Column 3 drops grassland variables. Column 4 adds wetland variables treated as exogenous. Column 5 adds variables of total precipitation the in non-breeding season from last September to March in the current year. Column 6 replaces year effects by a quadratic time trend that is common to all route buffers.

Table A4 Robustness to the use of lags as instruments

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Lagged grassland bird species richness | 0.191** | 0.174** | 0.202** | 0.190** | 0.119* | 0.128* |
| | (0.062) | (0.056) | (0.061) | (0.065) | (0.058) | (0.058) |
| ln(grassland) | -0.258 | -0.358 | -0.299 | -0.292 | -0.280 | -0.229 |
| | (0.216) | (0.226) | (0.225) | (0.230) | (0.214) | (0.227) |
| Lagged ln(grassland) | 0.710*** | 0.783*** | 0.720*** | 0.690** | 0.729*** | 0.782*** |
| | (0.185) | (0.193) | (0.205) | (0.209) | (0.177) | (0.187) |
| ln(cropland) | -0.280 | -0.386 | -0.366 | -0.314 | -0.290 | -0.257 |
| | (0.255) | (0.250) | (0.265) | (0.252) | (0.224) | (0.238) |
| Lagged ln(cropland) | 0.323 | 0.389* | 0.401 | 0.353 | 0.278 | 0.267 |
| | (0.200) | (0.192) | (0.207) | (0.208) | (0.173) | (0.185) |
| ln(developed land) | -1.601*** | -1.673*** | -1.615*** | -1.703*** | -1.567*** | -1.636*** |
| | (0.366) | (0.390) | (0.385) | (0.375) | (0.321) | (0.341) |
| Lagged ln(developed land) | 0.235 | 0.269* | 0.255 | 0.253 | 0.234 | 0.238 |
| | (0.137) | (0.134) | (0.141) | (0.134) | (0.133) | (0.139) |
| temperature of BBS | -0.006 | -0.005 | -0.004 | -0.006 | -0.010 | -0.011 |
| | (0.006) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) |
| windy of BBS | 0.015 | 0.055 | 0.028 | 0.041 | 0.051 | 0.052 |
| | (0.074) | (0.070) | (0.075) | (0.077) | (0.069) | (0.070) |
| sky of BBS | -0.025 | -0.031 | -0.046 | -0.029 | -0.014 | -0.026 |
| | (0.059) | (0.059) | (0.065) | (0.066) | (0.057) | (0.059) |
| ln(open water) | 0.245** | 0.256** | 0.267** | 0.264** | 0.252** | 0.224* |
| | (0.091) | (0.092) | (0.097) | (0.098) | (0.089) | (0.090) |
| Lagged ln(open water) | -0.141 | -0.133 | -0.107 | -0.098 | -0.110 | -0.130 |
| | (0.101) | (0.102) | (0.112) | (0.115) | (0.101) | (0.103) |
| ln(spring precipitation) | 1.356* | 1.566** | 1.380* | 1.580* | 0.892 | 0.897 |
| | (0.603) | (0.595) | (0.650) | (0.678) | (0.602) | (0.634) |
| Lagged ln(spring precipitation) | 0.908 | 1.138 | 0.925 | 0.864 | 0.592 | 0.456 |
| | (0.680) | (0.633) | (0.735) | (0.762) | (0.669) | (0.713) |
| ln(square of spring precipitation) | -0.895** | -1.012*** | -0.872** | -0.981** | -0.770** | -0.728* |
| | (0.297) | (0.290) | (0.311) | (0.317) | (0.294) | (0.299) |
| Lagged ln(square of spring precipitation) | -0.814* | -0.899** | -0.757* | -0.735* | -0.734* | -0.640* |
| | (0.312) | (0.292) | (0.335) | (0.346) | (0.303) | (0.315) |
| Constant | 10.535*** | 10.984*** | 10.322*** | 11.132*** | 11.885*** | 11.558*** |
| | (2.770) | (3.078) | (2.927) | (2.747) | (2.791) | (2.901) |
| Number of instruments | 34 | 39 | 43 | 49 | 26 | 29 |

*Notes:* * $p < 0.05$, ** $p < 0.01$. Heteroskedasticity-robust standard errors in parentheses. The dependent variable in all specifications is the level of grassland bird species richness. Year effects included in all specifications. Lagged dependent variable is endogenous in all specifications. There are 903 observations for 129 routes. Column 1 is the results of our preferred model that uses only the nearest valid lags and the exogenous variables as instruments. Column 2 adds the second nearest valid lags as instruments. Column 3 adds the second and third nearest valid lags as instruments. Column 4 uses all valid lags as instruments. Column 5 uses a collapsed instrument matrix from the first to third nearest valid lags. Column 6 uses a collapsed instrument matrix from all valid lags.

Table A5 Results using different cropland variables

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Lagged grassland bird species richness | 0.191** | 0.193** | 0.189** | 0.169** | 0.169** |
| | (0.062) | (0.063) | (0.064) | (0.062) | (0.062) |
| ln(grassland) | -0.258 | -0.205 | -0.111 | -0.252 | -0.207 |
| | (0.216) | (0.211) | (0.218) | (0.208) | (0.201) |
| Lagged ln(grassland) | 0.710** | 0.639** | 0.651** | 0.680** | 0.634** |
| | (0.185) | (0.179) | (0.199) | (0.185) | (0.184) |
| ln(cropland) | -0.280 | - | 0.174 | -0.266 | - |
| | (0.255) | - | (0.445) | (0.248) | - |
| Lagged ln(cropland) | 0.323 | - | 0.091 | 0.324 | - |
| | (0.200) | - | (0.356) | (0.199) | - |
| ln(corn) | - | -0.042 | - | - | -0.045 |
| | - | (0.164) | - | - | (0.177) |
| Lagged ln(corn) | - | 0.088 | - | - | 0.152 |
| | - | (0.131) | - | - | (0.138) |
| ln(wheat) | - | - | - | 0.000 | 0.000 |
| | - | - | - | (0.001) | (0.001) |
| Lagged ln(wheat) | - | - | - | 0.001 | 0.001 |
| | - | - | - | (0.001) | (0.001) |
| ln(soybeans) | - | - | - | - | -0.093 |
| | - | - | - | - | (0.106) |
| Lagged ln(soybeans) | - | - | - | - | 0.068 |
| | - | - | - | - | (0.112) |
| ln(developed land) | -1.601** | -1.547** | -1.670** | -1.594** | -1.559** |
| | (0.366) | (0.363) | (0.311) | (0.330) | (0.319) |
| Lagged ln(developed land) | 0.235 | 0.222 | 0.229 | 0.240 | 0.241 |
| | (0.137) | (0.137) | (0.138) | (0.137) | (0.135) |
| temperature of BBS | -0.006 | -0.006 | -0.006 | -0.008 | -0.008 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| windy of BBS | 0.015 | 0.001 | -0.007 | 0.006 | -0.004 |
| | (0.074) | (0.074) | (0.074) | (0.072) | (0.072) |
| sky of BBS | -0.025 | -0.024 | -0.026 | -0.022 | -0.015 |
| | (0.059) | (0.061) | (0.060) | (0.059) | (0.058) |
| ln(open water) | 0.245** | 0.224* | 0.228** | 0.243** | 0.245** |
| | (0.091) | (0.088) | (0.085) | (0.087) | (0.088) |
| Lagged ln(open water) | -0.141 | -0.121 | -0.094 | -0.119 | -0.107 |
| | (0.101) | (0.101) | (0.099) | (0.098) | (0.101) |
| ln(spring precipitation) | 1.356* | 1.343* | 1.402* | 1.515** | 1.547** |
| | (0.603) | (0.620) | (0.620) | (0.572) | (0.585) |
| Lagged ln(spring precipitation) | 0.908 | 0.650 | 0.698 | 1.082 | 0.936 |
| | (0.680) | (0.655) | (0.611) | (0.641) | (0.619) |
| ln(square of spring precipitation) | -0.895** | -0.871** | -0.884** | -0.926** | -0.928** |
| | (0.297) | (0.300) | (0.301) | (0.282) | (0.282) |
| Lagged ln(square of spring precipitation) | -0.814* | -0.702* | -0.726* | -0.860** | -0.792** |
| | (0.312) | (0.301) | (0.288) | (0.296) | (0.285) |
| Constant | 10.535** | 10.561** | 8.911** | 10.370** | 9.250** |
| | (2.770) | (2.786) | (2.407) | (2.472) | (2.332) |

*Notes:* * $p < 0.05$, ** $p < 0.01$. Heteroskedasticity-robust standard errors in parentheses. The dependent variable in all specifications is the level of grassland bird species richness. Year effects included in all specifications. Lagged dependent variable is endogenous in all specifications. There are 903 observations for 129 routes. Column 1 is the results of our preferred model. In column 2 we replace cropland variables by corn as our variable of interest for cropland. In column 3 the cropland variable is measured by total acreage of corn, soybeans, and wheat. In column 4 the cropland measure is the same as our preferred model in column 1, but wheat variables are added to the regression as wheat provides better habitat for birds than that provided by corn and soybean. In column 5 we replace cropland variables by three individual crops, namely, corn, soybeans, and wheat.