Three Essays in Applied Economics

by

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Abstract

This dissertation consists of three empirical essays as three chapters, which sheds lights on select research questions on education economics, biodiversity, and water sustainability in the United States.

Chapter 1 determines whether the 1862 land grant universities that do better in USNWR rankings really have the ability to charge higher tuition and offer less financial aid than institutions that do less well in the rankings. Developing a demand-supply frame work to deduce relevant hypotheses, and drawing relevant data on 44 land grant universities from 2005 to 2014, we find that parameters estimated using a generalized linear model (GLM) approach suggest each one unit improvement in national ranking is associated with an increase in (a) inflation adjusted in-state sticker price by 0.33% to entering undergraduates, (b) inflation adjusted out-of-state sticker price by 0.35% to entering undergraduates, and (c) inflation adjusted financial aid per undergraduate student by 0.33%. In addition, each one-unit improvement in the USNWR ranking score is associated with more increase in the inflation adjusted out-of-state sticker price relative to its in-state counterpart across the1862 land grant universities.

Chapter 2 examines the impact of wind turbines on breeding bird abundance by using a fine scale, spatial longitudinal dataset for 1,670 wind turbines and 86 bird observation routes located in 36 states in the United States over 2008-2014. We find that the establishment of one additional wind turbine, on average, leads to disappearance of about three breeding birds. The aggregate effect of the U.S. on-shore wind turbines on breeding bird count is 151,630, a magnitude at the lower end of existing estimates that range between 20,000 and 573,000. We also find that turbine size is a critical determinant of the magnitude of this impact, with turbine tower height positively, but blade length negatively, associated with aggregate breeding bird

abundance. Grassland breeding bird abundance increases by up to 0.81 following the establishment of an additional wind turbine, although it is insensitive to tower height or blade length. Our findings provide important implications for policies related to wind facility siting and wind turbine development that can enhance the sustainability of wind energy.

Chapter 3 estimates the effects of the federal crop insurance premium subsidy on freshwater withdrawals for irrigation among U.S. counties to the west of the 100th meridian. Our results indicate that a 1% increase in premium subsidy leads to 0.446% (about 475,901 acre-feet/year) and 0.673% (about 474,026 acre-feet/year) increase in total freshwater withdrawals for irrigation and fresh surface water withdrawals for irrigation, respectively. The elasticity of total freshwater withdrawals for irrigation and fresh surface water withdrawals for irrigation with respect to revenue insurance premium subsidy is more than twice as large as those with respect to yield insurance premium subsidy. Groundwater withdrawals for irrigation are not found responsive to crop insurance premium subsidy. The findings suggest that the impact of crop insurance on irrigation mainly occurs at the intensive margin rather than at the extensive margin. Moreover, because the elasticities are all non-negative, moral hazard should not be a dominant factor in the relationship between crop insurance subsidies and freshwater withdrawals for irrigation. Thus, exploring causality in the food-water nexus, this study underscores the unintended effect of the federal crop insurance program on water resources sustainability in the United States.

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List of Abbreviations

AIC	Akaike’s information criterion
AID	Average Financial Aid
BACI	Before-after-control-impact
BBS	Breeding Bird Survey
BIC	Schwarz’s Bayesian information criterion
CBO	Congressional Budget Office
CDL	Cropland Data Layer
EDM	Equilibrium Displacement Models
FE-IV	Fixed Effects-Instrumental Variable Approach
GIS	Geographic Information System
GLM	Generalized Linear Model
IAISTF	Inflation Adjusted In-state Undergraduate Tuition and Fees
IPCC	Intergovernmental Panel on Climate Change
IPEDS	Integrated Postsecondary Education Data System
NCES	National Center for Educational Statistics
NOAA	National Centers for Environmental Information
OLS	Ordinary Least Squares
PRISM	Parameter-Elevation Regressions on Independent Slopes Model
PSPDL	Premium Subsidy Per Dollar of Liability
RFE	Reduced-form Elasticities
RMA	Risk Management Agency

USDA	United States Department of Agriculture
USGS	United States Geological Survey
USNWR	U.S. News and World Report

Chapter 1: Price Discounting at U.S. Land Grant Universities: A Supply-Demand Analysis

Introduction

The *U.S. News and World Report* (hereafter, *USNWR*) has been publishing rankings of colleges and universities every fall for the last 35 years in a report titled *"Best Colleges."* The release of new USNWR rankings each year becomes front page news among local and national news media, institutional websites, and alumni publications all across the country (Monks et al. 1999, p. 44; Jones 2016, p. 247).

University administrators, particularly those at the research universities, believe that revenue is linked to USNWR rankings and act accordingly (Bastedo and Bowman 2011, p.3). The astonishing amount of attention the USNWR rankings have been gaining since 1983 among higher education leaders across the country raises an important question: Do the research universities that do better in USNWR rankings really have the ability to charge higher tuition and offer less financial aid than institutions that do less well in the rankings? Undoubtedly, an empirical investigation of this question will be beneficial to university Presidents, Deans, higher education agencies, academic associations, and ad-hoc lobbying groups.

Economic literature indicates that research about economic impact of USNWR rankings on institutions' pricing policies is only beginning to emerge in the higher education literature. Monks and Ehrenberg (1999) made the first attempt to empirically analyze USNWR ranking's effects on institutions' pricing policies. They used data on pricing policies for 11 years on 30 privately controlled universities, which are the member institutions in the Consortium for Financing Higher Education. Their ranking data consisted of numerical ranks of (a) the top 25 institutions in each category for the first eight years of their study period, (b) the top 50 national universities, and (c) top 40 national liberal arts colleges for rest of the years. Therefore, for any missing data on numerical ranking, they assigned the value 25. Explanatory variables used in their price analysis comprise of lagged USNWR ranking, average endowment per student at an institution, institutional dummy variables, year dummy variables, and ‘dummy of lagged rank > 25.’ Using simple regression technique, they examined four dependent variables in logarithmic form: gross tuition revenue, average financial-aid-adjusted tuition, self-help contribution from students, and net tuition[1]. Their results indicate that if the position of a private university declines in the USNWR ranking the institute does not lower its published tuition, instead the institute becomes more generous in offering financial aid. Moreover, each one unit decrease in the ranking score (say from 100 to 101) of a private school in one year leads to a decrease in net tuition by 0.003% in the following year to both aided and non-aided students. However, the decrease in the aid-adjusted tuition (0.004%) is larger than the decrease in net tuition (0.003 %) for that private school. All of those institutions in their sample are privately controlled, therefore, their findings are not useful for pricing behavior of public universities where there exists price discrimination between in-state and out-of-state students.

In a subsequent study, Meredith (2004) expanded the above-mentioned study by using fixed effects regression approach on a relatively bigger sample—233 public and private schools classified as national doctoral universities. Unlike Monks and Ehrenberg (1999), he assigned negative sign to the numeric values of the collected USNWR ranking data for top 25 schools for the time period 1990 to 1999. Additional dummy variables were created to represent private and small universities. Moreover, the author collected data from the Integrated Postsecondary Education Data System (IPEDS) on three variables: (a) total enrollment, (b) total value of private

[1] Net tuition is defined as the difference between published tuition and fees minus average financial aid received by a student.

gifts, grants and contracts, and (c) federal Pell Grants given to undergraduate students. The author, however, did not use any control for a school's ability to offer financial aid to its undergraduate students. The results indicate that changes in rank affect private and public schools differently—improving in rank from the second to first quartile lowers a public school's acceptance rate by over 4 % while it affects a private school by 1.35%. The author, however, did not use any control for a school's ability to offer tuition discount. Furthermore, this study did not examine how the relationship between the *USNWR* national ranking and tuition varies between private and public universities.

Bastedo and Bowman (2011) examined how USNWR rankings affect financial indicators in public universities: (a) federal, state, local and private research grants and contracts, (b) alumni donations, (c) total funding from foundations, (d) in-state tuition and fees, and (e) out-of-state tuition and fees. The authors created dummy variable to measure various tiers of university ranking. Moreover, the six-year graduation rate, freshman retention rate, and acceptance rate were used to determine changes in institutional quality. Financial data on research and development funds came from the National Science Foundation for the years 1998, 2000, 2002, and 2006. Data on tuition and fees were collected from the IPEDS. Unlike above mentioned two studies, they applied structural equation models on 225 national universities. Moreover, the authors reverse-coded the acceptance rate and standardized all other variables with a mean zero and standard deviation of one to ensure that relative variances among all variables be equal in the structural equation model. Besides, the authors could not become satisfied about the quality of the data. The authors note that "the data needed to access change over time within universities has been difficult, if not impossible, to obtain." The authors, however, unambiguously argue that more empirical work is required to enrich our understanding of organizational change in higher education.

Based on this research, this paper limits its focus only to the 1862 land grant universities[2]. These public research universities and their rankings receive astonishing amount of public attention every year (Monks and Ehrenberg, 1999). These universities are the first set of the national universities established “to promote the liberal and practical education of the industrial classes in the several pursuits and professions in life” (Title-7 U.S. Code § 304). By providing major educational resources to the American society these universities play an important role in the educational system in the United States. Moreover, they are consistently doing better in the USNWR rankings. However, no empirical work has been done to understand the relationship between an improvement in the USNWR rankings and pricing policies of these group of institutions. Therefore, the purpose of this research is to determine whether 1862 land grant universities that do better in USNWR rankings have the ability to charge higher tuition and offer less financial aid than institutions that do less well in the rankings.

This article attempts to empirically answer the primary question by using OLS, Fixed Effects Model, and Generalized Linear Model (GLM) regression approach on a balanced panel dataset that contains 420 observations. Unlike any prior study, we use state wise annual

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[2] There are three branches of the land grant colleges and universities family. It includes 110 universities across the country. All of them share a common mission and common challenges (Martin and Hipp, 2016). However, this study focuses only on the 1862 land grant universities. This group of universities were set up under the Morrill Act of 1862. This act is officially titled as "An Act Donating Public Lands to the Several States and Territories which may provide Colleges for the Benefit of Agriculture and the Mechanic Arts". Sponsored by Vermont Congressman Justin Morrill, President Abraham Lincoln signed the bill into law on July 02, 1862. Based on the census of 1860, it gave each state 30,000 acres of public land for each Senator and Representative. The land was then to be sold and the money from the sale of the land was to be put in an endowment fund which would provide support for the colleges in each of the states. Sixty-nine colleges have been funded by these land grants, including Cornell University, the University of Wisconsin at Madison and Auburn University. The Morrill Acts have become a major educational resource and an important part of the educational system in the United States.

unemployment rate, and log of state level annual median household income as two control variables. We also use log of average endowment, and log of total undergraduate enrolment as two other control variables. Moreover, to record direct effect of *USNWR* rankings on pricing decisions, we deploy inflation adjusted published in-state tuition, inflation adjusted published out-of-state tuition, and inflation adjusted average financial aid to undergraduate students as three dependent variables in their logarithmic form. Parameters estimated using the GLM approach suggest each one-unit improvement in national ranking is associated with an increase in inflation adjusted in-state sticker price to entering undergraduates by 0.33 percent, inflation adjusted out-of-state sticker price to entering undergraduates by 0.35% and inflation adjusted financial aid per undergraduate student by 0.33%. In addition, each one-unit improvement in the *USNWR* ranking score is associated with more increase in the inflation adjusted out-of-state sticker price relative to its in-state counterpart across the1862 land grant universities.

This paper proceeds as follows. Section 2 develops a supply-demand framework and deduce three testable hypotheses. Section 3 contains a brief discussion of econometric methods used for analyzing the data. Section 4 contains the description of the data collected from various sources. Section 5 presents the results. And section 6 presents conclusion of the study.

The Supply-Demand Framework

In this section, we develop an equilibrium displacement model to deduce hypotheses about how selected variables such as academic ranking affects the price of university services and the financial aid provided to students. The model is similar to the supply-demand framework developed by Kinnucan et al. (2006) in their analysis of the relationship between state aid and student performance in Alabama’s county schools. In that study observed school spending and outcome data are viewed as generated by an equilibrium process. The market for educational services consists of a supply curve that reflects the marginal costs of providing the services, and a demand curve that reflects students' willingness to pay for the services. The intersection of the curves defines an equilibrium price (per-pupil spending) and an equilibrium quantity (students' standardized test scores, a performance indicator). In present study, equilibrium price is defined as the average gross and net tuition paid by students in a given year, and equilibrium quantity is defined as the total undergraduate student enrollment in that year.

Our primary objective is to derive a set of comparative static results that can be used to guide the empirical analysis and assist in interpretation of results. A major advantage of the EDM approach to comparative static analysis is that results are expressed in terms of elasticities, which facilitates interpretation. Overviews of the EDM approach to economic analysis, including its limitations, are provided by Piggott, (1992) and by Wohlgenant, (2011)[3].

We followed a three-step procedure to derive a set of comparative static results.

Step 1. The structural model: The structural model consists of the following five equations:

(1)	$Q_S = S(P_G, \bar{C})$	(supply of education services)
(2)	$Q_D = D(P_N, \bar{Y})$	(demand for education services)
(3)	$P_G = P_N + AID$	(gross price)
(4)	$AID = f(P_G, \bar{Y}, \bar{N})$	(student aid)
(5)	$Q_S = Q_D \equiv Q$	(market clearing)

where Q_S and Q_D quantity supplied and demanded of education services; P_G and P_N are the gross and net tuition for those services; AID is the average amount of financial aid received by an

[3] Reviewing literature on partial equilibrium framework, we find that Muth (1965) introduces EDM as a research tool for price analysis. The key features of EDM analysis are: (a) a market equilibrium is defined by a set of demand and supply functions without assuming any specific functional forms; (b) the market is disturbed introducing a change in a set of exogenous variables; (c) the impacts of those induced disturbances are captured in elasticity form. Moreover, EDM uses few assumptions and generates "rich" and useful analytical results in derived total elasticity form (Piggott 1992). Existing literature indicates that EDM approach has become more sophisticated over time (e.g., see Alston 1991; Kinnucan and Myrland 2005).

undergraduate student. The overbar ($^{\overline{\ }}$) indicates exogenous variables. Specifically, $\bar{C}$ is a vector of supply shifters, $\bar{Y}$ is a vector of demand shifters (including the university's *USNWR* ranking), and $\bar{N}$ is a vector of exogenous variables that affect student aid (e.g., the level of a university's endowment). In this model, students respond to the net price P_N, which is lower than the gross price P_G that the university responds to. The model consists of four endogenous variables (Q, P_G, P_N, AID) and three exogenous variables (or, more precisely, vectors of exogenous variables).

Step 2. The Equilibrium Displacement Model: Taking total derivatives, the structural model can be expressed as the equilibrium displacement model as follows:

(1') $Q_S^* = \varepsilon\, P_G^* + \varepsilon_{\bar{C}}\, \bar{C}^*$

(2') $Q_D^* = \eta\, P_N^* + \eta_{\bar{Y}}\, \bar{Y}^*$

(3') $P_G^* = K_{P_N}\, P_N^* + K_{AID}\, AID^*$

(4') $AID^* = \alpha_{P_G} P_G^* + \alpha_{\bar{Y}}\, \bar{Y}^* + \alpha_{\bar{N}}\, \bar{N}^*$

(5') $Q_S^* = Q_D^* = Q^*$

where asterisked variables indicate relative change (e.g., $Q_D^* = dQ_D/Q_D$). The Greek letters represent either partial elasticities of demand and supply for educational services or structural elasticities that indicate relative horizontal shift of the supply curve to its left or demand curve to its right for a small increase in the respective shifters. The signs and definitions of these elasticities are given in Table 1.1.

In Table 1.1, $\varepsilon\ and\ \eta$ are the partial elasticity of demand and supply, respectively, for educational services; $\varepsilon_{\bar{C}}$ is a structural elasticity that indicates the responsiveness of supply to changes in changes in a representative supply shifter (e.g., faculty salaries); $\eta_{\bar{Y}}$ is a structural elasticity that indicates the responsiveness of demand to changes in a representative demand shifter (e.g., academic ranking); α_{P_G}, $\alpha_{\bar{Y}}$, and $\alpha_{\bar{N}}$ are structural elasticities that indicates the sensitivity of financial aid to changes in the sticker price, a demand shifter, the university's endowment respectively. In this study we assume the supply curve is upward sloping ($\varepsilon > 0$), the demand curve is downward sloping ($\eta < 0$), the representative supply shifter (faculty salaries) shifts the supply curve to the left ($\varepsilon_{\bar{C}} < 0$), and the representative demand shifter (academic ranking) shifts the demand curve to the right ($\eta_{\bar{Y}} > 0$). The parameters in equation (3'), viz., K_{P_N} $(= P_N/P_G)$ and K_{AID} $(= AID/P_G)$ indicate the division of gross tuition between net tuition and financial aid in the initial equilibrium where $K_{P_N} + K_{AID} = 1$. The parameters in the financial aid equation are signed as follows: $\alpha_{P_G} > 0$, $\alpha_{\bar{Y}} < 0$ and $\alpha_{\bar{N}} > 0$. All else equal, universities compensate for a higher sticker price by offering more aid; an increase in academic ranking reduces the need to offer aid; and an increase in the endowment increases the ability to provide aid.

Step 3. The Reduced Form of the Equilibrium Displacement Model: Solving equations (1')-(5') simultaneously for three endogenous variables of our interest we obtain the following three reduced form equations. Derivation of these three equations are given in the Appendix C.

(6a) $P_G^* = \left[\frac{\mathrm{K}_{\mathrm{P_N}}\eta_{\bar{Y}} - \mathrm{K}_{\mathrm{AID}}\,\alpha_{\bar{Y}}\,\eta}{\mathcal{D}}\right]\bar{Y}^* - \left[\frac{\mathrm{K}_{\mathrm{AID}}\,\alpha_{\bar{N}}\,\eta}{\mathcal{D}}\right]\bar{N}^* - \left[\frac{K_{P_N}\,\varepsilon_{\bar{C}}}{\mathcal{D}}\right]\bar{C}^*$

(6b) $P_N^* = \left[\frac{\eta_{\bar{Y}}\left(1-\mathrm{K}_{\mathrm{AID}}\,\alpha_{P_G}\right)-\mathrm{K}_{\mathrm{AID}}\,\alpha_{\bar{Y}}\,\varepsilon}{\mathcal{D}}\right]\bar{Y}^* - \left[\frac{\mathrm{K}_{\mathrm{AID}}\,\alpha_{\bar{N}}\,\varepsilon}{\mathcal{D}}\right]\bar{N}^* - \left[\frac{\varepsilon_{\bar{C}}(1-\mathrm{K}_{\mathrm{AID}}\,\alpha_{P_G})}{\mathcal{D}}\right]\bar{C}^*$

(6c) $AID^* = \left[\frac{\mathrm{K}_{\mathrm{P_N}}\,\alpha_{P_G}\,\eta_{\bar{Y}} + \alpha_{\bar{Y}}\,(K_{P_N}\,\varepsilon - \eta)}{\mathcal{D}}\right]\bar{Y}^* + \left[\frac{\alpha_{\bar{N}}\,(\mathrm{K}_{\mathrm{P_N}}\varepsilon - \eta)}{\mathcal{D}}\right]\bar{N}^* - \left[\frac{K_{P_N}\,\alpha_{P_G}\,\varepsilon_{\bar{C}}}{\mathcal{D}}\right]\bar{C}^*$

where $\mathcal{D} = [\mathrm{K}_{\mathrm{P_N}}\,\varepsilon - \eta\,(1 - \mathrm{K}_{\mathrm{AID}}\,\alpha_{P_G})] > 0$.

The common denominator of these coefficients, $\mathcal{D}$, is positive under the assumptions stated above. Moreover, focusing on the second component in $\mathcal{D}$, we assume that $\mathrm{K}_{\mathrm{AID}}\,\alpha_{P_G} < 1$, which implies $\frac{\partial AID}{\partial P_G} < 1$ (i.e., a \$1 increase in gross tuition results in less than a \$1 increase in financial aid). Our panel data set supports this assumption (see Table 1.2). To illustrate, in Table 1.2, the sample mean of the in-state sticker price is \$10,335 in a year and the sample mean of the financial aid per student is \$7,799 in a year. Hence, the ratio of financial aid and gross tuition is less than unity, which upholds the assumption.

Based on these assumptions, the equations (6a) – (6c) provide total elasticities for each of the three endogenous variables—gross tuition (P_G), net tuition (P_N), and financial aid (AID)—with respect to three vectors of exogenous variables, viz. supply shifters, demand shifters, and factors that affect student financial aid. Specifically, equation (6a) delineates the effects of changes in the exogenous variables on equilibrium sticker price. Interpreting $\bar{Y}^*$, $\bar{N}^*$, and $\bar{C}^*$ as relative changes in academic ranking, endowment, and faculty salaries, respectively, the coefficients of these variables are their respective reduced-form elasticities (RFEs). The RFE indicates the *net* effect of the exogenous variable on sticker price, i.e., the effects after allowing the other endogenous variables in the model, namely Q, P_N and AID, to adjust to the supply or demand shock. Under the stated assumptions about the signs of the structural elasticities the RFEs all have positive signs, i.e., $P_G^*/\bar{Y}^* > 0$, $P_G^*/\bar{N}^* > 0$ and $P_G^*/\bar{C}^* > 0$. The model predicts that an isolated increase in academic ranking, endowment, or faculty salaries will increase the sticker price. These results are intuitive.

Equation (6b) delineates the effects of changes in the exogenous variables on the equilibrium net price. The coefficients of $\bar{Y}^*$, $\bar{N}^*$, and $\bar{C}^*$ indicate the responsiveness of equilibrium net price to isolated 1% changes in these variables when Q, P_G and AID are permitted to adjust. Under the stated assumptions about the signs of model parameters $P_N^*/\bar{Y}^* > 0$, $P_N^*/\bar{N}^* < 0$ and $P_N^*/\bar{C}^* > 0$. The model predicts that an isolated increase in academic ranking or faculty salaries increases net price, while an isolated increase in endowment reduces the net price. All else equal, students who attend universities with larger endowments pay less, while they pay more if they attend universities that have higher faculty salaries or academic ranking.

Equation (6c) delineates the effects of changes in the exogenous variables on the equilibrium financial aid. The coefficients of $\bar{Y}^*$, $\bar{N}^*$, and $\bar{C}^*$ indicate the responsiveness of equilibrium financial aid to isolated 1% changes in these variables when Q, P_G and P_N are permitted to adjust. Under the stated assumptions about the signs of the partial and structural elasticities the parameters in equation (6c) have positive signs, i.e., $AID^*/\bar{Y}^* > 0$, $AID^*/\bar{N}^* > 0$ and $AID^*/\bar{C}^* > 0$. Hence, the model predicts that an isolated increase in academic ranking, endowment, or faculty salaries will increase the financial aid. All else equal, students who attend universities that have higher academic ranking, higher faculty salaries or larger endowments receive higher financial aid.

Combining all three reduced form equations, it is evident that, in the supply side, an increase in rank of a university brings more endowment into its system, therefore, university administrators can offer more aid, hire expensive faculty, and elevate its sticker price. On the demand side, an increase in parents' income (or increase in unemployment rate) raises demand for educational services. In the end, therefore, equilibrium price, equilibrium quantity of the educational service, and financial aid per students go up.

Hypotheses

Based on our supply-demand framework and our understanding of the resource dependence of the land grant universities and their organizational responses to ranking systems (e.g., see, Elsbach and Kramer 1996; Espeland and Sauder 2007; Sauder and Fine 2008; Bastedo and Bowman 2010), this paper aspires to test the following hypotheses:

H1: The *USNWR* national ranking (USNR) is statistically significant and positively related to inflation adjusted in-state undergraduate tuition and fees (IAISTF) charged by the 1862 land grant institutions. In other words, an improvement in USNWR national rank of one (i.e., more favorable ranking, say from 4th to 3rd) in one year positively affects inflation-adjusted in-state tuition and fees charged to incoming undergraduate students in the following year, i.e., $\frac{P_G^*}{\bar{Y}^*} > 0$.

H2: The *USNWR* world ranking (USWR) is statistically significant and positively related to inflation adjusted out-of-state undergraduate tuition and fees charged by the 1862 land grant institutions. In other words, an improvement in USNWR world rank of one (i.e., more favorable ranking, say from 6th to 5th) in one year positively affects inflation-adjusted out-of-state tuition and fees charged to incoming undergraduate students in the following year, i.e.,

$\frac{P_G^*}{\bar{Y}^*} > 0$.

H3: The *USNWR* ranking is statistically significant and positively related to inflation adjusted average financial aid offered to their incoming undergraduate students by the 1862 land grant institutions. In other words, an improvement in any of the USNWR's national rank or world rank by one (i.e., more favorable ranking, say from 45th to 44th) in one year positively affects inflation adjusted average financial aid offered to incoming undergraduate students in the following year, i.e., $\frac{AID^*}{\bar{Y}^*} > 0$.

Methodology

In this paper, we are interested in analyzing how national and world ranking affects inflation adjusted undergraduate tuition and financial aid on three outcome variables over a 10-year time period for the 1862 land grant universities. We incorporate four control variables to guard against omitted-variable bias when estimating the ranking effect. All explanatory variables vary over time. We assume that each of these universities has its own individual characteristics that may influence the explanatory variables. For example, an 1862 land grant university could influence the respective state's research policy that could have some effect on agricultural production, trade, state's GDP, and business practices of the companies, which may influence annual median household income and annual employment rate in that particular state. As a result, we need to control for this impact or bias on the outcome variables. For exploring the relationship of each outcome variables with the explanatory variables within a university, we estimate three regressions models—OLS, Fixed Effects (FE) model, and Generalized Linear Model— with robust standard errors.

The system of three equations that we estimate can be written as:

(1) $Y_{it} = \alpha_i + \beta_i X_{it} + u_{it}$,

where Y_{it} is a vector of three outcome variables. This study deals with three outcome variables: inflation adjusted in-state undergraduate tuition and fees, inflation adjusted out-of-state undergraduate tuition and fees, and inflation adjusted average financial aid.

X_{it} is a vector contains negative values of the USNWR national Ranking, negative values of the Shanghai world ranking (which is a proxy of the USNWR world ranking), log of state wise annual median household income, state wise annual unemployment rate, log of average endowment, and log of total undergraduate endowment. u_{it} is the error term.

Unlike previous work, this paper incorporates state wise annual unemployment rate, and log of state wise annual median household income, as control variables in its models. As per my knowledge, no empirical study has used state level median income and unemployment rate as control variables while examining effect of the *USNWR* rankings on pricing behaviors of the public universities. However, this study considers them worthy to consider as control variables because they are the indicators of the economic health of a state. An argument in favor of these control variables would be that relative to a poor state such as Mississippi, parents in a wealthy state such as Colorado can afford to pay more for higher education of their children. Moreover, a richer state government can offer more funds to its land grant institutes to support its in-state undergraduate students.

Furthermore, log of inflation adjusted average endowment, and log of total undergraduate enrollment are used as two other control variables. We consider the total undergraduate enrollment as a control variable because it's a good indicator of the size of a university. The undergraduate students are the main student pool in a university. They also contribute the most to the revenue generated as tuition and fees. Increase in total undergraduate enrollments may increase operation costs in a given academic year, however, at the same time, it may be considered as economies of scale due to decrease in variable costs per student as long as the university has not reached at its maximum capacity. Having unutilized capacity such as lower student-teacher ratio or abundance of space in the classrooms, library and recreation centers, a university administration may decide to charge less to enroll even more undergraduate students. The land grant universities are in principle committed to provide services to their stakeholders.

We conducted the Hausman test that is widely used to differentiate between fixed effects model and random effects model in panel data. We obtained large values of the Hausman test statists for the three equations at 1% level of significance. Table 1.3 presents the parameter estimates of the FE models with robust standard errors, instead of random effect model because the large value of the Hausman test statistics suggests that it's the FE models that will generate consistent parameter estimates.

We also estimated the Pearson correlation coefficients with level of significance. The results indicated existence of statistically significant numerous pairwise correlation coefficients. As a result, we decided to estimate equation (1) again by using a Generalized Linear Model— with robust standard errors. The estimated GLM parameters are presented in Table 1.4.

No one of the closely related prior studies used GLM in their studies. Another major difference between the framework used in this paper and that used in the previous works is that one previous study controlled for a university's ability to generate revenue by considering only average endowment as the controlling variable (e.g., Monks and Ehrenberg 1999). Meredith (2004) thought about incorporating yearly changes in endowment, however, he could not construct a yearly endowment series in his data set. Meredith (2004) also could not address a university's ability to offer financial aid to its undergraduate students. However, like Meredith's (2004), we incorporate a yearly endowment series in our study.

Moving forward, Bastedo and Bowman (2011) used changes in quality indicators and prior reputation as controls and examined a research university's ability to charge higher in-state tuition and fees, out-of-state tuition and fees. However, no one of these studies used log of average endowment, state wise annual unemployment rate, and log of inflation adjusted state wise annual median household income as control variables. Besides, no study has examined a university's ability to offer higher financial aid to undergraduate students. By incorporating these control variables, and estimating a Generalized Linear Model with robust standard errors, this study strengthens the empirical understanding of a public university's' (and 1862 land grant universities in particular) ability to charge higher inflation adjusted in-state tuition and fees, inflation adjusted out-of-state tuition and fees, and inflation adjusted financial aid to its undergraduate students.

A possible limitation of our empirical study is that we neither conducted any test for endogeneity nor tried to correct it. As the reviewers rightly pointed out, enrollment level, an explanatory variable in our model, might have larger endogeneity problems than average state household income. As a result, the coefficients estimated from the equation (1), might be biased. There is potential for both positive and negative bias on the estimates due to endogeneity problem, therefore, this study does not reach at any definite conclusion about the overall bias. It is, however, obvious that unless changes in instructional as well as research activities are correlated with movements in the ranking's indexes, the bias will be minimal. Monks and Ehrenberg (1999) and Meredith (2004) argued that a good instrumental variable for USNWR rankings could have resolved the endogeneity problem. Monks and Ehrenberg (1999) did not provide a valid instrument. Meredith (2004) thought that redefining the USNWR rankings by excluding indexes related to the outcome variables could be a possible instrument. Meredith (2004), however, acknowledged the fact that it is not possible to have his proposed instrument until more USNWR ranking data points become available. Lastly, this study suffers from missing data points. As a result, estimated coefficients obtained by eliminating missing observations may not depict accurate power of an 1862 land grant university on its pricing policy gained by any upward movement on the USNWR ranking list.

Data

This study limits its focus to the 1862 land grant universities. The sample includes 44 land grant universities. The Item-A in the appendix presents the list of the 1862 Land Grant Universities considered for this study. The focus is restricted only to this group of institutions because they always remain at the center of public attention across the country, however, no empirical study has tested the above mentioned three hypotheses for those schools.

Data were compiled from five different sources. The data on pricing policies were drawn from the National Center for Educational Statistics (NCES) and its Integrated Postsecondary Education Data Systems (IPEDS). It includes five variables for 10 consecutive years between 2005 and 2014 the academic: (a) published in-state undergraduate tuition and fees, (b) published out-of-state undergraduate tuition and fees, (c) average amount of federal, state, local, institutional or other sources of grant aid dollars received by undergraduate students (i.e., average financial aid), (d) total full time undergraduate enrollment, and (e) total endowment. Total endowment was divided by total undergraduate enrollment to obtain average endowment per student. For a few years, average amount of financial aid was calculated by, first, adding up total amount of aid came from federal government, state government, local government, and from the institution. After that, the total aid amount was divided by total number of undergraduate students received those aids in the respective institution. Variables were transformed into logarithmic form wherever it was necessary. Data on median household income at the state level (at 2014 constant US dollars) were obtained from the U.S. Census Bureau. The state level unemployment data were obtained from the U.S. Bureau of Labor Statistics. And the national ranking data were obtained from the USNWR's annual reports called "Best Colleges." Data for world ranking (WRANK) came from the ShanghaiRanking Consultancy. This paper uses the ShanghaiRanking's world ranking data as a proxy of the USNWR's world ranking for the selected sample.

An improved national or world rank corresponds to a lower numeric value, as a result, like Meredith (2004), we have modified numerical ranking values by multiplying them with minus one to make the signs on its coefficient conventional. World ranking data are not available for nine universities. We, therefore, removed those universities from our sample.

The outcome variables are log of inflation adjusted in-state tuition and fees, log of inflation adjusted out-of-state tuition and fees, and log of inflation adjusted average financial aid offered to the undergraduate students in the sample. Appendix-B presents definition of each variable. In addition, Table 1.2 presents the descriptive statistics of all these variables.

Estimation Results

We estimate parameters from equation (1) for three depended variables in their logarithmic forms by using OLS, Fixed effects, and generalized linear model estimation approaches. Table 1.3 presents parameter estimates for OLS and Fixed effects models. Table 1.4 presents the generalized linear model estimation results. Robust standard errors are presented in the parenthesis in both of the tables.

The first rows in Table 1.3 and Table 1.4 contain estimates for one-unit improvement in the U.S. News and World Report's national ranking across the 1862 land grant universities. The second row presents estimates for the Shanghai world ranking of the same group of universities. Due to difficulty in accessing USNWR world ranking data for the study period the Shanghai world ranking data have been used as a proxy of the USNWR's world ranking. The following four rows contain estimates for the four control variables: state wise unemployment rate, state wise median household income, average endowment per undergraduate student, and total undergraduate enrollment. Putting unemployment rate aside, other three control variables are specified in logarithmic form. The estimated coefficients of the logarithmic form of control variables represent the approximate percentage changes in the price outcome associated with one percent change in the respective control variable; therefore, those estimates are the elasticities.

Table 1.3 reveals that the fixed effects estimates for the *USNWR* national ranking have statistically significant and negative association with inflation adjusted tuition and fees offered to incoming undergraduate students across the 1862 land grant universities. Each one-unit improvement in the USNWR national ranking score, from say 60 to 59, in one year leads to a decrease (a) in inflation adjusted in-state tuition and fees by approximately 0.47% and (b)out-of-sate tuition and fees by approximately by 0.30% for the incoming undergraduate students in the next year. The fixed effects model estimates on world rankings, which are presented in row 2 in Table 1.3, reveal similar trend: each one-unit improvement in world ranking score of an 1862 land grant university in one year leads to approximately 0.10% decrease in inflation adjusted in-state tuition and fees and approximately 0.08% decrease in inflation adjusted out-of-state tuition and fees. In addition, columns 5 and 6 reveal that each one-unit improvement in the world ranking score can causes a decrease in inflation adjusted average financial aid offered to incoming undergraduate students by approximately 0.03%, however, the fixed effects estimate is statistically insignificant. Both estimates lead us to a conclusion that each one-unit improvement in either USNWR national ranking score or world ranking score in one year leads to decrease in inflation adjusted net tuition and fees to all undergraduate students in an 1862 land grant university in the next year. Moreover, fixed effects estimation results reveal that each one-unit improvement in the USNWR national ranking or world ranking score adversely affects inflation adjusted in-state tuition and fees more relative to inflation adjusted out-of-state tuition and fees in an 1862 land grant university.

However, neither the OLS nor the fixed effects regression approaches can be used to examine the effect of national and world rankings on tuition and financial aid. These OLS-based estimates are downward biased. Pearson correlation coefficients for most of the explanatory variables indicate that our explanatory variables are pairwise correlated, and the correlation coefficients are mostly statistically significant. As a result, approaches such as GLM would be more suitable for our study.

Table 1.4, therefore, presents estimates for the main class of GLM that incorporates both systematic effects and random effects. The first row in Table 1.4 indicates that the USNWR national ranking is associated with higher tuition and financial aid levels. More precisely, row 1 in in Table 1.4 shows that each one-unit improvement in USNWR national ranking score of an 1862 land grant university in one year is associated with an increase in (a) inflation adjusted in-state sticker price by 0.33% to entering undergraduates, (b) inflation adjusted out-of-state sticker price by 0.35% to entering undergraduates, and (c) inflation adjusted financial aid per undergraduate student by 0.33%. In addition, each one-unit improvement in the USNWR ranking score is associated with more increase in the inflation adjusted out-of-state sticker price relative to its in-state counterpart across the1862 land grant universities.

These findings are consistent with economic framework (i.e., $\frac{P_G^*}{\bar{Y}^*} > 0$ and $\frac{AID^*}{\bar{Y}^*} > 0$), and the existing literature. However, further investigation is required to gain better understanding of the actual effect of rankings on tuition and financial aid across the 1862 land grant universities. For example, unlike our findings presented in Table 1.4, Monks and Ehrenberg (1999), the closest study to our work, found that each one unit decrease in ranking score leads to 0.0001% decrease in gross tuition, (which is statistically insignificant) and 0.003% decrease in the net tuition (at 1% significance level) to both aided and non-aided students in the private schools. Meredith (2004), the second closest study to this paper, however, did not infer any definitive conclusion on the relationship between the *USNWR* national ranking and tuition. Bastedo and Bowman (2011), which is the most recent work available in my knowledge, partially contradicts the above-mentioned findings. Their results, however, suggested that national ranking affects out-of-state tuition more than the in-state tuition, which corroborates results presented in Table 1.4.

Row 4 in Table 1.4 shows that endowment per student, a control variable for a university's financial health, has statistically significant and positive association with inflation adjusted in-state and out-of-state tuition and fees. The reason behind this association is that copiousness of financial resource makes a university administration capable of hiring high quality faculty more and maintaining a low teacher-student ratio. Since educational services are neither inferior goods nor luxury goods, therefore, the law of demand holds; meaning, universities with higher level of endowment lower student-teacher ratio that raises demand for their educational services. This shifts the downward slopping demand curve to the right that leads to an increase in market equilibrium price of the educational services.

Row 5 in Table 1.4 shows that state wise median household income, another control for the financial health of a state, has statistically significant positive association with all three dependent variables. The reason behind this outcome might be that parents with higher median household income prefer to behold their children graduate from a better ranked university. In other words, parents with higher median household income raise the demand for educational services in a relatively high ranking university that puts upward pressure on in-state and out-of-state tuition and fees across 1862 land grant universities that always remain at the center of public attention.

Row 6 in Table 1.4 shows that the state wise unemployment rate, the third control variable in our model, has statistically significant positive association with tuition and average financial aid. The reason behind this outcome might be that unemployed people with high school diploma find it worthy to earn a college degree from a better ranked university that will increase their odds of securing high paid jobs upon graduation from a high ranked university.

Conclusions

This study examines an important problem faced by university administrators across 1862 land grant universities while determining in-state, out-of-state sticker price, and appropriate amount of average financial aid for incoming undergraduate students: Do the research universities that do better in USNWR rankings really have the ability to charge higher tuition and offer less financial aid than institutions that do less well in the rankings?

In this study, we first develop a demand-supply framework to generate three hypotheses. Based on those theory-driven hypothesis, we evaluate how the *USNWR* national ranking and *Shanghai* world ranking (which is a proxy for the *USNWR* world ranking) are associated with inflation adjusted in-state tuition and fees, inflation adjusted out-of-state tuition and fees, and inflation adjusted financial aid per undergraduate student in an 1862 land grant university in the United States.

We estimate three econometric models—OLS, Fixed Effects model, and a system of Generalized Linear Model. We also estimate the Pearson correlation coefficients with level of significance. The results indicate existence of statistically significant numerous pairwise correlation coefficients, which suggest that the OLS estimates are downward biased. We, therefore, put emphasis in our analysis on the Generalized Linear Model, which is a multivariate approach.

Our estimates affirm the importance of college rankings on tuition and financial aid across 1862 land grant universities. Results indicate that each one-unit improvement in national ranking is associated with an increase in (a) inflation adjusted in-state sticker price by 0.33

percent to entering undergraduates, (b) inflation adjusted out-of-state sticker price by 0.35% to entering undergraduates, and (c) inflation adjusted financial aid per undergraduate student by 0.33%. In addition, each one-unit improvement in the USNWR ranking score is associated with more increase in the inflation adjusted out-of-state sticker price relative to its in-state counterpart across the1862 land grant universities.

A caveat of our empirical study is that we neither conducted any test for endogeneity nor tried to correct it. As a result, estimated coefficients might be biased. There is potential for both positive and negative bias on the estimates due to endogeneity problem. This study, therefore, does not reach at any definite conclusion about the overall bias. Having said that, however, it is obvious that unless changes in instructional as well as research activities are correlated with movements in the ranking's indexes, the bias will be minimal.

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Table 1.1. Definition and Signs of the Partial Elasticities

Partial and Structural Elasticity	Definition	Sign
(1)	(2)	(3)
η	$\frac{\partial Q_D}{\partial P_N}\frac{P_N}{Q_D}$	< 0
$\eta_{\bar{Y}}$	$\left(\frac{\partial Q_D}{\partial \bar{Y}}\frac{\bar{Y}}{Q_D}\right)$	> 0
ε	$\left(\frac{\partial Q_S}{\partial P_G}\frac{P_G}{Q_S}\right)$	> 0
$\varepsilon_{\bar{C}}$	$\left(\frac{\partial Q_S}{\partial \bar{C}}\frac{\bar{C}}{Q_S}\right)$	< 0
α_{P_G}	$\left(\frac{\partial AID}{\partial P_G}\frac{P_G}{AID}\right)$	> 0
$\alpha_{\bar{Y}}$	$\left(\frac{\partial AID}{\partial \bar{Y}}\frac{\bar{Y}}{AID}\right)$	< 0
$\alpha_{\bar{N}}$	$\left(\frac{\partial AID}{\partial \bar{N}}\frac{\bar{N}}{AID}\right)$	> 0

Table 1.2. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
World Ranking of a University	420	185	140	2	504
U.S. News National Ranking of a University	420	90	41	12	201
Financial Aid per Student ($)	420	7,799	4,031	2,439	32,587
Total Undergraduate Enrollment	420	22,815	8,139	9,235	44,201
Total Endowment in a University	390	1.49E+09	9.41E+08	3.51E+08	5.71E+09
In-State Sticker Price ($)	420	10,335	5,830	3,465	47,286
Out-Of-State Sticker Price ($)	420	24,928	6,246	9,608	47,286
Unemployment Rate in a State (%)	420	6.59	2.23	2.6	13.7
Median Household Income ($)	420	56,369	8,486	40,020	79,915

Table 1.3. Estimation Results for OLS and Linear Fixed Effects (FE) Models

	Log In-State Tuition		Log Out-of-State Tuition		Log Average Financial Aid	
	OLS	FE	OLS	FE	OLS	FE
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Negative of *USNWR*	-0.0019	-0.0047**	0.00028	-0.0030**	0.0009	-0.0035
National Ranking	(0.0013)	(0.0021)	(0.0008)	(0.0013)	(0.0011)	(0.0025)
Negative of *Shanghai*	-0.0009***	-0.001***	-0.0006***	-0.0008***	-0.0013***	-0.0003
World Ranking	(0.0002)	(0.0003)	(0.00017)	(0.0002)	(0.0002)	(0.0004)
Log of Total UG Enrollment	0.529***	0.560***	0.363***	0.509***	0.279**	1.449***
	(0.098)	(0.137)	(0.0759)	(0.095)	(0.121)	(0.313)
Log of Endowment/Student	0.373***	0.390**	0.214***	0.314***	0.229**	0.851***
	(0.127)	(0.164)	(0.071)	(0.113)	(0.109)	(0.304)
Log of Median Household	-0.187	-0.531***	0.129	-0.216	0.395***	-0.367
Income	(0.133)	(0.162)	(0.124)	(0.168)	(0.147)	(0.238)
Unemployment Rate	0.0326***	0.027***	0.029***	0.020***	0.108***	0.0829***
	(0.003)	(0.0027)	(0.003)	(0.002)	(0.007)	(0.007)
Intercept	1.182	4.211	2.388	3.329	-1.662	-11.882*
	(2.428)	(3.482)	(1.795)	(2.994)	(2.20)	(5.922)

Notes: Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.4. GLM Model Estimates with Robust Standard Errors

Variable	Log of In-State Tuition (1)	Log of Out-Of-State Tuition (2)	Log of Avg. Financial Aid (3)
Negative of USNWR National Ranking	0.0033***	0.0035***	0.0033***
	(0.0005)	(0.0004)	(0.0005)
Negative of Shanghai World Ranking	-0.00048***	0.0002*	-0.00065***
	(0.0001)	(0.0001)	(0.0001)
Log of Total Undergraduate Enrollment	-0.058	-0.190***	-0.158
	(0.059)	(0.043)	(0.066)
Log of Endowment per Student	0.079**	-0.062**	0.042
	(0.038)	(0.028)	(0.054)
Log of Median Household Income	0.727***	0.319***	0.424***
	(0.092)	(0.061)	(0.096)
Unemployment Rate	0.059***	0.052***	0.107***
	(0.006)	(0.003)	(0.006)
Intercept	0.683	9.185***	4.778**
	(1.480)	(1.012)	(1.583)

Note: Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Item A: List of the 1862 Land Grant Universities

Auburn University	North Carolina State University at Raleigh
University of Arkansas	University of Nebraska-Lincoln
University of Arizona	University of New Hampshire-Main Campus
University of California-Berkeley	Rutgers University-New Brunswick
University of California-Davis	Cornell University
University of California-Riverside	Ohio State University-Main Campus
Colorado State University-Fort Collins	Oregon State University
University of Connecticut	Pennsylvania State University-Main Campus
University of Delaware	University of Rhode Island
University of Florida	Clemson University
University of Georgia	The University of Tennessee-Knoxville
University of Hawaii at Manoa	Texas A & M University-College Station
Iowa State University	Utah State University
University of Illinois at Urbana-Champaign	Virginia Polytechnic Institute and State University
Purdue University-Main Campus	University of Vermont
Kansas State University	Washington State University
University of Kentucky	University of Wisconsin-Madison
Louisiana State University and Agricultural & Mechanical College	University of Wyoming
University of Massachusetts-Amherst	
University of Maryland-College Park	
Michigan State University	
University of Minnesota-Twin Cities	
University of Missouri-Columbia	
Montana State University	

Item B: Definition of the Variables

Definition of the below furnished variables are available at https://nces.ed.gov/ipeds/datacenter/DataFiles.aspx

1. **In-State Tuition: "**The tuition charged by institutions to those students who meet the state's or institution's residency requirements."
2. **Out-of-State Tuition: "**The tuition charged by institutions to those students who do not meet the institution's or state's residency requirements."
3. **Fees:** "Fixed sum charged to students for items not covered by tuition and required of such a large proportion of all students that the student who does NOT pay the charge is an exception."
4. **Total Undergraduate Enrollment:** "Total unduplicated count of all undergraduates enrolled. Here, unduplicated count is defined as the sum of students enrolled for credit with each student counted only once during the reporting period, regardless of when the student enrolled. Moreover, the an undergraduate student is defined as a student enrolled in a 4- or 5-year bachelor's degree program, an associate's degree program, or a vocational or technical program below the baccalaureate."
5. **Average Financial Aid:** "Average amount of grant aid received by undergraduate students. Grant aid includes and grant or scholarship aid received, from the federal government, a state or local government, the institution, and other sources known by the institution."

Item C: Derivation of the EDM

The structural model consists of the following five equations:

$(A1)\ \ Q_S = S(P_G, \bar{C})$	(supply of education services)
$(A2)\ \ Q_D = D(P_N, \bar{Y})$	(demand for education services)
$(A3)\ \ P_G = P_N + AID$	(gross price)
$(A4)\ \ AID = f(P_G, \bar{Y}, \bar{N})$	(student aid)
(A5) $\ Q_S = Q_D \equiv Q$	(market clearing)

Taking total derivatives, the model can be expressed in percentage changes as follows:

$$dQ_S = \frac{\partial Q_S}{\partial P_G}\, dP_G + \frac{\partial Q_S}{\partial \bar{C}}\, d\bar{C}$$

$$\frac{dQ_S}{Q_S} = \left(\frac{\partial Q_S}{\partial P_G}\frac{P_G}{Q_S}\right)\frac{dP_G}{P_G} + \left(\frac{\partial Q_S}{\partial \bar{C}}\frac{\bar{C}}{Q_S}\right)\frac{d\bar{C}}{\bar{C}}$$

$$(A1')\ \ Q_S^* = \varepsilon\, P_G^* + \varepsilon_{\bar{C}}\, \bar{C}^*$$

$$dQ_D = \frac{\partial Q_D}{\partial P_N}\, dP_N + \frac{\partial Q_D}{\partial \bar{Y}}\, d\bar{Y}$$

$$\frac{dQ_D}{Q_D} = \left(\frac{\partial Q_D}{\partial P_N}\frac{P_N}{Q_D}\right)\frac{dP_N}{P_N} + \left(\frac{\partial Q_D}{\partial \bar{Y}}\frac{\bar{Y}}{Q_D}\right)\frac{d\bar{Y}}{\bar{Y}}$$

$$(A2')\ \ Q_D^* = \eta\, P_N^* + \eta_{\bar{Y}}\, \bar{Y}^*$$

$$dP_G = dP_N + d\,AID$$

$$\frac{dP_G}{P_G} = \frac{P_N}{P_G}\,\frac{dP_N}{P_N} + \frac{AID}{P_G}\,\frac{dAID}{AID}$$

$$(A3')\ \ P_G^* = K_{P_N}\, P_N^* + K_{AID}\, AID^*$$

$$dAID = \frac{\partial AID}{\partial P_G}\, dP_G + \frac{\partial AID}{\partial \bar{Y}} d\bar{Y} + \frac{\partial AID}{\partial \bar{N}} d\bar{N}$$

$$\frac{dAID}{AID} = \left(\frac{\partial AID}{\partial P_G}\frac{P_G}{AID}\right)\frac{dP_G}{P_G} + \left(\frac{\partial AID}{\partial \bar{Y}}\frac{\bar{Y}}{AID}\right)\frac{d\bar{Y}}{\bar{Y}} + \left(\frac{\partial AID}{\partial \bar{N}}\frac{\bar{N}}{AID}\right)\frac{d\bar{N}}{\bar{N}}$$

$(A4')\quad AID^* = \alpha_{P_G} P_G^* + \alpha_{\bar{Y}}\, \bar{Y}^* + \alpha_{\bar{N}}\, \bar{N}^*$

$dQ_S = dQ_D \equiv dQ$

$\frac{dQ_S}{Q_S} = \frac{dQ_D}{Q_D} = \frac{dQ}{Q}$

$(A5')\quad Q_S^* = Q_D^* = Q^*$

Reduced Form for P_G^*
Plugging ((A4') into (A3') we obtain:

$P_G^* = K_{P_N} P_N^* + K_{AID}\alpha_{P_G} P_G^* + K_{AID}\alpha_{\bar{Y}}\, \bar{Y}^* + K_{AID}\alpha_{\bar{N}}\bar{N}^*$

$K_{P_N} P_N^* = P_G^* - K_{AID}\alpha_{P_G} P_G^* - K_{AID}\alpha_{\bar{Y}}\, \bar{Y}^* - K_{AID}\alpha_{\bar{N}}\bar{N}^*$

$(A6')\quad P_N^* = \left[\frac{\left(1 - K_{AID}\,\alpha_{P_G}\right)}{K_{P_N}}\right] P_G^* - \left[\frac{K_{AID}\alpha_{\bar{Y}}}{K_{P_N}}\right] \bar{Y}^* - \left[\frac{K_{AID}\,\alpha_{\bar{N}}}{K_{P_N}}\right] \bar{N}^*$

Plugging (A6') into (A2') we obtain:

$(A7')\quad Q_D^* = \left[\frac{\eta\left(1 - \mathrm{K_{AID}}\,\alpha_{P_G}\right)}{K_{P_N}}\right] P_G^* - \left[\frac{\mathrm{K_{AID}}\alpha_{\bar{Y}}\eta}{K_{P_N}}\right] \bar{Y}^* - \left[\frac{\mathrm{K_{AID}}\,\alpha_{\bar{N}}\,\eta}{K_{P_N}}\right] \bar{N}^* + \eta_{\bar{Y}}\, \bar{Y}^*$

Equating (A7') with (A1') we obtain

$\varepsilon\, P_G^* + \varepsilon_{\bar{C}}\, \bar{C}^* = \left[\frac{\eta\left(1 - \mathrm{K_{AID}}\,\alpha_{P_G}\right)}{K_{P_N}}\right] P_G^* - \left[\frac{\mathrm{K_{AID}}\alpha_{\bar{Y}}\eta}{K_{P_N}}\right] \bar{Y}^* - \left[\frac{\mathrm{K_{AID}}\,\alpha_{\bar{N}}\,\eta}{K_{P_N}}\right] \bar{N}^* + \eta_{\bar{Y}}\, \bar{Y}^*$

$\left[\varepsilon - \frac{\eta - \mathrm{K_{AID}}\,\alpha_{P_G}\eta}{K_{P_N}}\right] P_G^* = \left[\eta_{\bar{Y}} - \frac{\mathrm{K_{AID}}\alpha_{\bar{Y}}\,\eta}{K_{P_N}}\right] \bar{Y}^* - \left[\frac{\mathrm{K_{AID}}\,\alpha_{\bar{N}}\,\eta}{K_{P_N}}\right] \bar{N}^* - \varepsilon_{\bar{C}}\, \bar{C}^*$

$\left[\frac{K_{P_N}\varepsilon - \eta + \mathrm{K_{AID}}\,\alpha_{P_G}\eta}{K_{P_N}}\right] P_G^* = \left[\frac{K_{P_N}\eta_{\bar{Y}} - \mathrm{K_{AID}}\alpha_{\bar{Y}}\,\eta}{K_{P_N}}\right] \bar{Y}^* - \left[\frac{\mathrm{K_{AID}}\,\alpha_{\bar{N}}\,\eta}{K_{P_N}}\right] \bar{N}^* - \varepsilon_{\bar{C}}\, \bar{C}^*$

$P_G^* = \left[\frac{K_{P_N}\eta_{\bar{Y}} - \mathrm{K_{AID}}\alpha_{\bar{Y}}\,\eta}{K_{P_N}\varepsilon - \eta(1 - \mathrm{K_{AID}}\,\alpha_{P_G})}\right] \bar{Y}^* - \left[\frac{\mathrm{K_{AID}}\,\alpha_{\bar{N}}\,\eta}{K_{P_N}\varepsilon - \eta(1 - \mathrm{K_{AID}}\,\alpha_{P_G})}\right] \bar{N}^* - \left[\frac{K_{P_N}\varepsilon_{\bar{C}}}{K_{P_N}\varepsilon - \eta(1 - \mathrm{K_{AID}}\,\alpha_{P_G})}\right] \bar{C}^*$

$(A8')\quad P_G^* = \left[\frac{K_{P_N}\eta_{\bar{Y}} - \mathrm{K_{AID}}\alpha_{\bar{Y}}\,\eta}{\mathcal{D}}\right] \bar{Y}^* - \left[\frac{\mathrm{K_{AID}}\,\alpha_{\bar{N}}\,\eta}{\mathcal{D}}\right] \bar{N}^* - \left[\frac{K_{P_N}\varepsilon_{\bar{C}}}{\mathcal{D}}\right] \bar{C}^*$

where $\mathcal{D} = K_{P_N}\varepsilon - \eta\,(1 - \mathrm{K_{AID}}\,\alpha_{P_G})$

Reduced Form for P_N^*
From equation *(A6') we obtain*

$$\left(1 - K_{AID}\ \alpha_{P_G}\right)P_G^* = K_{P_N}\ P_N^* + K_{AID}\ \alpha_{\bar{Y}}\ \bar{Y}^* + K_{AID}\ \alpha_{\bar{N}}\ \bar{N}^*$$

$$(A9')\quad P_G^* = \left[\frac{K_{P_N}}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* + \left[\frac{K_{AID}\alpha_{\bar{Y}}}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}}{1 - K_{AID}\ \alpha_{P_G}}\right]\ \bar{C}^*$$

Plugging (A9') into (A1') we obtain:

$$(A10')\ Q_s^* = \left[\frac{K_{P_N}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* + \left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{N}^* + \varepsilon_{\bar{C}}\ \bar{C}^*$$

Equating (A10') with (A2') we obtain

$$\eta\ P_N^* + \eta_{\bar{Y}}\ \bar{Y}^* = \left[\frac{K_{P_N}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* + \left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{N}^* + \varepsilon_{\bar{C}}\ \bar{C}^*$$

$$\left[\eta - \frac{K_{P_N}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* = \left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}} - \eta_{\bar{Y}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{N}^* + \varepsilon_{\bar{C}}\ \bar{C}^*$$

$$\left[\frac{\eta\left(1 - K_{AID}\ \alpha_{P_G}\right) - K_{P_N}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* = \left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon - \eta_{\bar{Y}}\left(1 - K_{AID}\ \alpha_{P_G}\right)}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{N}^* + \varepsilon_{\bar{C}}\ \bar{C}^*$$

$$\left[\frac{\eta - K_{AID}\ \alpha_{P_G}\eta - K_{P_N}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* = \left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon - \eta_{\bar{Y}} + K_{AID}\ \alpha_{P_G}\ \eta_{\bar{Y}}}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{N}^* + \varepsilon_{\bar{C}}\ \bar{C}^*$$

$$\left[\frac{-\left(K_{P_N}\ \varepsilon - \eta + K_{AID}\ \alpha_{P_G}\eta\right)}{1 - K_{AID}\ \alpha_{P_G}}\right] P_N^* = \left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon - \eta_{\bar{Y}} + K_{AID}\ \alpha_{P_G}\ \eta_{\bar{Y}})}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{Y}^* + \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{1 - K_{AID}\ \alpha_{P_G}}\right] \bar{N}^* + \varepsilon_{\bar{C}}\ \bar{C}^*$$

$$P_N^* = -\left[\frac{K_{AID}\alpha_{\bar{Y}}\ \varepsilon - \eta_{\bar{Y}}\left(1 - K_{AID}\ \alpha_{P_G}\right)}{K_{P_N}\varepsilon - \eta\left(1 - K_{AID}\ \alpha_{P_G}\right)}\right] \bar{Y}^* - \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{K_{P_N}\varepsilon - \eta\left(1 - K_{AID}\ \alpha_{P_G}\right)}\right] \bar{N}^* - \left[\frac{\varepsilon_{\bar{C}} - K_{AID}\ \alpha_{P_G}\varepsilon_{\bar{C}}}{K_{P_N}\varepsilon - \eta\left(1 - K_{AID}\ \alpha_{P_G}\right)}\right]\ \bar{C}^*$$

$$P_N^* = -\left[\frac{-\left\{\eta_{\bar{Y}}\left(1 - K_{AID}\ \alpha_{P_G}\right) - K_{AID}\alpha_{\bar{Y}}\ \varepsilon\right\}}{K_{P_N}\varepsilon - \eta\left(1 - K_{AID}\ \alpha_{P_G}\right)}\right] \bar{Y}^* - \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{K_{P_N}\varepsilon - \eta\left(1 - K_{AID}\ \alpha_{P_G}\right)}\right] \bar{N}^* - \left[\frac{\varepsilon_{\bar{C}} - K_{AID}\ \alpha_{P_G}\varepsilon_{\bar{C}}}{K_{P_N}\varepsilon - \eta\left(1 - K_{AID}\ \alpha_{P_G}\right)}\right]\ \bar{C}^*$$

$$(A11')\qquad P_N^* = \left[\frac{\eta_{\bar{Y}}\left(1 - K_{AID}\ \alpha_{P_G}\right) - K_{AID}\alpha_{\bar{Y}}\ \varepsilon}{\mathcal{D}}\right] \bar{Y}^* - \left[\frac{K_{AID}\ \alpha_{\bar{N}}\ \varepsilon}{\mathcal{D}}\right] \bar{N}^* - \left[\frac{\varepsilon_{\bar{C}} - K_{AID}\ \alpha_{P_G}\varepsilon_{\bar{C}}}{\mathcal{D}}\right]\ \bar{C}^*$$

where $\mathcal{D} = [\mathrm{K}_{\mathrm{P_N}}\, \varepsilon - \eta\, (1 - \mathrm{K}_{\mathrm{AID}}\, \alpha_{P_G})]$

Reduced Form for AID^*

Plugging equation *(A8')* from above into the equation (A4') we obtain:

$$AID^* = \alpha_{P_G} \left[\left(\frac{K_{P_N} \eta_{\bar{Y}} - \mathrm{K}_{\mathrm{AID}} \alpha_{\bar{Y}}\, \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right) \bar{Y}^* - \left(\frac{\mathrm{K}_{\mathrm{AID}}\, \alpha_{\bar{N}}\, \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right) \bar{N}^* - \left(\frac{K_{P_N} \varepsilon_{\bar{C}}}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right) \bar{C}^* \right] + \alpha_{\bar{Y}}\, \bar{Y}^* + \alpha_{\bar{N}}\, \bar{N}^*$$

$$AID^* = \left[\frac{K_{P_N}\, \alpha_{P_G}\, \eta_{\bar{Y}} - \mathrm{K}_{\mathrm{AID}} \alpha_{\bar{Y}}\;\, \alpha_{P_G}\, \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{Y}^* + \alpha_{\bar{Y}}\, \bar{Y}^* - \left[\frac{\mathrm{K}_{\mathrm{AID}}\, \alpha_{\bar{N}}\;\, \alpha_{P_G} \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{N}^* + \alpha_{\bar{N}}\, \bar{N}^* - \left[\frac{K_{P_N}\, \alpha_{P_G}\, \varepsilon_{\bar{C}}}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{C}^*$$

$$AID^* = \left[\frac{K_{P_N}\, \alpha_{P_G}\, \eta_{\bar{Y}} - \mathrm{K}_{\mathrm{AID}} \alpha_{\bar{Y}}\;\, \alpha_{P_G}\, \eta + K_{P_N} \alpha_{\bar{Y}}\, \varepsilon - \alpha_{\bar{Y}} \eta + \mathrm{K}_{\mathrm{AID}} \alpha_{\bar{Y}}\;\, \alpha_{P_G} \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{Y}^* - \left[\frac{\mathrm{K}_{\mathrm{AID}}\, \alpha_{P_G}\, \alpha_{\bar{N}}\;\, \eta - K_{P_N}\, \alpha_{\bar{N}}\;\, \varepsilon + \alpha_{\bar{N}}\;\, \eta - K_{AID}\, \alpha_{P_G} \alpha_{\bar{N}}\;\, \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{N}^* - \left[\frac{K_{P_N}\, \alpha_{P_G}\, \varepsilon_{\bar{C}}}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{C}^*$$

$$AID^* = \left[\frac{K_{P_N}\, \alpha_{P_G}\, \eta_{\bar{Y}} + K_{P_N} \alpha_{\bar{Y}}\, \varepsilon - \alpha_{\bar{Y}} \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{Y}^* - \left[\frac{- K_{P_N}\, \alpha_{\bar{N}}\;\, \varepsilon + \alpha_{\bar{N}}\, \eta}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{N}^* - \left[\frac{K_{P_N}\, \alpha_{P_G}\, \varepsilon_{\bar{C}}}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{C}^*$$

$$AID^* = \left[\frac{K_{P_N}\, \alpha_{P_G}\, \eta_{\bar{Y}} + \alpha_{\bar{Y}} \left(K_{P_N}\, \varepsilon - \eta \right)}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{Y}^* - \left[\frac{- \alpha_{\bar{N}}\, \left(K_{P_N}\, \varepsilon - \eta \right)}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{N}^* - \left[\frac{K_{P_N}\, \alpha_{P_G}\, \varepsilon_{\bar{C}}}{K_{P_N} \varepsilon - \eta \left(1 - K_{AID}\, \alpha_{P_G} \right)} \right] \bar{C}^*$$

$$(A12')\; AID^* = \left[\frac{K_{P_N}\, \alpha_{P_G}\, \eta_{\bar{Y}} + \alpha_{\bar{Y}} \left(K_{P_N}\, \varepsilon - \eta \right)}{\mathcal{D}} \right] \bar{Y}^* + \left[\frac{\alpha_{\bar{N}}\, \left(K_{P_N}\, \varepsilon - \eta \right)}{\mathcal{D}} \right] \bar{N}^* - \left[\frac{K_{P_N}\, \alpha_{P_G}\, \varepsilon_{\bar{C}}}{\mathcal{D}} \right] \bar{C}^*$$

where $\mathcal{D} = [\mathrm{K}_{\mathrm{P_N}}\, \varepsilon - \eta\, (1 - \mathrm{K}_{\mathrm{AID}}\, \alpha_{P_G})]$

Chapter 2: Effect of Wind Turbines on Bird Abundance: A National Scale Analysis Based on Fixed Effects Models

Introduction

Wind energy is widely viewed as one of the most promising alternatives to fossil fuels because it can significantly contribute to reductions in greenhouse gas (GHG) emissions (Intergovernmental Panel on Climate Change (IPCC) 2011, p.19). The IPCC predicts that by 2050 electricity generated from wind farms may account for more than 20% of global electricity supply (IPCC 2011, p.95). The U.S. Department of Energy even aims to reach this 20% mark by 2030 and a 35% mark by 2050 in the United States (USDOE 2015). By the end of 2017, the total installed wind energy capacity in the United States had reached 88,973 megawatts (MW) (about 8% of total U.S. electricity generating capacity), more than a 20-fold increase when compared with 4,147 MW in 2001 (American Wind Energy Association (AWEA) 2018; U.S. Energy Information Agency (USEIA) 2017).

The rapid growth of wind energy, however, has raised concerns about the impact of wind turbines on birds (Erickson et al. 2014; Diffendorfer et al. 2015a; Schuster et al. 2015; Homoya et al. 2017). Wind turbines can have both direct and indirect impacts on birds. The direct impacts are fatalities caused by collisions between birds and wind turbines while the indirect impacts include birds' avoidance and habitat loss due to wind farm construction and operation (Diffendorfer et al. 2015a; Garcia et al. 2015; Masden et al. 2010; May 2015; and Smith and Dwyer 2016). Although there have been a large number of studies focusing on the impacts of wind turbines on bird abundance (see Erickson et al. 2014 and Schuster et al. 2015 for comprehensive reviews), these studies suffer from major limitations. Loss et al. (2013) point out that most of the wind energy studies are industry reports that are not peer reviewed. Jones, Pejchar, and Kiesecker (2015) state that "[t]he majority of data is held by hired consultants and is rarely publicly available." Moreover, the majority of the existing studies are based upon samples collected from a few wind farms with focus on some specific bird species (Sovacool 2009; 2013). As Sovacool (2013) writes,

> "A study that focused only one or two wind farms, therefore, could produce exceptionally high or low estimates of avian mortality as a result of the specific weather, type of wind farm, number of birds in the area, species of birds, quality of researchers collecting carcasses, terrain and siting, and form of wind technology that are not representative for all or even most wind turbines."

Therefore, inferences of studies based on a few wind farms are not reliable for regional or national policy agendas. By arguing that the data used in individual studies are non-representative samples and that research methods across studies are inconsistent, Huso and Dalthorp (2014) even claim that "an accurate estimate of total bat fatality is not currently possible." Due to the similar nature of wind turbines' effect on birds with that on bats, the claim of Huso and Dalthorp may also apply to the estimate of wind turbines' effect on birds. Despite these concerns, there is still a dearth of studies that employ large samples on wind farms and bird species count to study the causal relationship between wind turbines and bird abundance at the national and regional levels (Diffendorfer et al. 2015a; May 2015; Jones et al. 2015).

The purpose of this article is to fill this research gap by utilizing publicly available datasets that support a national-level analysis. By focusing on overall breeding bird abundance and grassland breeding bird abundance and by using fixed effects models, we aim to quantify the impacts of the establishment of wind turbines and of turbine characteristics (i.e., tower height and blade length) while controlling for many other factors that may also affect bird abundance, such as land cover, weather, and geographical locations. We include tower height and blade length in our analysis because wind turbines are becoming taller and larger (Homoya et al. 2017, p.96; Caduff et al. 2012) and this change causes further concerns about wind energy's impact on birds (Loss et al. 2013). Moreover, conflicting results of turbine height on bird fatality exist. Loss et al. (2013) show that turbine height is positively associated with fatalities whereas Smallwood and Karas (2009) find that repowering in Altamont Pass Wind Resource Area in California involving installation of taller and larger turbines reduces bird fatalities. These conflicting results indicate that further research on the impact of turbine characteristics is in order. Finally, we are also interested in grassland breeding birds' responses because grassland bird population in the United States have been declining faster than any other bird species over recent decades (Hill et al. 2014; Mineau and Whiteside 2013; Shaffer and Buhl 2016). Therefore, in this study, we will treat grassland breeding birds as a separate group in addition to the total breeding birds.

We harness detailed and spatially explicit data from four publicly available datasets on wind turbines, breeding bird abundance, land use, and weather across the contiguous United States. The datasets for wind turbines, land use, and weather cover the entire contiguous United States whereas the dataset for breeding bird abundance include data collected from more than 3,000 observation routes set by USGS (to be discussed in the next section). We then overlay the four datasets over the 2008-2014 period to construct a unique longitudinal dataset that contains annual breeding bird count data for up to 86 breeding bird observation routes and data for 1,670 wind turbines located within the 1,600-meter buffer zones of these 86 routes. The large amount of wind turbines covered in our dataset are located across 36 states in the United States and have various characteristics in terms of their models and siting. Therefore, when compared with data collected from a few specific wind farms within one or two years, the dataset used in this study has the advantages of much larger geographical scope and longer temporal framework. As a result, it provides a more representative sample and hence mitigates, at least to some extent, the sample section bias. In addition, the land-use and weather data included in our dataset, together with the statistical technique employed in the analysis (to be discussed below), mitigate the omitted variable bias.

Moreover, the dataset allows us to employ a well-developed statistical technique, fixed effects models for longitudinal data analysis in this study (Wooldridge 2003, p.461), to mitigate potential estimation bias caused by site specific factors such as geographical characteristics and many other factors that are unobservable to us but can affect bird abundance. The fixed effects models enable us to conduct the counterfactual analysis holding all other factors constant while examining the impact of a single factor, which cannot be achieved by simply studying the correlation coefficient between bird abundance and variables associated with wind turbines (Wooldridge 2003, pp.13-19 and p.461). Therefore, our study offers a more reliable and precise evaluation of effects of wind turbines on breeding birds in the United States. The present study differs significantly from the one by Loss et al. (2013) and Erickson et al. (2014) that uses data or results from existing studies to estimate the bird collision mortality caused by wind farms across the United States. It also differs from Diffendorfer et al. (2015a) who evaluate the impacts of wind turbines on birds and bats at national and regional levels by combining literature review, expert evaluation, and species demographic modeling on species-specific basis. The closest approach to the one in the present study is employed by Shaffer and Buhl (2016), who utilize a before-after-control-impact (BACI) approach to analyze the effects of wind turbines on breeding grassland birds. However, they only focus on three areas in Dakotas of the United States. Our study, in contrast, covers 86 bird observation routes located in 36 states of the United States.

In sum, by constructing a unique longitudinal dataset and by employing the fixed effects models, the present study complements the existing studies regarding wind turbines' impacts on bird abundance. It also sheds new insights on wind energy policies and wind energy development regarding facility siting, wind turbine designs, and the heterogeneous impact of wind turbines across bird species.

Data and estimation approach

The breeding bird count data are obtained from the North American Breeding Bird Survey (BBS) compiled by the U.S. Geological Survey (USGS, 2018). This dataset includes annual bird count data for over 400 breeding bird species along more than 3,000 observation routes across the United States since 1966. Each observation route is about 40km long and has 50 observation stops, 800 meters apart, on it. Each year around June, the most active bird breeding period in the United States, observers go through observation stops along observation routes to record the number of breeding birds seen or heard within a 400-meter radius of each stop for three minutes.[4]

Data for onshore wind turbines and their characteristics are obtained from the USGS as well (USGS 2014). This dataset provides detailed information for each of the 48,976 onshore wind turbines established over 1981-2014 including a standing turbine's latitude and longitude, establishment year, tower type, tower height, blade length, and power generation capacity. For detailed description of the wind turbine dataset, we refer readers to Diffendorfer et al. (2015b).

[4] The observers are volunteers that include amateur birders and professional biologists. See webpage "Participating in the North American Breeding Bird Survey" (https://www.pwrc.usgs.gov/bbs/participate/, accessed February 20, 2019) for details about requirements for BBS participation. Although any observers who contribute to the BBS dataset must complete a brief methodology training, it is likely that large heterogeneity in data collection skills exists across these voluntary observers. Moreover, due to the voluntary nature of bird observations for BBS, there is no guarantee that one route is observed by the same volunteer across different years.

Figure 2.1 depicts the geographical distribution of bird observation routes and wind farms in March 2014, from which we can see that a wind farm may overlap with bird observation routes. Therefore, we overlay the Geographic Information System (GIS) layers of the data for wind turbines and bird observation routes described above to identify observation routes with one or more wind turbines inside an R-meter buffer zone of the routes (R equals 400, 800, or 1,600 in this study). We vary the size of buffer zone to examine how birds' responses to wind turbines may change as the distance between wind turbines and observation route increases. We identify 47 observation routes that have at least one wind turbine within 400-meter buffer zone in at least one year between 2008 and 2014. If we enlarge the size of buffer zone to 800 (respectively, 1,600) meters, then there are 62 (respectively, 86) routes that have at least one wind turbine within the buffer zone. Figure 2.2 shows a sample route and wind farm located in Minonk, Illinois in 2014, from which we can see that the observation route, Monica (route number 34026), has 12 wind turbines within its 400-meter buffer zone.

Because bird observation routes are relatively long (about 40km each), we evenly split each identified route into two segments and treat each segment as the minimum analysis unit. This split is possible because a) the bird count data are recorded at observation stops for each route and the stop-level data are publicly available; b) the latitude and longitude for each wind turbine are available; and c) data for all other explanatory variables (i.e., land use and weather) are in fine scales no larger than 4km-by-4km (to be discussed below). Each segment's total breeding bird count in a year is calculated by aggregating bird count in that year across all available stops on the segment. Grassland bird species are identified by following Peterjohn and Sauer (1993). We aggregate bird count across all identified grassland bird species on a segment in a year to construct a grassland bird abundance variable for the segment.

The wind turbine characteristics (i.e., tower height and blade length) associated with an observation segment are calculated by using simple average of the characteristics of turbines within a certain buffer zone of the segment. If there is no wind turbine within a segment's buffer zone, then both the turbine number and turbine characteristics are set to be zero for this segment. Note that although a route is selected only if it has bird count data and at least one turbine within its *R*-meter buffer zone in at least one year over 2008-2014, it is possible that a segment of a selected route may have no turbine within its buffer zone if all turbines close to the route cluster around the other segment.

Splitting each route into two segments enhances the analysis in the following ways. First, it more precisely captures the effects of wind turbines on bird abundance when compared with analysis based on whole routes. This is because a route is as long as 40km and the potential effects caused by establishment of wind turbines may be attenuated by large amount of bird in such a long route. Second, not every segment has wind turbines in its vicinity. Segments without turbines can act as a natural control group for segments with wind turbines in a certain buffer zone. Third, statistically, by evenly splitting a route into two segments and then taking difference between variables associated with the two segments, we remove common but unobservable factors of the two segments that may affect bird counts, such as the quality and skills of observers who collect the data as well as regional shocks such as droughts, pest outbreaks, or urban development.

Data for land use are obtained from the Cropland Data Layer (CDL) created by the U.S. Department of Agriculture (USDA) (2014). The CDL data contain detailed land-use information for the United States at the 56m-by-56m scale over 2008-2009 and at the 30m-by-30m scale over 2010-2014. We overlay the CDL data with bird observation segments to obtain land cover information (e.g., cropland acreage and grassland acreage) within 400-meter buffer zone of each segment. Following Evans and Potts (2015), we choose 400-meter buffer zone because birds are observed within 400-meter radius of each stop. Veech et al. (2012) show that enlarging the size of buffer zone to 10km does not significantly affect the landscape composition within a buffer zone. We obtain daily weather information for each segment from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) that generates detailed weather information across the contiguous United States at 4km-by-4km grid level (PRISM, 2018). We utilize weather information associated with the data grid that covers the middle point of a segment to represent weather for that segment. Monthly average of daily mean temperature and monthly total precipitation are used in our analysis to better capture the variability in weather conditions. Since bird abundance data are mostly collected in June each year, we focus on monthly temperature and precipitation between March and May to capture the impact of spring weather on bird abundance (Evans and Potts 2015).

By processing the aforementioned datasets for bird counts, wind turbines, land use, and weather, we construct a longitudinal dataset for a seven-year period between 2008 and 2014. This time range is determined by data availability because CDL data at national level are not available before 2008 whereas the wind turbine data are not available after 2014 at the time of writing of this article. One advantage of using data between 2008 and 2014 is that wind power capacity increased sharply between 2008 and 2014 (Smith and Dwyer 2016), which provides data variation necessary for the statistical analysis. The longitudinal dataset comprises of 86 bird observation routes and 1,670 wind turbines. Table 2.1 presents the summary statistics of variables when the size of the buffer zone equals 400, 800, and 1,600 meters, respectively. From Table 2.1 we can see that the average number of turbines within the 400-, 800-, and 1,600-meter buffer zones for a segment is 3, 5, and 8, respectively, with some segments having as many as 114 wind turbines within a buffer zone and some segments having no turbine in the vicinity. We now present the statistical model to be used for the analysis.

We are interested in examining the causal relationship between wind turbine establishment within a certain buffer zone of an observation segment and the number of birds observed on that segment. For simplicity we assume a linear relationship between bird count and the explanatory variables, which can be written as,

$$Y_{ijt} = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{T}_{ijt} + \boldsymbol{\beta}_2 \boldsymbol{X}_{ijt} + \alpha_{ij} + \gamma_{it} + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} stands for bird count on route $i \in \{1, ..., N\}$, segment $j \in \{1, 2\}$, in year t $\in \{2008, ..., 2014\}$, where N is the number of observation routes included in the analysis; β_0 is a constant; $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are coefficient vectors to be estimated; $\boldsymbol{T}_{ijt}$ represents a vector that includes total wind turbine number, tower height, and blade length of wind turbines observed within a certain buffer zone of route i, segment j, in year t; for segment-years that have no turbines within a buffer zone, $\boldsymbol{T}_{ijt} = \mathbf{0}$; and $\boldsymbol{X}_{ijt}$ is a vector of time-varying control variables such as land use, temperature, and precipitation.[5] Additionally, α_{ij} represents fixed effects (i.e. time-invariant factors) for segment j of route i that may affect bird count, such as geographical locations (e.g., close to lakes or wetlands) and wind farm characteristics; γ_{it} stands for factors that are common

[5] Due to data limitation, we cannot directly control for all the time-varying and segment-specific factors that may affect one segment but not the other of an observation route (e.g., point pollution, fine scale weather shocks, as well as oil or gas extraction on one segment but not the other). However, by including land coverage and weather variables, we can, at least partially, control for the impact of segment-specific land-use changes and some weather shocks. Moreover, these factors may cause biases in opposing directions and cancel each other out. We thank an anonymous referee for a comment that led to the clarification of this caveat of our analysis.

to the two segments on one route but may vary across years, such as the training and capability of the observers who collect the bird count data for a route. Finally, ϵ_{ijt} is an error term such that $\mathrm{E}(\epsilon_{ijt} \mid \boldsymbol{T}, \boldsymbol{X}, \alpha, \gamma) = 0,$ where $\mathrm{E}(\cdot)$ is the expectation operator.

Due to the limitation of data, variables in α_{ij} and γ_{it} are not observable to us and hence cannot be fully controlled for. If they are correlated with any variables in $\boldsymbol{T}_{ijt}$ or $\boldsymbol{X}_{ijt}$, then the ordinary least squares (OLS) analysis on equation (1) will generate biased and inconsistent estimates (Wooldridge 2003, p.439). An example of the correlation between α_{ij} and $\boldsymbol{T}_{ijt}$ is that the geographical location of a segment may determine the number of turbines close to that segment. In order to eliminate α_{ij} and γ_{it}, we first take difference between the two segments on the same route in the same year and then analyze the differenced data by using fixed effects models. Specifically, based on equation (1) we have

$$\Delta Y_{it} = \boldsymbol{\beta}_1 \Delta \boldsymbol{T}_{it} + \boldsymbol{\beta}_2 \Delta \boldsymbol{X}_{it} + \Delta \alpha_i + \Delta \epsilon_{it}, \tag{2}$$

where $\Delta Z_{it} \equiv Z_{i1t} - Z_{i2t}$ for any $Z \in \{Y, \boldsymbol{T}, \boldsymbol{X}, \epsilon\}$ and $\Delta \alpha_i \equiv \alpha_{i1} - \alpha_{i2}$. It is readily checked that γ_{it} is eliminated because it is a constant across the two segments of one observation route in year t. We then apply fixed effects regressions to equation (2) to remove the time-invariant variable, $\Delta \alpha_i$, as well as to estimate $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ (see Chapter 14 in Wooldridge (2003) for a detailed discussion regarding fixed effects models). The analysis is conducted by using version 14 of Stata®, a general-purpose statistical software package. Note that $\boldsymbol{\beta}_1$ in equation (2) is identical to $\boldsymbol{\beta}_1$ in equation (1) and should be interpreted as the marginal effect of an additional turbine (or unit of turbine characteristics) on bird abundance on an observation segment.

Note that the specification in equation (1) is similar to a generalized difference-in-difference (DID) specification under a panel data framework (Pischke 2005; Imbens and

Wooldridge 2009; and Simintzi et al. 2015). However, our approach takes advantage of an obvious structure of the dataset: segments enter our dataset in pairs due to splitting observation routes. By taking difference between the two segments within each pair, we are able to remove year fixed effects and other relevant factors shared by the two segments but unobservable to the researchers. This cannot be achieved by estimating model (1) using a two-way fixed effects estimator. Our approach follows the same idea as that in the line of literature in labor economics that studied returns of education based on samples of twins. In that line of literature, researchers first take difference between each pair of twins to remove genetic variation so that to better control for unobservable factors such as genes and ability that may influence both wage and education (see, e.g., Ashenfelter and Krueger 1994; Bonjour et al. 2003).

We consider two model specifications based on equation (2). The first specification is parsimonious and does not contain any turbine characteristics (i.e., turbine height and blade length) whereas the second specification includes these two characteristics as explanatory variables. Wind turbines are becoming taller with longer blades over time to be economically and environmentally efficient (Caduff 2012). However, taller and larger turbines may be associated with higher risks to potential bird species (Loss et al. 2013; Smith and Dwyer 2016). Therefore, omitting turbine characteristics is likely to cause omitted variable bias and inconsistency of the estimation (Wooldridge 2003, p.91 and p.168). Comparing results under the two model specifications will illustrate the magnitude of this bias. We are aware that tower height and blade length are correlated. However, as long as the correlation is not perfect, it will not affect the unbiasedness and consistency of the estimation (Wooldridge 2003, Theorems 3.1 and 5.1). A much larger concern is the inconsistency and biasedness of estimation caused by the omitted variables. We estimate the two model specifications of equation (2) to study breeding birds' responses to wind turbines within 400-, 800-, and 1,600-meter buffer zones. Furthermore, we examine both overall breeding birds' and grassland breeding birds' responses to wind turbines.

Results

Table 2.2 presents the main results regarding breeding birds' responses to establishment of wind turbines. Columns (1) and (2) examine the responses to turbines within 400-meter buffer zone. Responses to turbines within 800-meter (respectively, 1,600-meter) buffer zone are included in columns (3) and (4) (respectively, (5) and (6)). In Table 2.2, the odd-number columns include the parsimonious model specification in which tower height and blade length are not controlled for; even-number columns are the full models that control for these turbine characteristics. We find that the coefficients of number of wind turbines under the parsimonious specification are negative but statistically insignificant across all models with different buffer zone sizes. Under the full specification models, however, the coefficient of number of wind turbines is negative and statistically significant, with magnitude about twice as large as that under the parsimonious specifications. This result indicates that when turbine characteristics are omitted then the estimation bias on the coefficient of number of wind turbines can be large. Moreover, the *p*-values for *F* tests in Table 2.2 show that the parsimonious models (columns (1), (3), and (5)) do not pass *F* test. That is, we cannot reject the null hypothesis that the coefficients in these models are jointly insignificant. However, for the full specification models under 400-meter and 800-meter buffer zone (i.e., columns (2) and (4)), we can reject the null hypothesis at 1% significance level. For the full specification model under the 1,600-meter buffer zone (i.e., column (6) in Table 2.2), we cannot reject the null hypothesis of *F* test. One should note that failing to reject the null hypothesis of *F* test does not indicates that each individual explanatory variable in the model is statistically insignificant. We refer readers to Wooldridge (2003, pp.148-149) for a detailed discussion about the relationship between *F* test and statistical significance of an individual variable.

Column (2) in Table 2.2 shows that the coefficient of variable "Number of Wind Turbines" is -3.096. The asterisk after the coefficient indicates that the estimate is statistically significant at 10% level, based on *t* statistic derived from the coefficient and the standard error that is shown in the parentheses below the coefficient. Here the coefficient, -3.096, should be interpreted as all else equal, the establishment of one additional turbine within the 400-meter buffer zone of a bird observation segment, on average, leads to disappearance of 3.1 breeding birds within the same buffer zone of the segment. This effect is causal because we derive this effect while holding other factors unchanged. We refer readers to Wooldridge (2003, pp. 13-19) for a detailed discussion about causal effect in regression analysis.

Column (2) in Table 2.2 also shows that, everything else equal, a one-meter increase in average tower height for turbines within 400-meter buffer zone of a segment, on average, leads to an increase in observed head count of breeding birds by 4.26. On the contrary, a one-meter increase in average blade length of turbines within 400-meter buffer zone, on average, leads to a decrease in bird count by 7.9. These results indicate that blade length may be one of the critical factors associated with wind turbines that negatively affect bird abundance. These findings about the impacts of wind turbine number and blade length are consistent with some existing studies (e.g., Smith and Dwyer 2016; Percival 2003; Loss et al. 2013). However, we find opposing effects of tower height when compared with those in Loss et al. (2013) in which the authors show that tower height has negative impacts on bird abundance. One should note that Loss et al. (2013) do not separate the effects of tower height from those of blade length. Therefore, their finding that higher turbines reduce bird abundance may actually be driven by the facts that (a) higher turbines typically have longer blade length (IPCC 2011, p.96) and (b) longer blade length increases the blade swept area and hence birds' collision risk.

Our statistical approach allows us to conduct the counterfactual analysis holding all other factors constant while examining the impact of a single factor. Therefore, the coefficient of tower height in column (2) of Table 2.2 should be interpreted as everything else being equal, a one-meter increase in tower height of wind turbines within 400-meter buffer zone of a bird observation segment will increase the bird count of the observation segment by 4.26. We believe that this finding is reasonable because bird fly paths are typically 18-24 meters above ground (Masden et al. 2010), further increasing tower height from average height (37 meters) will push a turbine's swept-area higher than bird fly path and hence reduce collision risks. Coefficient of crop acreage is negative but statistically insignificant.

A comparison of results across columns (2), (4), and (6) in Table 2.2 shows that as we enlarge the size of buffer zone from 400 meters to 1,600 meters, the impacts of wind turbine numbers and of wind turbine characteristics weaken. For instance, when we focus on the 400-meter buffer zone, then the coefficient of number of wind turbines is about -3.1. When we focus on wind turbines within the 1,600-meter buffer zone, however, the value becomes -0.97. This is reasonable because, on average, the further a wind turbine is from an observation route, the weaker the disturbing effects caused by the wind turbine will be on birds around the observation route. We also notice that when we enlarge the buffer zone to 1,600 meters, then the impact from tower height and blade length are no longer statistically significant. This suggests that the impact of turbines decay across space over fairly short distances. Therefore, to reduce wind turbines' effect on bird abundance, wind facility sitting should be about one mile away from areas with high habitat density. Across all model specifications, the overall breeding bird count is not sensitive to precipitation. However, mean temperature in April has positive and statistically significant impact on bird counts. Mean temperatures in March and May do not have statistically significant impacts.

The available data do not allow us to distinguish between the direct effect (i.e., fatalities from collisions) versus indirect effect (i.e., habitat loss and birds' avoidance) of wind turbines. Thus, our results can only be interpreted as aggregate impact of wind turbines on bird abundance in the vicinity of the turbines. Based on the results in Table 2.2, a back-of-the-envelope calculation shows that the 48,976 wind turbines as of March 2014 would reduce total breeding bird count in their proximity area by 151,630 (calculated by using 48,976 times -3.096, the coefficient of number of wind turbines in column (2) of Table 2.2), either caused by bird collisions or avoidance, or both. Existing literature estimates that the annual bird fatality caused by wind turbines in the United States ranges between 20,000 and 573,000 (Loss et al. 2013); our results are at the lower end of the range.

The results about how wind turbines affect grassland bird abundance are presented in Table 2.3, which has the same structure as that of Table 2.2 except that we now include grassland acreage instead of cropland acreage in the regressions. The p-values for F tests in Table 2.3 indicates that the parsimonious models do not pass F test whereas the full specification models under 400-meter and 800-meter buffer zones pass the test at 10% significance level. Under 1,600 meter buffer zone, even the full specification model does not pass F test. This is intuitive because turbines located further away from the observation routes have little impact on bird counts of the routes. Our results indicate that establishment of one additional turbine within a given buffer zone of a bird observation segment, on average, leads to a small increase in the observed grassland breeding bird count ranging from 0 to 0.81 across the three types of buffer zone. This seemingly surprising finding is not inconsistent with existing literature. For instance, by conducting surveys between 2009 and 2011 on breeding grassland songbirds around wind turbines on one wind farm in the north-central Texas, Hale et al. (2014) find that wind turbines lead to increase in population density of a few grassland bird species within 400m buffer zone. Shaffer and Buhl (2016) find that two out of nine species included in their study are either not affected or attracted by wind turbines. The underlying reasons for this might be barrier or disturbance caused by mechanical or human activities on a wind farm that reduce density of avian predators around wind turbines (Smith and Dwyer 2016; Winder et al. 2014). Table 2.3 also reveals that although increase in tower height (respectively, blade length) is positively (respectively, negatively) associated with grassland bird abundance which is similar to what we find in Table 2.2 for overall breeding bird abundance, their coefficients are statistically insignificant. This is perhaps because the two opposing forces underlying wind turbines' impacts on grassland bird abundance (i.e., decrease in predation risks vs. increase in collision risks) cancel out with each other.

Robustness

In this section we probe the robustness of our results to alternative variable or model specifications.[6] First, since turbines established in different years or owned by different wind farms may differ in their characteristics, one may be concerned that the use of average values of turbine height and blade length masks the heterogeneity of turbine characteristics and hence of their impacts. To address this concern, we further examine the heterogeneity across turbines

[6] We are indebted to two anonymous reviewers for comments and suggestions that led to the investigation documented in this section.

associated with an observation segment. We first identify the minimum, maximum, and standard deviation of turbine tower height and of blade length associated with each segment-year observation that has at least one turbine within a certain buffer zone. Then we obtain the average of the minimum, of the maximum, and of the standard deviations, respectively, across all the segment-year observations. Table 2.5 in Appendix presents these average values, from which we can see that the difference between the average minimum and average maximum values of a turbine characteristic is quite small. For instance, within the 400-meter buffer zone, the difference between the average maximum and the average minimum tower height is only about 1.4 meters, which is about 1.8% of the average minimum tower height. This indicates that wind turbines near a segment are quite homogeneous. The reason is that these turbines were likely established in the same year by the same developer.

Nevertheless, we re-run the regressions by replacing average values of tower height and of blade length with the maximum values of these two characteristics. See Columns (1) and (4) of Table 2.4 for results considering the 400-meter buffer zone. Due to space limitation, we present results considering the 800-meter and 1,600-meter buffer zones in Tables 2.6 and 2.7 in Appendix, respectively. As expected, due to the homogeneity of turbines near a segment, the regression results are close to what we have obtained based on the average turbine characteristics. For instance, when the average turbine tower height and blade length are included in the regressions for overall breeding bird counts, the coefficient of the number of wind turbines is -3.096, -1.667, and -0.970 for 400-meter, 800-meter, and 1,600-meter buffer zones, respectively (see columns (2), (4), and (6) of Table 2.2). When the maximum turbine tower height and blade length are used, the coefficient of turbine number becomes -2.924, -

1.683, and -0.965 under the three buffer zones, respectively, with similar significance levels (see Column (1) of Tables 2.4, 2.6, and 2.7).

Second, turbine number itself within a certain buffer zone does not reflect the impact of geographical distribution of winder turbines on bird abundance. For example, 100 evenly distributed turbines along an observation segment may have quite different impact on bird abundance than the same 100 turbines clustered around a point on the segment do. Because turbines within a wind farm are typically clustered together (as shown in Figure 2.2), the number of wind farms associated with a segment could be a measure of dispersion of wind turbines along a segment. Therefore, in addition to turbine number, we further control for the number of wind farms associated with an observation segment in the regressions. The results are presented in Tables 2.4, 2.6, and 2.7 (see Column (2) in these tables for overall breeding bird results and Column (5) for grassland breeding bird results). We find that the coefficient of the number of wind farms is insignificant regardless of bird types or buffer zones considered. Moreover, the sign, size, and significance levels of the coefficients of turbine number, tower height, and blade length are not affected much by including the number of wind farms in the regressions. This is perhaps because for most observation segments there is only one wind farm nearby. The lack of variation of the wind farm number variable in our dataset renders its own coefficient insignificant and other variables' coefficients only slightly affected by its inclusion.

Third, so far we have assumed a linear relationship between the number of wind turbines and bird abundance. However, the impact of wind turbines may be non-linear as shown in previous studies regarding the house price effect of wind turbines (e.g., Jensen et al. 2018). Therefore, we include a quadratic term of wind turbine numbers in the regressions. Results are presented in Tables 2.4, 2.6, and 2.7 as well (see Column (3) of these tables for overall breeding bird results and Column (6) for grassland breeding bird results). We find that as compared with the results from our basic model (i.e., Columns (2), (4), and (6) in Tables 2.2 and 2.3), the coefficient of the linear term of the wind turbine number has the same sign and similar magnitude. On the other hand, the coefficient of the quadratic term is insignificant regardless of bird types or buffer zone considered. Statistics of Akaike's information criterion (AIC) and of Schwarz's Bayesian information criterion (BIC) are smaller under the basic models (without the quadratic term) than under the models including the quadratic term (see Table 2.A4), indicating the basic models should be preferred (Cameron and Trivedi 2010, p.359).

Conclusions and Policy Implications

As many countries promote wind energy via various policies such as pricing laws, quota, tax credits, and direct subsidies (Saidur et al. 2010), the impact of wind energy development on wildlife have been put under scrutiny. This study examines wind turbines' impacts on breeding birds in the United States based on a unique dataset. Unlike previous studies that are mainly site- or species-specific, or that estimate national effects based on literature review, we harness tremendous information from four extensive and publicly available datasets on wind turbines, breeding bird abundance, land use, and weather information that cover the entire contiguous United States. Our data and approach mitigate concerns regarding the sample selection bias and omitted variable bias. Therefore, this study offers a more reliable evaluation of effects of wind turbines on overall breeding birds and grassland breeding birds in the United States.

Our estimates reveal that on average, the establishment of one additional turbine within a given proximity of a bird observation segment leads to disappearance of 1 to 3 breeding birds, depending on the size of buffer zone where wind turbines are located. Moreover, establishment of one additional turbine, on average, leads to a small increase in the abundance of grassland bird ranging from 0 to 0.81 around a bird observation segment. Based on the total number of onshore turbines at the 48,976 as of March 2014, we estimate that about 151,630 breeding birds are affected by wind energy in the United State. Although our estimate is at the lower end of the range of estimates from existing literature (i.e., from 20,000 to 573,000), the negative effect is expected to only increase due to ambitious goals of wind energy development in the United States and around the world (USDOE 2015; Saidur et al. 2010). Therefore, policy makers and wind energy developers should take into account the negative impacts of winder energy on bird abundance when improving policy instruments for wind energy or when developing new wind energy facilities. The findings of this study have the following implications for wind energy policies and developments.

First, our results show that breeding bird abundance responds more to turbines within a shorter distance and the impact of wind turbines fades quickly as the distance increases. When the distance increases to 1,600 meters, the impacts of wind turbines on breeding birds become largely insignificant. Therefore, wind energy policies may consider preventing wind turbines from being located within 1,600-meter bufferzones of areas with high density of bird habitat. This finding is also of practical interest because it can assist wind energy developers in making siting decisions for wind facilities, particularly in cases under which wind energy abundance and bird abundance are a tradeoff for siting decisions.

Second, our statistical approach has disentangled the effects of tower height from those of blade length and shown that the turbine height and blade length have opposing effects. That is, the higher the turbine towers are, the smaller the negative effect on overall breeding birds is; however, the longer the blade length, the larger the negative impact. Although wind turbines have become taller and larger (Caduff et al. 2012), in order to reduce the impact of wind turbines on breeding birds, future wind energy policies may need to particularly encourage taller, but not larger, turbines. Again, the tradeoff between energy generating (longer blade length preferable) and bird impact reduction (shorter blade length preferable) should be considered; results in this study can be used to reach informed decisions that balance the two aspects.

Finally, our results show that the impacts of turbines differ between overall breeding bird and grassland breeding birds. This indicates that responses of bird abundance to wind turbines may differ across bird species. Therefore, when making siting decisions for wind facilities, developers and policy makers should consider responses of specific bird species to wind turbines in candidate siting locations. Our analysis mainly focuses on aggregate abundance of breeding bird and masks the heterogeneity of responses across bird species. Therefore, there exists room for future research to examine how specific bird species of interest respond to wind turbines at national or regional level based on the dataset and approach developed in the present study.

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Wind farm

Bird observation route

Figure 2.1. Distribution of Wind Farms and Bird Observation Routes in the United States (2014)

Notes: Wind farm data are obtained from USGS (2014) and bird observation route data are from North American Breeding Bird Survey (BBS), USGS.

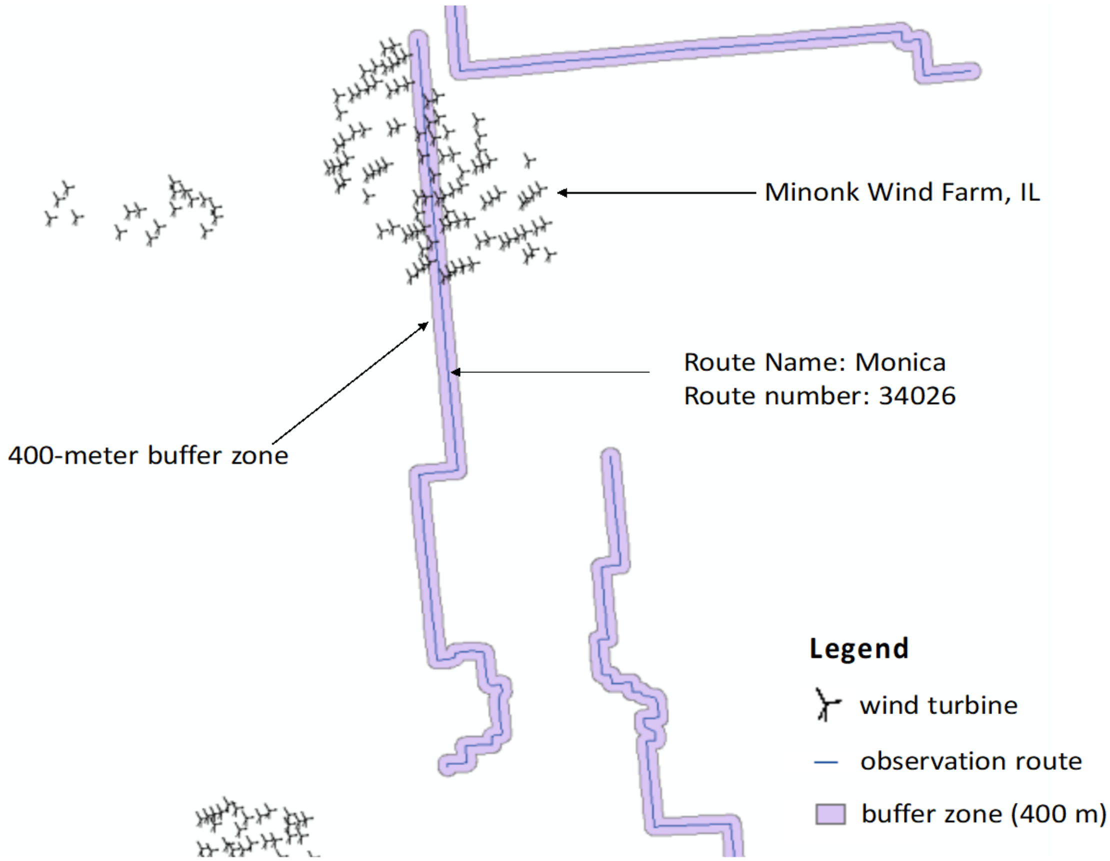

Figure 2.2. A sample of bird observation routes and wind turbines located in Minonk, Illinois (2014)

Notes: Wind turbine data are obtained from USGS (2014) and bird observation route data are from North American Breeding Bird Survey (BBS), USGS.

Table 2.1. Summary Statistics of Variables Used in the Fixed Effects Models

	400-meter buffer zone				800-meter buffer zone				1,600-meter buffer zone			
Variables	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Number of Birds Observed in a Route	407	209	31	1,546	386	198	31	1,546	381	182	31	1,546
Grassland Birds Observed in a Route	70	69	0	445	60	65	0	445	54	65	0	445
Crop Acreage in a Route (acre)	1,152	961	0	2,821	1,087	959	0	2,821	1,033	966	0	2,821
Grassland Acreage in a Route (acre)	950	872	7	2,972	837	806	0	2,972	776	772	0	2,972
Number of Turbines within buffer zones	3	6	0	31	5	10	0	59	8	16	0	114
Average Height of a Tower (meter)	37	40	0	100	33	39	0	100	33	39	0	100
Average Blade Length (meter)	19	21	0	53	17	21	0	52	17	20	0	53
Mean Temperature in March (°C)	4	6	-6.58	21	4	5	-6.58	21	3	5	-6.92	21
Mean Temperature in April (°C)	9	4	1.10	26	10	4	1.10	26	9	4	1.10	26
Mean Temperature in May (°C)	15	4	6.80	27	15	3	6.80	27	15	3	6.80	27
Average Precipitation in March (mm)	48	36	0	177	52	44	0	414	56	44	0	414
Average Precipitation in April (mm)	82	51	0	238	82	52	0	238	84	52	0	301
Average Precipitation in May (mm)	91	60	0	360	94	61	0	360	98	59	0	360

Table 2.2. Coefficient Estimates of Model (2) when Dependent Variable is Overall Breeding Birds Count

Variables	400-meter buffer zone		800-meter buffer zone		1,600-meter buffer zone	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Wind Turbines	-1.410	-3.096*	-0.716	-1.667**	-0.696	-0.970**
	(1.566)	(1.580)	(0.676)	(0.698)	(0.473)	(0.423)
Average Tower Height		4.264***		2.919**		2.069
		(1.241)		(1.379)		(1.632)
Average Blade Length		-7.856***		-5.105**		-3.578
		(2.437)		(2.520)		(2.959)
Crop Acreage	-0.016	-0.025	0.010	0.010	-0.008	-0.011
	(0.163)	(0.153)	(0.127)	(0.121)	(0.108)	(0.105)
Mean Temperature in March	-5.891	-15.270	0.993	-8.623	-35.661	-43.494
	(69.869)	(70.140)	(47.380)	(47.697)	(36.082)	(36.472)
Mean Temperature in April	220.740**	223.121**	199.961**	205.419**	134.203*	141.880*
	(106.903)	(107.287)	(87.215)	(86.533)	(73.246)	(71.410)
Mean Temperature in May	-164.633	-164.423	-141.672	-144.581	-121.177*	-122.011*
	(128.584)	(127.745)	(104.037)	(104.442)	(69.386)	(69.131)
Mean Precipitation in March	-1.015	-1.068	-1.037	-1.081	-1.461*	-1.490*
	(1.175)	(1.177)	(0.893)	(0.887)	(0.796)	(0.797)
Mean Precipitation in April	0.712	0.529	0.390	0.293	0.426	0.371
	(1.016)	(1.048)	(0.756)	(0.767)	(0.609)	(0.624)
Mean Precipitation in May	-0.068	-0.036	-0.037	-0.034	-0.007	-0.002
	(0.368)	(0.365)	(0.271)	(0.271)	(0.228)	(0.229)
Constant	-32.225*	-29.105	-16.821	-16.876	-24.490***	-24.050***
	(17.878)	(17.247)	(15.468)	(15.034)	(7.337)	(7.222)
No. of observations	176	176	243	243	326	326
p-values for *F* tests	0.117	0.001	0.099	0.003	0.324	0.147

Notes: Robust standard errors of coefficient estimates are the in parentheses. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. Here the number of observations is the number of segment differences in equation (2). Therefore, the number of observations in this table is a half of the number of observations in Table 2.1 or less. It can be less than a half because if a route is only observed for one year in the dataset then this route will be dropped in the fixed effects models (Wooldridge 2003, p.468).

Table 2.3. Coefficient Estimates of Model (2) when Dependent Variable is Grassland Breeding Birds Count

Variables	400-meter buffer zone		800-meter buffer zone		1,600-meter buffer zone	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Wind Turbines	0.195	0.809*	0.145	0.419**	0.114	0.131
	(0.300)	(0.439)	(0.106)	(0.200)	(0.083)	(0.089)
Average Tower Height		0.456		0.312		0.356
		(0.673)		(0.554)		(0.332)
Average Blade Length		-1.179		-0.842		-0.708
		(1.359)		(1.017)		(0.679)
Grassland Acreage	-0.016	-0.014	-0.016	-0.012	-0.018	-0.016
	(0.022)	(0.021)	(0.016)	(0.015)	(0.013)	(0.013)
Mean Temperature in March	-27.449	-25.344	-16.442	-15.192	-8.290	-8.817
	(24.048)	(24.304)	(15.285)	(15.412)	(11.995)	(12.337)
Mean Temperature in April	27.957**	20.545	24.238**	20.096**	12.274	12.634
	(13.772)	(12.337)	(10.932)	(9.626)	(10.547)	(10.087)
Mean Temperature in May	-26.202	-21.364	-18.590	-19.838	-0.176	-0.450
	(20.308)	(18.998)	(15.763)	(15.033)	(12.355)	(12.450)
Mean Precipitation in March	0.036	0.042	0.021	0.023	-0.027	-0.024
	(0.176)	(0.180)	(0.139)	(0.144)	(0.116)	(0.118)
Mean Precipitation in April	-0.068	-0.082	-0.145	-0.170	-0.190	-0.202*
	(0.130)	(0.138)	(0.113)	(0.121)	(0.116)	(0.116)
Mean Precipitation in May	-0.020	0.012	0.005	0.021	0.022	0.024
	(0.061)	(0.065)	(0.050)	(0.052)	(0.039)	(0.040)
Constant	-1.263	-0.008	-4.781***	-4.348***	-5.166***	-5.008***
	(1.507)	(2.202)	(1.170)	(1.305)	(0.727)	(0.814)
No. of observations	166	166	228	228	310	310
p-values for *F* tests	0.026	0.072	0.030	0.097	0.153	0.209

Notes: Robust standard errors of coefficient estimates are the in parentheses. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. Here the number of observations is the number of segment differences in equation (2). Therefore, the number of observations in this table is a half of the number of observations in Table 2.1 or less. It can be less than a half because if a route is only observed for one year in the dataset then this route will be dropped in the fixed effects models (Wooldridge 2003, p.468).

Table 2.4. Coefficient Estimates from Different Variable or Model Specifications (400-meter Buffer Zone)

	Overall Breeding Birds			Grassland Breeding Birds		
	Maximum Characteristics	Number of Farms	Square Term	Maximum Characteristics	Number of Farms	Square Term
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Wind Turbines	-2.924†	-4.462***	-4.463	1.045*	0.426	1.209
	(1.770)	(1.422)	(4.962)	(0.574)	(0.541)	(1.417)
Square of Wind Turbines			0.050			-0.014
			(0.203)			(0.043)
Tower Height	3.326***	5.168***	4.613**	-0.215	0.653	0.362
	(1.073)	(1.579)	(1.735)	(0.698)	(0.807)	(0.757)
Blade Length	-6.172***	-9.933***	-8.410***	0.0710	-1.636	-1.032
	(1.937)	(3.243)	(3.078)	(1.299)	(1.656)	(1.448)
Number of Wind Farms		21.09			4.759	
		(15.34)			(4.072)	
Land Coverage	-0.022	-0.038	-0.032	-0.014	-0.012	-0.015
	(0.156)	(0.162)	(0.183)	(0.022)	(0.022)	(0.021)
Temperature (March to May)	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation (March to May)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176	176	176	166	166	166
p-values for *F* tests	0.04	0.002	0.001	0.08	0.04	0.0007

Notes: Robust standard errors are the in parentheses. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. The dagger, †, denotes 10.8% level of significance. Columns (1) to (3) include results for overall breeding birds whereas columns (4) to (6) include results for grassland breeding birds. Columns (1) and (4) use the maximum tower height and blade length associated with an observation segment as a measure of tower characteristics. All other columns use the average tower height and blade length as a measure of tower characteristics. Columns (2) and (5) include the number of wind farms in the proximity of an observation segment in regressions. Columns (3) and (6) include the square term of wind turbine numbers in regressions.

Appendix

Table 2.A1. Characteristics of Turbines in the Proximity of Observation Segments

	Tower height (meters)			Blade length (meters)		
	Ave. Min.	Ave. Max.	Ave. STD.	Ave. Min.	Ave. Max.	Ave. STD.
400-meter buffer zone	77.2	78.6	0.7	39.6	40.8	0.6
800-meter buffer zone	75.6	76.9	0.7	38.6	40.1	0.7
1,600-meter buffer zone	74.2	76.9	1.1	37.8	40.0	0.9

Note: We first identify the minimum, maximum, and standard deviation of a characteristic of the turbines for each segment-year observation that has at least one wind turbine within a certain buffer zone. Then we obtain the average of the minimum, of the maximum, and of the standard deviations, respectively, across all the segment-year observations that have at least one wind turbine within a certain buffer zone.

Table 2.A2. Coefficient Estimates from Different Variable or Model Specifications (800-meter Buffer Zone)

	Overall Breeding Birds			Grassland Breeding Birds		
	Maximum Characteristics	Number of Farms	Square Term	Maximum Characteristics	Number of Farms	Square Term
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Wind Turbines	-1.683**	-1.407†	-2.029	0.537*	0.579*	0.474
	(0.779)	(0.991)	(2.823)	(0.274)	(0.302)	(0.794)
Square of Wind Turbines			0.007			-0.0009
			(0.053)			(0.012)
Average Tower Height	2.708**	2.642*	3.098	-0.175	0.164	0.288
	(1.131)	(1.532)	(2.239)	(0.669)	(0.589)	(0.730)
Average Blade Length	-4.751**	-4.501	-5.391	0.037	-0.516	-0.803
	(2.002)	(2.845)	(3.795)	(1.180)	(1.108)	(1.261)
Number of Wind Farms		-5.847			-3.213	
		(11.01)			(4.162)	
Land Coverage	0.008	0.012	0.007	-0.012	-0.013	-0.012
	(0.123)	(0.121)	(0.138)	(0.015)	(0.015)	(0.015)
Temperature (March to May)	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation (March to May)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	243	243	243	228	228	228
p-values for F tests	0.01	0.002	0.003	0.046	0.185	0.0011

Note: Robust standard errors are the in parentheses. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. The dagger, †, denotes 16% level of significance. Columns (1) to (3) include results for overall breeding birds whereas columns (4) to (6) include results for grassland breeding birds. Columns (1) and (4) use the maximum tower height and blade length associated with an observation segment as a measure of tower characteristics. All other columns use the average tower height and blade length as a measure of tower characteristics. Columns (2) and (5) include the number of wind farms in the proximity of an observation segment in regressions. Columns (3) and (6) include the square term of wind turbine numbers in regressions.

Table 2.A3. Coefficient Estimates from Different Variable or Model Specifications (1,600-meter Buffer Zone)

	Overall Breeding Birds			Grassland Breeding Birds		
	Maximum Characteristics	Number of Farms	Square Term	Maximum Characteristics	Number of Farms	Square Term
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Wind Turbines	-0.965**	-0.980*	-1.177	0.150	0.136	-0.110
	(0.430)	(0.503)	(0.906)	(0.095)	(0.126)	(0.236)
Square of Wind Turbines			0.002			0.003
			(0.008)			(0.002)
Average Tower Height	2.179	2.072	2.123	0.023	0.353	0.418
	(1.337)	(1.646)	(1.752)	(0.403)	(0.328)	(0.333)
Average Blade Length	-3.825	-3.595	-3.645	-0.095	-0.699	-0.785
	(2.427)	(3.027)	(3.112)	(0.773)	(0.674)	(0.676)
Number of Wind Farms		0.562			-0.271	
		(11.25)			(4.064)	
Land Coverage	-0.013	-0.012	-0.015	-0.017	-0.016	-0.015
	(0.106)	(0.105)	(0.115)	(0.013)	(0.012)	(0.013)
Temperature (March to May)	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation (March to May)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Observations	326	326	326	310	310	310
p-values for *F* tests	0.14	0.1189	0.0001	0.18	0.253	0.002

Note: Robust standard errors are the in parentheses. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. Columns (1) to (3) include results for overall breeding birds whereas columns (4) to (6) include results for grassland breeding birds. Columns (1) and (4) use the maximum tower height and blade length associated with an observation segment as a measure of tower characteristics. All other columns use the average tower height and blade length as a measure of tower characteristics. Columns (2) and (5) include the number of wind farms in the proximity of an observation segment in regressions. Columns (3) and (6) include the square term of wind turbine numbers in regressions.

Table 2.A4. Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC) for the Models with and without the Quadratic Term of Number of Wind Turbines

		Overall Breeding Birds			Grassland Breeding Birds		
		400m buffer zone	800m buffer zone	1,600m buffer zone	400m buffer zone	800m buffer zone	1,600m buffer zone
AIC	with quadratic term	2171.4	2927.1	3881.8	1474.9	1970.6	2658.7
	without quadratic term	2169.5	2925.1	3879.8	1473.0	1968.6	2657.8
BIC	with quadratic term	2206.3	2965.5	3923.5	1509.1	2008.3	2699.8
	without quadratic term	2201.2	2960.0	3917.7	1504.1	2002.9	2695.2

Chapter 3: Crop Insurance Premium Subsidy and Irrigation Water Withdrawals in the Western United States

Introduction

We examine the impact of the federal crop insurance premium subsidy on freshwater withdrawals for irrigation in the western United States. Crop insurance premium subsidy has increased significantly since the Federal Crop Insurance Reform Act of 1994 (Figure 3.1) and has been under scrutiny for its impact on agricultural input use (Goodwin, Vandeveer, and Deal 2004; Miao, Hennessy and Feng 2016; Weber, Key, and O'Donoghue 2016; Deryugina and Konar 2017; Yu, Smith, and Sumner 2018). On the other hand, irrigated agriculture, the largest water user, consumes about 80 to 90 percent of the nation's total freshwater withdrawals (Schaible and Aillery 2017; Schaible 2017). Therefore, even a small percentage change in freshwater withdrawals for irrigation involves a large amount of water. As a result, better understanding of the relationship between policy incentive such as changes in the crop insurance premium subsidy and changes in freshwater withdrawals for irrigation is meaningful for improving the policy and freshwater conservation.

Highly subsidized federal crop insurance program has become the major instrument of the federal government to support U.S. farmers. It accounts for a large share of spending in the 2018 Farm Bill (Yu and Hendricks 2019; Wu, Goodwin, and Coble 2019). Measured in 2018 dollars, the premium subsidy amount has increased from \$1.20 billion in 2001 to \$6.17 billion in 2018 (Risk Management Agency (RMA) 2019). Moreover, according to the May 2019 baseline, the outlays for the insurance program are projected to be \$92 billion during 2019-2029 (CBO 2019). Government pays, on average, about 62% of total premium for the yield-based and revenue-based crop insurance policies, and almost 100% of total premium for catastrophic coverage (Shields 2015). All major crops in the United States are now protected either from yield loss or revenue loss by crop insurance (Shields 2015).

The crop insurance program, particularly the subsidy schedule, evolved significantly in the past thirty years. The Federal Crop Insurance Act of 1980 expanded the number of crops covered by crop insurance, with up to 30% of insurance premium covered by the federal government (Glauber 2013). Due to the limited premium subsidy, however, crop insurance take up was low during the 1980s and early 1990s (see Figure 3.1). The Crop Insurance Reform Act of 1994 significantly increased insurance premium subsidy rate (e.g., from 30% to 42% for insurance plans with 65% coverage level, excluding area-based plans), with a newly created catastrophic risk protection policy completely subsidized. Later on, the Agricultural Risk Protection Act of 2000 again increased premium subsidy rate, after which the subsidy rate remained quite stable, with smaller scale changes in the 2008 and 2014 Farm Bills (see Figure 1 in Yu, Smith, and Sumner 2018). Currently, for most insurance policies, the subsidy rates are 67%, 64%, 64%, 59%, 59%, 55%, 48%, and 38% for coverage levels at 50%, 55%, 60%, 65%, 70%, 75%, 80%, and 85%, respectively (see Table 1 in Shields 2015). Subsidy rate for the catastrophic coverage plans is still 100%. Among these coverage levels, 65% and 75% are the most commonly selected by farmers (Yu, Smith, and Sumner 2018), and 75% coverage plans are most popular for revenue insurance (see Table 4 in Du, Feng, and Hennessy 2017). Based on Babcock (2015), one possible explanation for why plans with 75% coverage level have become dominant in the market is that these plans perhaps provide farmers with the largest difference between indemnity received and premium paid. We refer readers to Babcock (2015) and Du, Feng, and Hennessy (2017) for further discussions about farmers' crop insurance coverage level choices.

On the other hand, meeting growing demands for water from competing sectors is one of the most important resource management issues in the United States (Yigzaw and Hossain 2016;

Wilson, Sleeter, and Cameron 2017). Since the World War II, the U.S. population has increased 2.35 folds (from 139.93 million in 1945 to 329.34 million in 2020), while total freshwater demand has tripled, which is expected to create water shortages in 40 states by 2024 (U.S. Environmental Protection Agency (USEPA) 2020). Crop irrigation consumes about 75% of total freshwater withdrawals at the national scale (IPBES 2019) and over 90% in many western states (USDA 2019). Farmers withdraw approximately 27.2 trillion gallons (83.38 million acre-feet) of freshwater per year to irrigate about 55.94 million acres of croplands (see Table 4 of USDA 2019), among which most is used in the western United States (defined as area to the west of the 100th Meridian in this study).

The existing crop insurance program may influence farmers' irrigation decisions via at least three channels. First, premium subsidies of crop insurance encourage farmers to plant crops on marginal lands (Miao, Hennessy, and Feng 2016; Claassen, Langpap, and Wu 2017), which may require more freshwater withdrawals for irrigation. Second, an increase in premium subsidy induces enterprise specialization among farm operators (see e.g., O'Donoghue, Roberts, and Key 2009), which may encourage farmers to specialize in water-intensive crops such as corn. Third, during extreme events such as drought when farmers should irrigate more to keep their crop alive, by ensuring guaranteed level of income for losses in crop yields or revenue, crop insurance program may disincentivize such effort (Deryugina and Konar 2017), a behavior known as moral hazard.

There is a growing body of literature focusing on the impacts of crop insurance program on farm inputs such as the uses of fertilizers, pesticides, and land (e.g., Goodwin, Vandeveer, and Deal 2004; Miao, Hennessy, and Feng 2016; Weber, Key, and O'Donoghue 2016; Claassen, Langpap, and Wu 2017; Yu, Smith, and Sumner 2018). These empirical studies find that crop insurance program has either small or no effect on farmers' input use decisions. Existing research, however, has not yet shed much light on the impact of crop insurance on freshwater withdrawals for irrigation in the United States. The sole exception is the study by Deryugina and Konar (2017). Analyzing county level freshwater withdrawals for irrigation data for two years (1990 and 1995), the authors find evidence that total freshwater withdrawals for irrigation is not much sensitive to insured acreage, with elasticity at 0.223. However, the authors mainly examine the immediate effects of the Federal Crop Insurance Reform Act of 1994, which had substantially raised premium subsidy and participation rate in 1995 (see Figure 3.1), on freshwater withdrawals for irrigation. Since the authors did not analyze data for the post-1995 era, their findings may not capture all institutional changes of the crop insurance program that have taken place in the last twenty-five years. Moreover, the authors do not control for weather variables in their analysis such as temperature and precipitation that obviously determine freshwater withdrawals for irrigation. By omitting weather information in regression, their estimated parameters are likely to suffer from the omitted variable bias because weather variation in a region can be correlated with production risk and hence insurance take-up in the region.

We examine the causal impacts of crop insurance program on scarce freshwater resources by exploiting more comprehensive and updated data based on the instrumental variable approach. In this endeavor, our study departs from the earlier literature in four ways. First, we construct a comprehensive dataset from 1989 to 2015 for contiguous U.S. counties to the west of the 100th meridian. The farm operators in these counties use 75% of total freshwater withdrawals and 89% of total fresh surface water withdrawals for irrigation within the United States (see Figure 3.2). Second, unlike the early literature, we construct a novel instrument that captures both temporal and spatial variation of premium subsidy during the entire study period. Third, instead of limiting our study to analyzing overall impact of insurance program on freshwater withdrawals for irrigation, we expand our analysis by exploring the extent to which the yield and revenue insurance policies influence freshwater withdrawals for irrigation. This is of interest because the federal crop insurance program protects insured farmers from crop yield or revenue losses. In the last two decades, however, more croplands have been insured with revenue insurance policies than yield insurance policies (see Figure 3.3). Therefore, better understanding of the influence of these two major types of insurance policies on environmental sustainability is in order. Additionally, we mitigate the omitted variable bias by incorporating relevant weather variables in our regressions. This study also adds to the literature on agricultural sustainability in that it highlights an unintended effect of crop insurance program, a risk management tool, on freshwater use. Early studies claim that agricultural is the major contributor to depletion of water resources (Ripl 2003; Lilienfeld and Asmild 2007; Scanlon et al., 2012; Perez-Quesada and Hendricks 2021). Our findings underscore the importance of the crop insurance program in contributing to water resource depletion caused by agriculture in the United States.

The main challenge in identifying the response of freshwater withdrawals for irrigation to the crop insurance premium subsidy is that the premium subsidy is endogenous to freshwater withdrawals for irrigation. For example, unobserved risk preferences of farmers may affect both their crop insurance choices and freshwater withdrawals for irrigation decisions. In addition, insurance premium reflects the riskiness of production on a farm, and the riskiness is associated with input uses including water. To address this endogeneity issue, we follow early literature (e.g., Yu, Smith, and Sumner 2018; Delay 2019) and use the interaction term between a county level annual premium subsidy rate at 75% coverage level of insurance policies and the county level percentage of insured acres in 1989 as the instrumental variable. This interaction term varies both temporally and spatially so that it has a stronger correlation with the premium subsidy than does premium subsidy rate or percentage of insured acres individually. Moreover, it is unlikely to be related with other factors influencing county-level freshwater withdrawals for irrigation during our sample period because the premium subsidy rate is set by national agricultural acts and the percentage of insured acres in 1989 is predetermined to our sample period (1990-2015).

Our estimates indicate that holding everything else constant, a 1% increase in the total premium subsidy amount leads to an increase in total freshwater withdrawals for irrigation by 155,073 million gallon (Mgal) (about 475,901 acre-feet) and fresh surface water withdrawals for irrigation by 154,462 Mgal (about 474,026 acre-feet) a year across all the western states. When evaluated at the sample means, the aforementioned numbers translate into 0.446 and 0.673 respectively in terms of freshwater withdrawal elasticity with respect to premium subsidy amount. We can see that, similar to earlier studies on the impact of crop insurance, the elasticities are less than unity. We do not find evidence that the federal crop insurance premium subsidy influences groundwater withdrawals for irrigation. Furthermore, we find that a 1% increase in subsidy amount for revenue insurance policies, on average, leads to over 2.3 times more total freshwater withdrawals for irrigation and fresh surface water withdrawals for irrigation than does the impact of a 1% increase in subsidy amount for yield insurance. Given that crop insurance's impact on expanding cropland is extremely small (with elasticity at 0.043 or even smaller found by Yu, Smith, and Sumner (2018) and Goodwin, Vandeveer, and Deal (2004)), our results suggest that crop insurance's impact on freshwater withdrawals for irrigation mainly occurs at the intensive margin rather than at the extensive margin. Moreover, because the elasticities are all positive, moral hazard should not be a dominant factor in the relationship between crop insurance subsidies and freshwater withdrawals for irrigation.

The rest of the article is organized as follows. In Section 2, we present a conceptual framework to discuss potential channels through which crop insurance program may affect freshwater withdrawals for irrigation. Section 3 describes the data and variables, and Section 4 explains our empirical strategy to identify the relationship between the focal variable and freshwater withdrawals. Empirical findings and robustness checks follow in Section 5. Section 6 concludes.

Conceptual Framework

This section presents an intuitive conceptual framework to explore potential channels through which the crop insurance premium subsidy may affect freshwater withdrawals for irrigation. We conjecture that the crop insurance program affects water use via three channels: land-use change, crop choices, and moral hazard, which are described in what follows.

It is reasonable to believe that if more land is cultivated then more freshwater will be withdrawn for irrigation. Early literature indicates that the highly subsidized crop insurance program encourages farmers to convert marginal land (e.g., grassland or pastureland) to cropland (Miao, Hennessy, and Feng 2016; Claassen, Langpap, and Wu 2017; Yu, Smith, and Sumner 2018). It is also worth noting that the subsidized crop insurance makes participation in the Conservation Reserve Program less attractive (Delay 2019). As a result, farmers may retain environmentally sensitive land for cropping, which may trigger more freshwater withdrawals for irrigation.

Second, crop choice can be another potential channel through which crop insurance program affects agricultural water use. Clearly, subsidized crop insurance alters the risk portfolio and expected returns of insured crops relative to uninsured crops (Goodwin, Vandeveer, and Deal 2004; Miao and Khanna 2017). It therefore affects crop mix (Yu and Sumner 2018) and consequently water uses. Moreover, subsidized crop insurance incentivizes crop specialization (O'Donoghue, Roberts, and Key 2009). This impact can increase or decrease freshwater withdrawals for irrigation because it may lead to increased cropping in either water-saving crops or water-intensive crops, depending on water availability and other resource endowment for crop production. This crop specialization effect of crop insurance premium subsidy can be viewed as an intensive margin effect as it is pertaining to production change within existing cropland.

Moral hazard occurs as a principal-agent problem in the insurance market where the insured agents do not take appropriate precautions, which may increase the risk of losses. Because insured farmers' irrigation behavior is imperfectly observable to the insurance providers, sufficient water may not be used for irrigation, which will increase the probability of yield loss or revenue loss relative to what the losses that the farmers would have incurred without insurance.[7] From a different perspective, if one view irrigation as a type of self-insurance, then to some extent the presence of crop insurance will crowd-out the use of irrigation and therefore reduce water use.[8]

It is unclear which channel discussed above dominates in actual agricultural production. Moreover, due to data limitation, we cannot differentiate the effects from the three channels. As

[7] To address the moral hazard problem, crop insurance policies have a good management practice clause, which asks farmers to provide "adequate water" to the insured crop lands. The good management practice clause, however, does not eliminate moral hazard problem (see e.g., Annan and Schlenker 2015; Deryugina and Konar 2017; Yu and Hendricks 2019).

[8] This substitutional relationship between crop insurance and some input uses has been discussed in detail in the literature. Recent examples include Woodard et al. (2012), Yu and Sumner (2018), and Miao (2020).

a result, we can only estimate the aggregate effect, which is an empirical question to be discussed in detail in the remaining sections of the paper.

Data and Variables

We specify three outcome variables for freshwater withdrawals for irrigation: fresh surface water withdrawals for irrigation, fresh groundwater withdrawals for irrigation, and total freshwater withdrawals for irrigation for a county-year combination. We obtain county-level data for these three variables from the United States Geological Survey (USGS) National Water Information System. These data are available for the period of 1985–2015 observed every five years. Freshwater withdrawal for irrigation is measured as average daily withdrawals for irrigation in a county (in million gallons per day, Mgal/d) in a reported calendar year by source such as fresh groundwater and fresh surface water (Dieter et al. 2018, p. 4). To measure irrigation water withdrawals, the USGS utilized both direct and indirect approaches where the direct approach includes personal contact, surveys, and data reported by individual water-right holders and the indirect approach includes estimates of crop water needs where ancillary data such as irrigated crop acreage, specific crop water-consumption coefficients, and soil-moisture balance are used (Dieter et al. 2018, p. 26; Bradley 2017, p. 31-33). The inclusion of estimated data causes measurement error in the outcome variable, which is likely correlated with the crop insurance premiums or liabilities. As a result, the crop insurance variable in the econometric model is endogenous. We use an instrumental variable approach to address the endogeneity issue of the insurance variable and conduct thorough robustness checks to establish the reliability of obtained results. Moreover, as Deryugina and Konar (2017) point out, due to this data issue (i.e., part of the withdrawal data are estimated), the estimates are more conservative and "should be viewed as lower bounds, because we would expect no relationship between crop insurance and solely approximated withdrawal data."

We obtain data for the federal crop insurance program from the *Summary of Business Reports* published by the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA).[9] The *Summary of Business Reports* data provide information on the county-level premium subsidy amount, liability amount, insured crop acreage, and coverage level. The coverage level information of insurance policies is available since 1989. This dataset, however, does not provide information for the irrigated and non-irrigated insured acreage at the county level. Following Yu, Smith, and Sumner (2018), we use the premium subsidy per dollar of liability (hereafter PSPDL) as the key explanatory variable in our analysis. This is because PSPDL captures the magnitude of premium subsidy and meanwhile mitigates the influence of crop prices on the premium subsidy amount. We construct PSPDL as follows. First, we calculate the total premium subsidy amount by summing the dollar amount of the premium subsidy paid for each type of insurance plans and each insured crop in a county-year. Similarly, we calculate the total liability amount for a county-year. Then, the PSPDL is equal to the total premium subsidy amount in a county-year divided by the respective total liability amount in that county-year. To examine the impact of yield insurance and, separately, revenue insurance, we also calculate PSPDL of these two types of insurance by following a similar procedure.

Moreover, to address the potential endogeneity of the PSPDL, we construct the instrumental variable as follows. We first calculate the premium subsidy rate for all buy-up coverage policies (including both yield and revenue insurance policies) with 75% coverage level as the total subsidy amount received by insured farmers with such policies divided by the total

[9] Available online at: https://www.rma.usda.gov/SummaryOfBusiness (accessed July 4, 2020).

premium of these policies for every county-year. We choose 75% coverage level because it is one of the most opted coverage levels and spans the full sample period. We then calculate a county-level percentage of insured acres in 1989, by using total insured acres divided by total harvested acres in a county in 1989. The instrumental variable is the product of this county-level percentage of insured acres in 1989 and the aforementioned premium subsidy rate at 75% coverage level. The validity of this instrumental variable is to be discussed in the next section.

Weather—particularly temperature and precipitation—affects soil moisture and evapotranspiration, and therefore influences farmers' irrigation decision. We control for county specific maximum temperature and monthly precipitation for the growing season that spans April to September. The weather data are obtained from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) managed by the Oregon State University.

By compiling the aforementioned variables, we construct a county-level unbalanced panel dataset at a five-year interval from 1990 to 2015 for 522 counties to the west of the 100^{th} meridian in the contiguous United States. We restrict our sample to these western counties because the western United States consumes the majority of freshwater withdrawals for irrigation in the country. From Figure 3.2 we can see that over 1990-2015, farmers in these selected counties used about 90% of fresh surface water withdrawals for irrigation and about 80% of total freshwater withdrawals for irrigation in the United States. In addition, due to lack of reporting standards and the consequent data inconsistencies and quality issues, irrigation data for the eastern states are "unsuitable for use in the development of predictive models" (Levin and Zarriello 2013). Tables 3.1 and 3.2 provide the summary statistics for the data used in this study.

Estimation Strategy

The empirical model is given by

$$Y_{it} = \beta_0 + \beta_1 PSPDL_{it} + \boldsymbol{\beta_2 X_{it}} + \delta_t + \gamma_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} stands for the freshwater withdrawals for irrigation in county $i \in \{1,...,N\}$ and year $t \in \{1990,1995,...,2015\}$, here N is the number of counties in the sample; β_0, β_1, and $\boldsymbol{\beta_2}$ are the coefficients or vector of coefficients to be estimated; $\boldsymbol{X_{it}}$ is a vector of time-varying control variables such as temperature and precipitation that capture weather variation.[10] Additionally, δ_t and γ_i stand for year and county fixed effects, respectively, where the former is used to control for national level shocks such as prices and technological changes whereas the latter is to control for time-invariant and unobservable variables that may affect aggregate freshwater withdrawals for irrigation such as geographical location and soil quality. Lastly, ε_{it} is an error term.

PSPDL can be endogenous for at least two reasons. First, when enrolling in the insurance program, farmers choose from a menu of subsidy rates for their preferred coverage level and quoted premium rates. However, the information about individual farmer's risk aversion parameter is unavailable to us. The risk aversion parameter is a confounding variable that influences participating farmers' insurance coverage level, premium, and thus PSPDL. It also affects a farmer's irrigation decisions because irrigation can be viewed as a form of self-insurance. Therefore, omitting the unobservable risk aversion variable may cause a bias in least-squares estimates of the PSPDL parameter. The second reason is reverse causality. Insurance premium reflects the riskiness of production on a farm, and the riskiness is determined by input uses including freshwater withdrawals for irrigation. Therefore, it is likely that famers' choices of insurance coverage levels depend on their expected freshwater withdrawals for irrigation.

[10] Note that coefficient β_1 measures the aggregate effect of PSPDL on freshwater withdrawals for irrigation. Due to data limitation, we cannot separate partial effects of the three potential channels discussed in the conceptual framework.

Third, the presence of insurance liability in PSPDL may cause the endogeneity of PSPDL. This is because insurance liability is determined by many factors such as futures prices, coverage levels, and crop yield history. Yield history is highly likely to be correlated with the error term of the empirical models in that factors affecting irrigation water use will also affect crop yields. In sum, PSPDL is endogenous and its least-squares estimator cannot be used for causal interpretation.

To address the potential endogeneity of PSPDL, early literature exploits a government-set exogenous variation in premium subsidy rates to construct an instrument (e.g., Yu, Smith, and Sumner 2018). Premium subsidy rates, which vary across the types of insurance policies and coverage levels, are determined by the farm bill legislations and implemented in all counties across the nation. Therefore, premium subsidy rates do have temporal (within-county) variation, but it does not have spatial (between-county) variation, which weakens the correlation between the instrumental variable and the endogenous variable. To overcome this issue, we follow the approach in Deryugina and Konar (2017) to use a predetermined crop insurance variable that is correlated with the current period insurance variable but uncorrelated with other time-varying variable that might affect water use. Specifically, we calculate the percentage of insured acres for each county in 1989, which is spatially varying but temporally invariant (see Figure 3.A1 in the Appendix for spatial variation of this percentage). We then obtain the product of this percentage of insured acres in 1989 and subsidy rates at 75% coverage level of insurance policies for each county-year in the spirit of DeLay (2019). We use this product as the instrumental variable for PSPDL.[11]

[11] With an assumption of monotonicity (i.e., the IV only causes the endogenous variable to change in one direction), Angrist, Imbens, and Rubin (1996) show that the IV estimator identifies the local average treatment effect (LATE) of compliers, individuals who positively respond to the IV. In the present study, the monotonicity assumption is reasonable because an increase in subsidy rate caused by legislation

We believe that this product is a valid instrument for the following reasons. First, as illustrated in Yu, Smith, and Sumner (2018) and Delay (2019), exogenous increase in the subsidy rates of insurance policies with 75% coverage level over time due to successive legislative changes provides within county variation in the premium subsidy amount, but remains unaffected by endogenous factors related to freshwater withdrawals for irrigation, which indicates that subsidy rates are correlated with PSPDL and uncorrelated with the error term in equation (1). Second, the percentage of insured acres in 1989 was predetermined before our sample period (1990-2015) and was not influenced by endogenous factors related to county level freshwater withdrawals for irrigation in the later years. One might be concerned that this predetermined spatial variation in insured acres in 1989 is correlated with the error term because some confounding factors (e.g., production risk and resource endowment in a county) that determine the insured acreage in 1989 persist in later years. In other words, if serial correlation exists in the error term, then this predetermined ratio of insured acreage in 1989 can be correlated with the error term in later years, which renders the instrumental variable invalid. We believe that, to some extent, the inclusion of year and county fixed effects can mitigate this concern. Year fixed effects can largely control for the national level shocks such as prices and technological changes that may be autocorrelated, while county fixed effects control for time-invariant confounding factors that may affect irrigation water withdrawals and cropland acreage such as geographical location and land endowment. Arguably, farmers' risk preferences, another potential confounding factor, are stable and can also be reflected in the fixed effects (see a recent

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changes will only increase the subsidy amount per dollar of liability. Therefore, the impact of PSPDL estimated in the present study is the impact within the group of farmers who takeup crop insurance responding to the increase of premium subsidy rate. We believe that this group of farmers (i.e., the compliers) are quite large and hence the IV estimates are of policy relevance because before the series of increases in premiums subsidy rate the insurance takeup rate was about 20% and after that it was more than 80% (Deryugina and Konar 2017).

discussion on the stability of risk preferences by Schildberg-Hörisch (2018)). Therefore, once we control for the current weather variables as well as the year and county fixed effects, it is unclear how and why the pre-determined insured acreage ratio might be correlated with the error term.

Results

For each freshwater withdrawal for irrigation variable (i.e., total, ground, and surface water withdrawals for irrigation), we estimate two specifications of equation (1). Although both specifications use fixed effects panel data models, the first specification (namely, FE) assumes that all the explanatory variables are strictly exogenous whereas the second one employs the instrumental variable approach (namely, FE-IV) to address the endogeneity of PSPDL. We use the estimated parameters from the FE-IV approach to quantify the causal relationships between the federal crop insurance program and freshwater withdrawals for irrigation. We also compare those parameters across the two major types of crop insurance policies—yield and revenue insurance policies.

In the FE-IV regression analysis, we use the Kleibergen-Paap *rk* LM statistic to detect under-identification. In addition, we use Cragg-Donald Wald *F* statistic and Kleibergen-Paap *rk* Wald *F* statistic critical values to examine if the instrument is weak. All these *F* statistics are larger than 10, which suggests that our instrumental variable passes the weak IV test. Over-identification is not relevant for our analysis because we have exactly same number of endogenous and instrumental variables. The standard errors are clustered at the level of climate divisions to allow the error term to be correlated among neighboring counties. A climate division is defined by the National Centers for Environmental Information (NOAA) and is a group of adjacent counties that share similar climatic conditions. For further details on climate divisions, we refer readers to NOAA (2021).

Main Results

Table 3.3 presents the estimation results of the aforementioned two specifications for each of the total, ground, and surface freshwater regressions. Columns (1)-(3) in the table present the estimated coefficients of the FE approach for which we assume that all explanatory variables are exogenous, whereas columns (4)-(6) in the table present the corresponding estimates of the FE-IV approach. The first-stage regression result of the FE-IV approach is presented in Table 3.A1 in the Appendix, where we show that the *F* statistics are quite large and the coefficient of the instrumental variable is statistically significant at 1% significance level. This indicates that the instrumental variable is strong.

Table 3.3 shows that the estimated coefficients of PSPDL in Columns (4)-(6) are substantially larger (over 4.5 times) relative to their counterparts in columns (1)-(3), suggesting that linear fixed effects estimates without using the instrumental variable approach suffer from downward bias. This downward bias may result from the reverse causality that irrigation, as a type of self-insurance for farmers, crowds out the demand for crop insurance.

Specifically, column (4) in Table 3.3 presents results for the total freshwater regression and shows that the estimated parameter of PSPDL is 1,179.53. When evaluated at the sample means of total freshwater withdrawals for irrigation and PSPDL (i.e., 182.49 Mgal/day and 0.069, respectively, see Table 3.1), the elasticity of total freshwater withdrawals for irrigation with respect to PSPDL is 0.446 (calculated as 1179.53×0.069/182.49).[12] This indicates that, holding everything else fixed, one percent increase in the premium subsidy amount in a county, on average, leads to a 0.446% (or 0.814 Mgal/Day) increase in total freshwater withdrawals for irrigation. The coefficient of PSPDL in column (5) that contains the regression results from the

[12] Because the analysis is based on data available every five years, we believe that the estimated elasticity is closer to a "long-run" elasticity than is an annual-data-based estimate.

model for groundwater withdrawal, however, is somewhat unexpected. Though the coefficient has a positive sign, nevertheless, it is statistically insignificant; it indicates that an increase in the premium subsidy does not influence farmers' groundwater withdrawal behavior. One plausible reason for this result is that unlike fresh surface water withdrawals, groundwater withdrawals for irrigation data for 17 western states may suffer from considerable measurement errors (Perrone and Jasechko 2017; Reilly et al. 2008), which attenuates the estimated coefficients toward zero.

Column (6) in Table 3.3, results from the surface water regression under the FE-IV approach, indicates that the coefficient of PSPDL is 1,175.79. This implies that, when evaluated at the sample means, a one-percent increase in the premium subsidy amount in a county, on average, leads to a 0.673% (or 0.811 Mgal/day) increase in fresh surface water withdrawals for irrigation.[13] Although not directly comparable due to the difference in data and econometric approach, our findings are largely consistent with earlier studies. Specifically, Deryugina and Konar 2017 find that a one-percent increase in the insured crop land, on average, leads to an increase in total freshwater, fresh groundwater, and fresh surface water withdrawals by 0.223%, 0.275%, and 0.148%, respectively.

A back-of-the-envelope calculation may put the elasticity discussed above in perspective. For total freshwater, the sample mean is 182.49 Mgal/Day/County across 522 counties. Therefore, we use 522×(182.49×365)×0.00446 to obtain that a 1% increase in the total premium subsidy amount leads to an increase in total freshwater withdrawals for irrigation by 155,073 Mgal (about 475,901 acre-feet) a year in these 522 counties. Calculated in a similar way, for fresh surface water, with the sample mean at 120.46 Mgal/Day/County, water withdrawal will increase by 154,462 Mgal (about 474,026 acre-feet) per year for a 1% increase in the total

[13] Here 0.673% is calculated by using (1175.79×0.069/120.46)%, where 120.46 is the sample mean of fresh surface water withdrawals in Mgal/day. In addition, 0.811 is calculated by using 0.673%×120.46.

premium subsidy amount. To put this in perspective, this 155,073 Mgal of water is about 6% of total urban water use in California in a year (Mount and Hanak 2009) and is about 0.02% of Ogallala Aquifer storage in 2013 (McGuire 2014).

The first row in Table 3.4 summarizes elasticity of total freshwater and fresh surface water withdrawals for irrigation with respect to the PSPDL of crop insurance. The groundwater column presents zero because the coefficients of the PSPDL coefficient in the groundwater regression is statistically insignificant in Table 3.3. The elasticity values of the crop insurance program in general are less than unity. However, given that crop insurance's impact on expanding cropland is extremely small (e.g., 0.043 or even smaller as shown by Yu, Smith, and Sumner (2018) and Goodwin, Vandeveer, and Deal (2004)), we conjecture that crop insurance's impact on irrigation mainly occurs at the intensive margin rather than at the extensive margin. Moreover, because the elasticities are all positive, we also postulate that moral hazard should not be a dominant factor in the relationship between crop insurance subsidies and freshwater withdrawals for irrigation.[14]

Yield and Revenue Insurance Policies

We now consider how the yield insurance and revenue insurance policies influence freshwater withdrawals for irrigation. These two major insurance policies for the field crops together accounted for 61.89% of total liability, and 91.23% of premium subsidy in 2019 (RMA 2019). By analyzing these two types of insurance policies separately, we expect to gain more insight into whether different insurance policies influence farmers' water use behavior differently.

[14] Note that the estimation cannot separate the partial effects of crop insurance from the intensive margin, extensive margin, and moral hazard channels. It could be the case that the effect of moral hazard is significant but is dominated by effects from the intensive or extensive margin.

While modeling the effect of yield insurance subsidies we construct the PSPDL variable using the subsidy amount and liability that are only associated with the yield insurance policies. We follow similar procedure for modeling the effect of revenue insurance subsidies. We analyze yield insurance data for 25-year time span beginning 1990 while for revenue insurance policies we rely on data from 1995 to 2015 because revenue insurance was not available until mid-1990's.

Table 3.5 presents the results of the FE-IV regression models for the yield insurance and revenue insurance policies.[15] Columns (1)-(3) present estimates for the yield insurance policies and columns (4)-(6) for the revenue insurance policies. Column (1), the total freshwater model, shows that the estimated value of the PSPDL parameter for yield insurance is 1147.213. This indicates that a 1% increase in the premium subsidy amount for yield insurance policies, when evaluated at sample means, leads to a 0.403% (or 0.769 Mgal/day) increase in total freshwater withdrawals for irrigation in a county. In the context of the studied region, this number translates into 138,592 Mgal more freshwater withdrawals for irrigation a year (calculated by using 0.769×365×494, where 494 is the number of counties in the yield insurance sample (see Table 3.2)). The corresponding coefficient for the revenue insurance is 1866.418 (see Column (4) in Table 3.5). It implies that for revenue insurance policies, a 1% increase in the premium subsidy amount, on average, leads to a 1.023% (or 1.866 Mgal/day) increase in total freshwater withdrawals for irrigation in a county, which leads to 313,982 Mgal more freshwater withdrawals for irrigation a year (calculated by using 1.866×365×461, where 461 is the number of counties in the revenue insurance sample (see Table 3.2)). By comparing the impacts of yield insurance policies on total freshwater withdrawals for irrigation and that of revenue insurance

[15] To conserve space, here we only present the results from fixed effects regression models with the instrumental variable (FE-IV), which are our preferred models.

policies, we find that a 1% increase in the subsidy amount for revenue insurance leads to about 2.3 times more total freshwater withdrawals for irrigation relative to yield insurance policies.

Like our main results, the fresh groundwater use remains unaffected for both the yield and revenue insurance policies. In addition, columns (3) in Table 3.5 indicates that a 1% increase in premium subsidy for yield insurance policies, on average, leads to a 0.609% (or 0.766 Mgal/day) increase in fresh surface water withdrawals for irrigation in a county, which leads to 138,171 Mgal more fresh surface water withdrawals for irrigation a year (calculated by using 0.766×365×494). Column (6), however, indicates that a 1% increase in the premium subsidy for revenue insurance, on average, leads to a 1.648% (or 1.895 Mgal/day) increase in fresh surface water withdrawals for irrigation in a county, resulting in 318,862 Mgal more fresh surface water withdrawals for irrigation a year (calculated by using 1.895×365×461). Comparing the magnitudes of fresh surface water withdrawals for irrigation, we find that a 1% increase of the total premium subsidy for revenue insurance policies causes about 2.3 times more pressure on the fresh surface water withdrawals for irrigation relative to that caused by yield insurance policies.

Table 3.4 shows that the elasticities of water withdrawals with respect to PSPDL of yield insurance policies are less than unity (see row 2), while those of revenue insurance policies are around unity. Therefore, we can infer that the revenue insurance policies lead to more water use, which is likely due to larger premium for revenue insurance than that for yield insurance. The groundwater column presents zero because the coefficients of the PSPDL in the groundwater regression is statistically insignificant (see Table 3.5).

Robustness

In this section we probe the robustness of the estimated effects of the federal crop insurance premium subsidy on freshwater withdrawals for irrigation. Here we present a brief summary about the many robustness checks we have conducted and leave the specific estimates and extended discussion to the Appendix.

Our first group of robustness checks aims to mitigate the concern that the share of insured acres in 1989, which is included in our instrumental variable, is endogenous. To mitigate this concern, we conducted three sets of robustness checks. First, we exclude the insured acreage ratio in 1989 from the instrumental variable and only use the premium subsidy rate of insurance policies with 75% coverage level as an instrumental variable. Second, we include state-specific time trends in the regressions to mitigate the possible correlation between the insured acreage ratio in 1989 with the error term. Third, we only use observations in 2000 and after to mitigate this possible correlation because under this scenario the insured acreage ratio in 1989 is 11 years apart from the error term. We find that the results in our preferred model (columns (4) to (6) in Table 3.3) are robust to these different specifications of IV, regression model, and data framework.

The second group of robustness checks focuses on the robustness of the main results to using a sub-sample states in the data or different specifications of some key independent variables. First, we re-run our preferred models based on a sample that excludes data from California where many crops (e.g., vegetables) have not had substantial insurance but used substantial amount of surface water. Moreover, California has a large number of dry wells that are not recorded or reported comprehensively, which may aggravate the measurement error problem in the data (Perrone and Jasechko, 2017). Second, we replace the year fixed effects by a linear time trend in our preferred models and re-run those models to explore the robustness of the results to this alternative way to control for the technological improvements and perhaps market environment changes. Third, the impact of crop insurance on irrigation water use could be non-linear. To capture this non-linear effects, we include the quadratic term for PSPDL in the models and re-run the regressions. We find that the results in our preferred model generally hold across all these robustness checks.

Conclusions

We estimate impacts of the crop insurance premium subsidy on freshwater withdrawals for irrigation in U.S. counties to the west of 100th meridian. We do so by analyzing a county-level panel dataset from 1990 to 2015 with a five-year step on freshwater withdrawals for irrigation and crop insurance information in the presence of weather variation and unobservable heterogeneity across counties. The instrumental variable approach is employed to address the endogeneity problem of the insurance variable. Moreover, by incorporating weather information in our regression, our estimates mitigate omitted variable bias that some earlier studies may suffer. Our regression results indicate that total and surface water withdrawals for irrigation respond positively to crop insurance premium subsidy, although the elasticities are generally less than unity. However, because the large amount of freshwater consumed by U.S. agriculture, even a small percentage change in farmers' demand for freshwater can have significant impact on water sustainability. Given earlier findings in the literature that crop insurance has nearly negligible impact on crop acreage, we conjecture that the impact of irrigation of crop insurance mainly occurs at the intensive margin and that moral hazard is not a dominant factor for freshwater withdrawals for irrigation. Moreover, unlike the early literature, we do not find much evidence that the federal crop insurance program influences groundwater withdrawals for irrigation, which might result from the large measurement errors of groundwater withdrawals.

Finally, we find that freshwater withdrawals for irrigation are more sensitive to the premium subsidy under revenue insurance than that under yield insurance.

This article contributes to the crop insurance literature as it deepens our understanding of the relationship between the crop insurance and water resources, which is, similar to land, fertilizer, or pesticides, an indispensable input for agricultural production. It also contributes to policy discussions of the irrigation water management because it confirms that the heavily subsidized crop insurance program has statistically significant impact on freshwater withdrawals for irrigation. To reduce federal debt over the next ten years, the Congressional Budget Office of the United States has been considering numerous options including an option for reducing premium subsidy that would save $21 billion from 2020 to 2028 (COB 2018, p.19). The present study shows that this option may provide two kinds of benefits: reducing federal debt and increasing freshwater sustainability.

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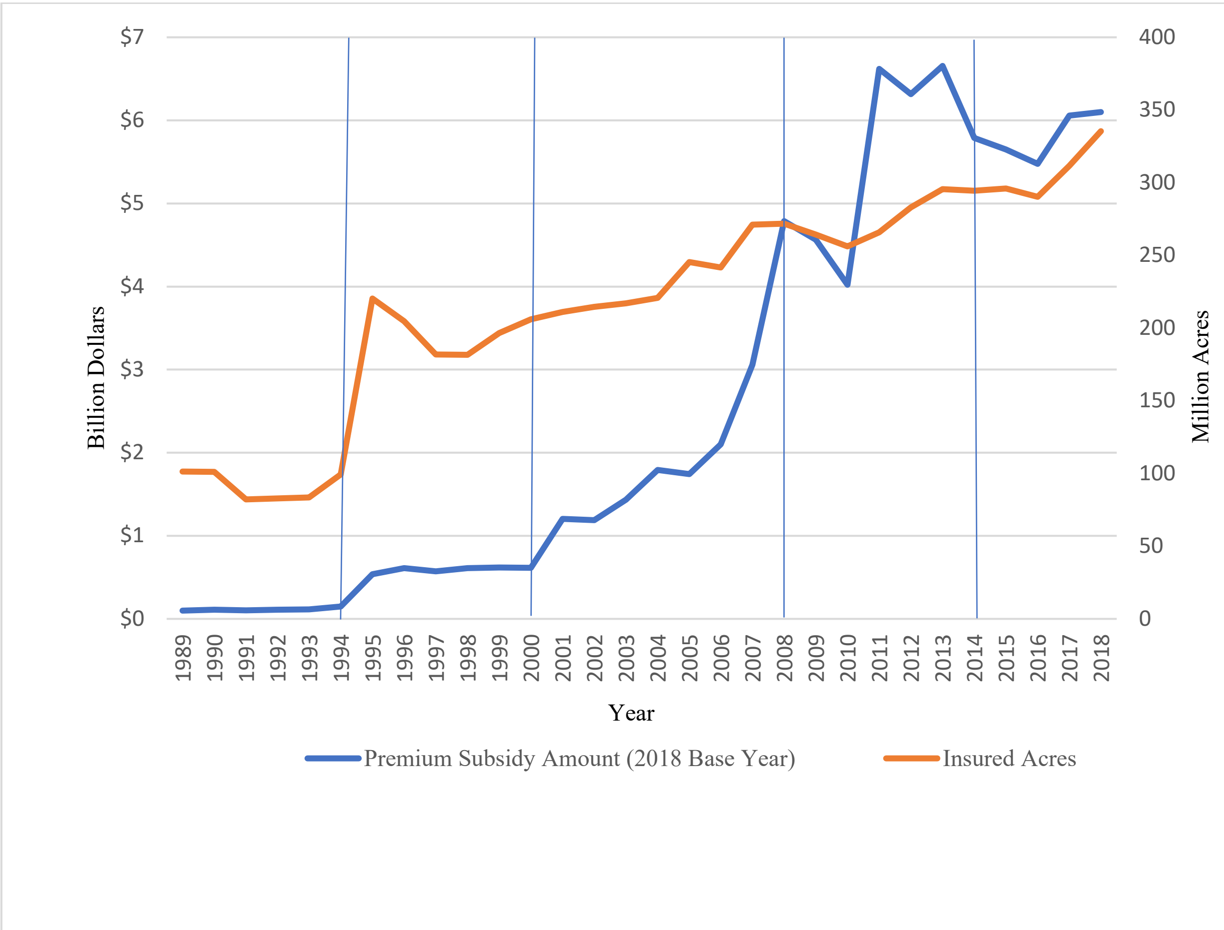

Figure 3.1. Crop Insurance Subsidy Amount in 2018 US Dollars and Insured Crop Acreage: 1990-2018

Source: Compiled by the authors using RMA's Summary of Business data.

Notes: The vertical lines denote farm bills or other legislative changes that caused major changes in crop insurance premium subsidy. From left to right, they stand for: 1) the Federal Crop Insurance Reform Act of 1994, which introduced a catastrophic (CAT) coverage and increased premium subsidy rate in 1995 and after; 2) the Agricultural Risk Protection Act of 2000, which again significantly increased premium subsidy rate beginning the 2001 crop year; 3) the Food, Conservation and Energy Act of 2008, which also changed subsidy rates beginning 2009 crop year; and 4)the Agricultural Act of 2014, which expanded existing coverage and authorized reimbursement of "shallow losses" beginning 2015 crop year.

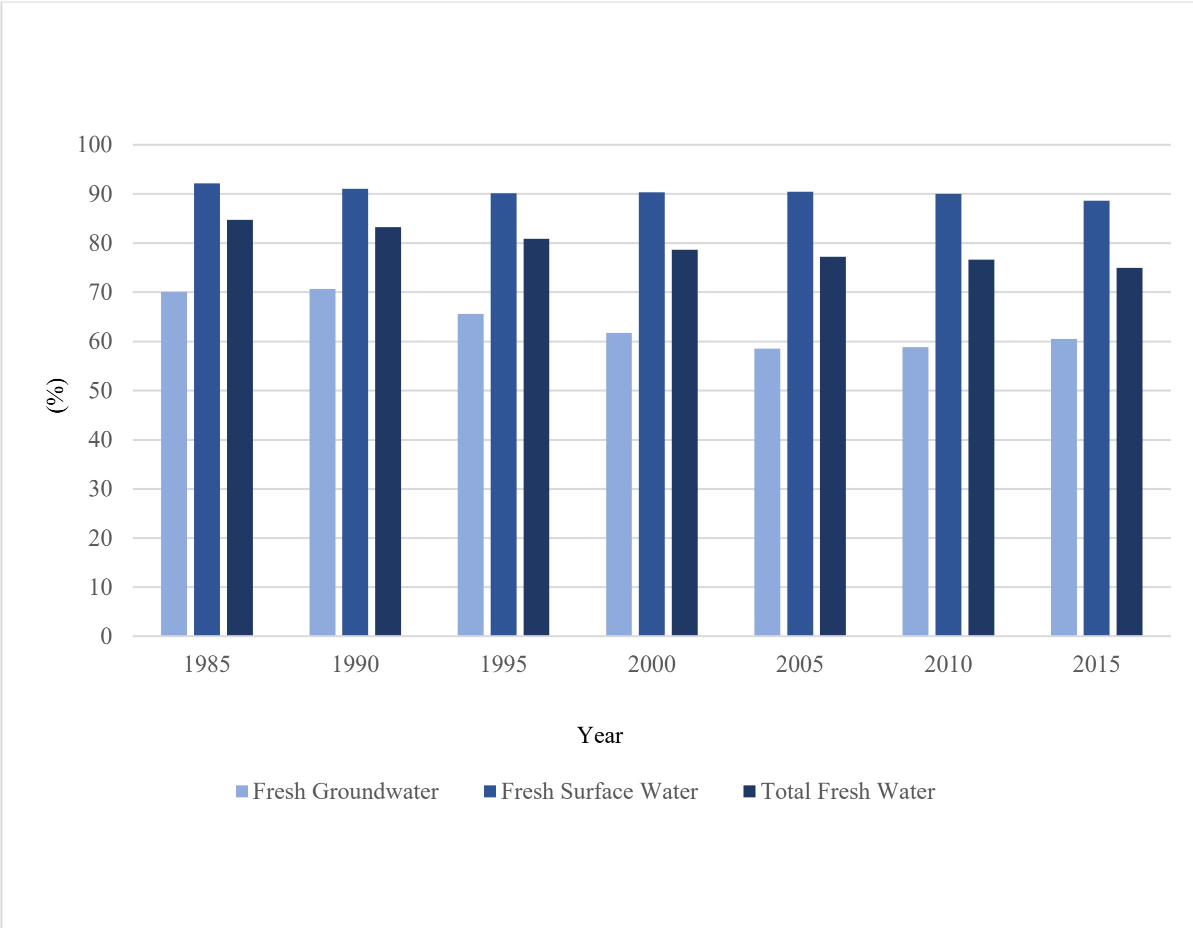

Figure 3.2. Percentage of Irrigation Fresh Water Withdrawals in the Western United States Used by Counties to the West of 100th Meridian over 1985-2015

Source: Compiled by the authors using data from the USGS National Water Information System.

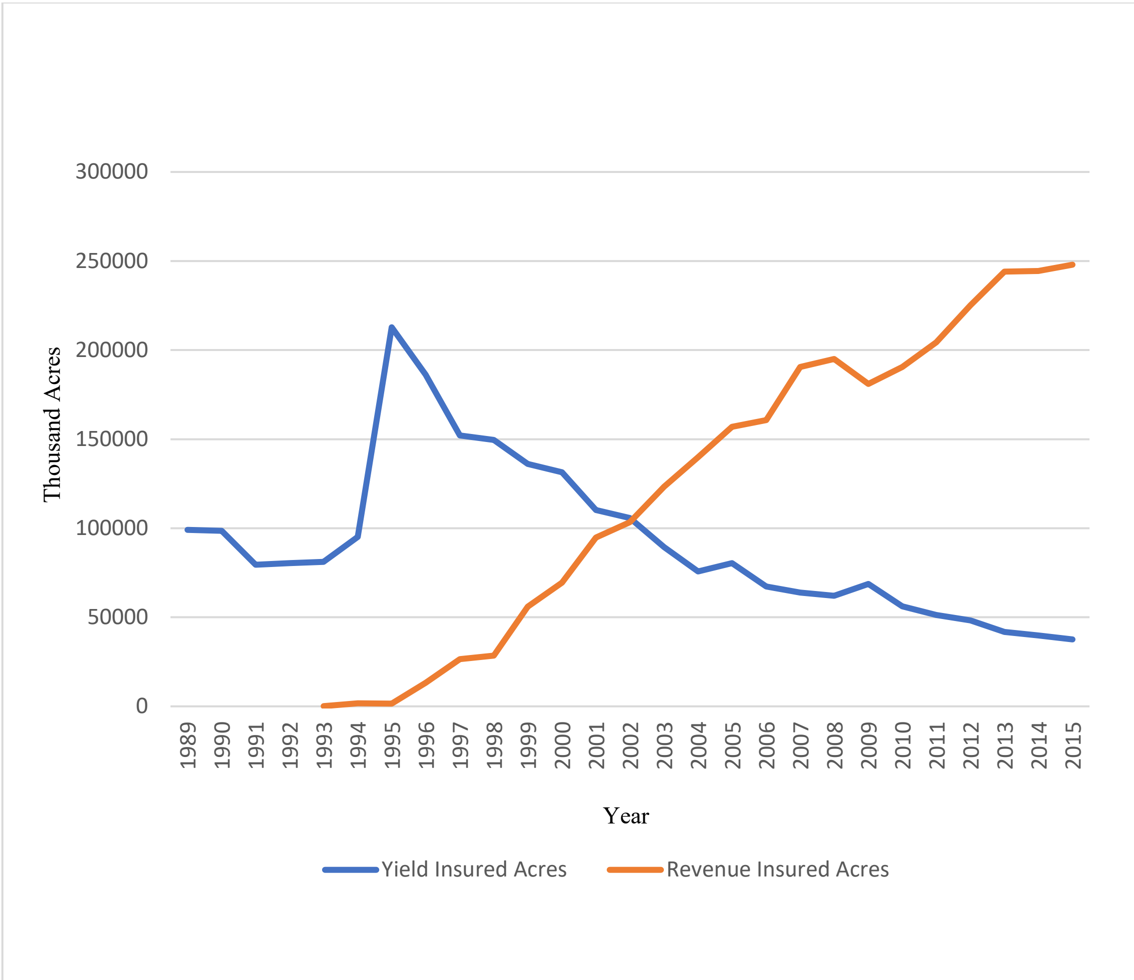

Figure 3.3. Acres Insured by Yield and Revenue Insurance Policies in the United States (in Thousand Acres)

Source: Compiled by the authors using data from RMA's Summary of Business.

Table 3.1. Summary Statistics of Data Used in Baseline Regressions

Variables (County Level; Number of counties: 522)	Mean	Std. Dev.	Min	Max
Dependent Variables for All Insurance Contracts				
Fresh Groundwater withdrawals (Mgal/day)	62.03	131	0	1,219
Fresh Surface-water withdrawals (Mgal/day)	120.46	220	0	1,784
Total Fresh Water withdrawals (Mgal/day)	182.49	310	0	2,834
Explanatory Variables				
Premium Subsidy Per Dollar Liability (PSPDL; $/$)	0.069	0.041	0.0029	0.241
Maximum Temperature in April (C)	17	4.8	7.1	29.61
Maximum Temperature in May (C)	20	4.8	11	33.4
Maximum Temperature in June (C)	26	4.7	16	39.35
Maximum Temperature in July (C)	30	3.5	21	41.68
Average Precipitation in April (mm)	50	31	1.1	241.18
Average Precipitation in May (mm)	74	32	1.3	184.24
Average Precipitation in June (mm)	57	32	0.56	280.23
Average Precipitation in July (mm)	44	28	0.004	177.57
Instrumental Variable: Key Components				
Subsidy Rate at 75% Coverage Level (%)	0.44	0.089	0.167	0.77
Insured Acres in the Year 1989	63,398	88768	0	647,677
Harvested Acres in the Year 1989	92,303	111779	100	769,805
Components of the Focal Variable				
Subsidy Amount ($)	1,233,265	1888394	71	2.25e+07
Liability Amount ($)	2.12e+07	4.73e+07	694	6.92e+08

Table 3.2. Summary Statistics for Yield and Revenue Insurance

Variables (County Level)	Mean	Std. Dev.	Min	Max
Yield Insurance (Number of Counties = 494)				
Fresh Groundwater withdrawals (Mgal/day)	65.12	134	0	1219
Fresh Surface-water withdrawals (Mgal/day)	125.75	225	0	1784
Total Fresh Water withdrawals (Mgal/day)	190.87	316	.0016	2834
PSPDL for Yield Insurance Policies (Ratio)	0.067	0.055	0.017	0.808
Revenue Insurance (Number of Counties = 461)				
Fresh Groundwater withdrawals (Mgal/day)	67.35	137	0	1149
Fresh Surface-water withdrawals (Mgal/day)	115	210	0	1582
Total Fresh Water withdrawals (Mgal/day)	182.358	304	0	2574
PSPDL for Revenue Insurance Policies (Ratio)	0.1	0.055	0.021	0.539

Table 3.3. Regression Results for the Linear Fixed Effects Models

	FE Models			FE-IV Models		
	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy Per Dollar of Liability (PSPDL)	239.711**	-16.758	256.469***	1,179.53**	3.74	1,175.79**
	(106.339)	(48.349)	(90.838)	(477.768)	(187.83)	(519.668)
Temperature in April	5.826***	4.089**	1.737	3.398	5.891**	-2.493
	(2.243)	(1.885)	(2.478)	(4.017)	(2.793)	(4.418)
Temperature in May	0.091	0.044	0.046	1.603	0.517	1.086
	(1.527)	(0.914)	(1.556)	(1.838)	(1.104)	(1.711)
Temperature in June	3.372*	-0.333	3.706*	5.492**	-0.406	5.898**
	(1.938)	(1.365)	(1.992)	(2.640)	(1.995)	(2.690)
Temperature in July	0.116	-4.910	5.026	-1.201	-7.345	6.144
	(2.538)	(3.008)	(3.179)	(3.089)	(4.541)	(4.537)
Precipitation in April	0.322***	0.076	0.246***	0.489***	0.098	0.391***
	(0.112)	(0.067)	(0.082)	(0.175)	(0.106)	(0.133)
Precipitation in May	0.069	-0.126**	0.194*	0.053	-0.155*	0.209
	(0.095)	(0.063)	(0.111)	(0.128)	(0.080)	(0.134)
Precipitation in June	-0.019	-0.041	0.021	-0.032	-0.056	0.024
	(0.048)	(0.037)	(0.048)	(0.071)	(0.051)	(0.063)
Precipitation in July	-0.130*	-0.232***	0.102*	-0.214**	-0.278***	0.064
	(0.073)	(0.078)	(0.062)	(0.100)	(0.098)	(0.095)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2692	2692	2692	2002	2002	2002
Number of Counties	484	484	484	381	381	381
Kleibergen-Paap *rk* LM (*p*-value)	-	-	-	0.022	0.022	0.022
Cragg-Donald Wald *F* stat	-	-	-	296.873	296.873	296.873
Kleibergen-Paap *rk* Wald *F*	-	-	-	17.939	17.939	17.939

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** p<0.01, ** p<0.05, * p<0.1. We define instrumental variable (IV) as the interaction between the subsidy rate at 75% coverage level and the ratio of insured acres over harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.

Table 3.4. Elasticities of Water Withdrawals with respect to Subsidy Per Dollar of Liability (PSPDL)

Variables	Total Fresh Water	Fresh Groundwater	Fresh Surface Water
PSPDL (all crop insurance)	0.446	0	0.673
PSPDL (yield Insurance)	0.403	0	0.609
PSPDL (revenue Insurance)	1.023	0	1.648

Source: These elasticity values are calculated by the authors using the estimated regression results from Tables 3.3 and 3.5 based on the sample means.

Table 3.5. FE-IV Regression Results for Yield and Revenue Insurance Policies

	Yield Insurance			Revenue Insurance		
	Total Water	Ground water	Surface Water	Total Water	Groundwater	Surface Water
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PSPDL	1147.213***	3.481	1143.732***	1866.418**	-29.173	1895.591*
	(400.774)	(182.378)	(443.992)	(807.196)	(315.863)	(969.925)
Temperature in April	4.857	5.891**	-1.034	-1.003	13.020**	-14.023*
	(3.403)	(2.682)	(3.798)	(6.153)	(5.083)	(8.377)
Temperature in May	1.421	0.512	0.91	12.802***	6.863***	5.939
	(1.796)	(1.113)	(1.754)	(4.698)	(2.04)	(4.077)
Temperature in June	4.902*	-0.409	5.310*	6.636	-5.948*	12.584*
	(2.667)	(1.937)	(2.717)	(6.256)	(3.429)	(6.64)
Temperature in July	0.25	-7.349	7.599	-7.541	-16.963***	9.422**
	(3.221)	(4.62)	(4.809)	(5.23)	(5.963)	(4.751)
Precipitation in April	0.516***	0.099	0.417***	0.499*	0.137	0.361
	(0.181)	(0.107)	(0.15)	(0.28)	(0.118)	(0.267)
Precipitation in May	0.12	-0.155*	0.276**	0.27	-0.221*	0.491**
	(0.132)	(0.084)	(0.139)	(0.215)	(0.125)	(0.226)
Precipitation in June	-0.044	-0.056	0.013	0.172	-0.132	0.304*
	(0.076)	(0.05)	(0.066)	(0.175)	(0.088)	(0.16)
Precipitation in July	-0.188	-0.279***	0.091	0.002	-0.312***	0.314**
	(0.136)	(0.099)	(0.143)	(0.153)	(0.101)	(0.145)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,996	1,996	1,996	1,286	1,286	1,286
Number of Counties	379	379	379	354	354	354
Kleibergen-Paap *rk* LM (*p-value*)	0.0053	0.0053	0.0053	0.0234	0.0234	0.0234
Cragg-Donald Wald *F* statistic	235.948	235.948	235.948	79.685	79.685	79.685
Kleibergen-Paap *rk* Wald F stat	39.682	39.682	39.682	20.929	20.929	20.929

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** p<0.01, ** p<0.05, * p<0.1. We define instrumental variable (IV) as the interaction between the subsidy rate at 75% coverage level, and the ratio of insured acres and harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.

Appendix

Item A. Robustness

In this item, we probe the robustness of the effects of the federal crop insurance premium subsidy on freshwater withdrawals for irrigation. We do so by varying the specifications of the instrumental variable, the independent variable, the temporal framework of the data, and the regression models. We find that overall, the main results discussed above are robust to these variations.

We first examine the robustness of the results of the preferred models (i.e., models (4)-(6) in Table 3.3) to a different specification of the instrumental variable. Recall that in the main results we use the interaction term between the premium subsidy rate for crop insurance policies with 75% coverage level in a year and county-level share of insured acres in 1989 as an instrumental variable. As we have discussed above, one might be concerned that the share of insured acres in 1989 across counties is endogenous as riskier counties might insure more in 1989 and thereafter. To mitigate this concern, we drop the county-level share of insured acres in 1989 when constructing the instrumental variable and only use the premium subsidy rate of insurance policies with 75% coverage level as an instrumental variable. The same instrument is used by Yu, Smith, and Sumner (2018). The regression results based on this new instrumental variable are presented in columns (1) to (3) in Table 3.A2, from which we can see that these results, with relatively larger estimates of the PSPDL coefficients, are comparable with our main results presented in columns (4)-(6) in Table 3.3.

To further mitigate the concern over the endogeneity of the insured acreage share in 1989, we include state-specific time trends in the FE-IV model. The rationale here is that controlling for the state-specific time trends would mitigate the correlation between the 1989 insured acreage share and the error term. The results are presented in columns (4)-(6) in Table 3.A2, from which we can see that the coefficients of PSPDL after we control for the state-specific time trends are slightly smaller than their counterparts in columns (4)-(6) in Table 3.3, indicating that our main results in columns (4)-(6) are robust to the inclusion of state-specific time trends and that the endogeneity concern of the 1989 insured acreage share can be partly mitigated.

Another way to alleviate the concern of the endogeneity of the share of insured acres in 1989 is to only use data that are much later than 1989, because, arguably, these data would be less likely being correlated with farmers' insurance decisions in 1989. Therefore, we also re-run our preferred models for overall crop insurance, yield insurance, and revenue insurance after excluding observations in 1990 and 1995. The results are presented in Table 3.A3. We can see that the PSPDL coefficients are qualitatively (signs and significance) the same and quantitatively similar to those in the main results (i.e., columns (4)-(6) in Table 3.3 and all columns in Table 3.5).

We further explore the robustness of the main results to the exclusion of data from California where many crops (e.g., vegetables) have not had substantial insurance but used substantial amount of surface water. Moreover, according to Perrone and Jasechko (2017), California has a large number of dry wells that are not recorded or reported comprehensively, which may aggravate the measurement error problem in the data. Table 3.A4 presents the regression results based on the sample without data for California. We can see that for total water withdrawal models and surface water withdrawal models across various types of insurance, the coefficient of PSPDL are comparable to, although smaller than, the PSPDL coefficients in the main results (columns (4) and (6) in Table 3.3; columns (1), (3), (4), and (6) in Table 3.5). For groundwater withdrawal models, the coefficient of PSPDL are now positive and statistically significant (see columns (2), (5), and (8) in Table 3.A4), which shows that measurement error may be the reason for the insignificant coefficient of PSPDL in groundwater withdrawal regressions in the main results (see Tables 3.3 and 3.5).

We also explore the sensitivity of the results to the modeling of technological improvement and market environment. In our preferred models, we currently use the year fixed effects to control for time specific effects such as technological or price shocks that are common to each county. An alternative way to control for the technological improvements and perhaps market environment changes is to use a simple time trend. We therefore replace the year fixed effects by a linear time trend in our preferred models and re-run those models. We present the respective regression results in columns (1)-(3) in Table 3.A5. These new set of results show that the primary coefficients of our interests become 899.89 for total freshwater, and 916.97 for surface water, which are statistically significant at 1% level. These coefficients, however, become slightly smaller in magnitude compared to their counterparts presented in columns (4) - (6) in Table 3.3. Similarly, results presented in the columns (4) - (6) in Table 3.A5 corroborate robustness of the main regression results for yield insurance presented in columns (1) - (3) in Table 3.5, respectively. For example, the magnitudes of the PSPDL coefficients presented in columns (4) - (6) in Table 3.A5 are quantitatively similar to their counterparts presented in columns (1) - (3) in Table 3.5. Moreover, estimated revenue insurance parameters which are presented in the columns (7) - (9) in Table 3.A5 indicate that main regression results presented in columns (4) - (6) in Table 3.5 are robust to switching year fixed effects to the linear time trend as well.

Finally, the impact of crop insurance on freshwater withdrawals for irrigation could be non-linear, and to capture the non-linear effects of the premium subsidy on water use, we include the quadratic term for PSPDL in the models and re-run the regressions. The results are presented in Table 3.A6, from which we can see that the coefficients of both the linear term and the quadratic term of PSPDL are statistically significant. Even though the coefficients of PSPDL is much larger in Table 3.A6 than their counterparts in Tables 3.3 and 3.5, the average marginal impact of PSPDL based on results in Table 3.A6 is similar to that based on results in Tables 3.3 and 3.5. For instance, based on the results in column (1) in Table 3.A6, when evaluated at the minimum value of PSPDL (i.e., 0.0029) then the marginal impact of PSPDL on total freshwater withdrawals for irrigation is 2,684.8 (calculated by using $2\times(-4341.78)\times0.0029+2709.95$). When evaluated at the minimum value of PSPDL (i.e., 0.241) then this marginal impact is 617.2. The simple average of these two marginal impacts is 1,651, which is comparable to the marginal impact in our main results, 1,179.5 (see column (4) in Table 3.3). Moreover, statistics of the Akaike's information criterion (AIC) and the Schwarz's Bayesian criterion (BIC) reveal that the specification of our baseline models (i.e., models with linear PSPDL) is preferred over its counterparts presented in the Table 3.A6 that includes a quadratic term of PSPDL.

Item B. Supporting Figures and Tables

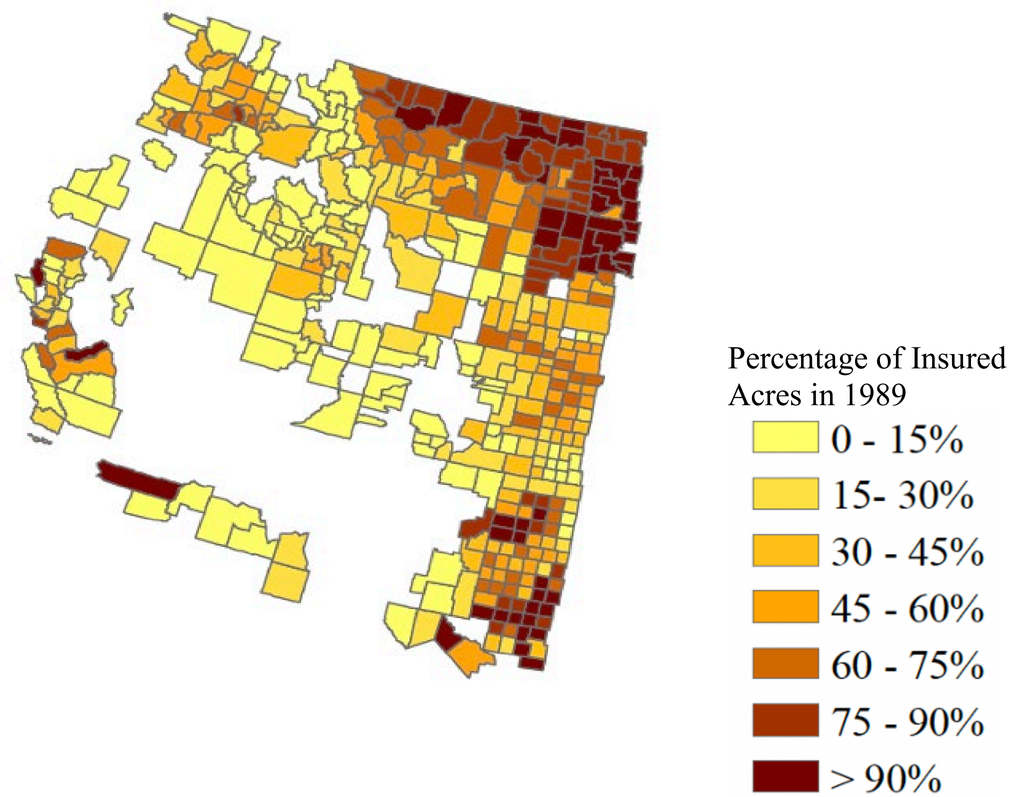

Figure 3.A1. Percentage of Insured Acres in 1989 Across Counties in the Western United States

Source: Created by the authors based on RMA's Summary of Business data.

Table 3.A1. First-stage Estimations for the FE-IV Models in Table 3.3.

Variables	Premium Subsidy Per Dollar of Liability (PSPDL)
Instrumental Variable (IV)	0.115***
	(0.027)
Temperature in April	0.001
	(0.001)
Temperature in May	0.000
	(0.000)
Temperature in June	-0.001*
	(0.000)
Temperature in July	0.000
	(0.000)
Precipitation in April	-0.000**
	(0.000)
Precipitation in May	0.000***
	(0.000)
Precipitation in June	0.000*
	(0.000)
Precipitation in July	0.000
	(0.000)
Year Fixed Effects	Yes
Number of Observations	2002
Number of Counties	381
Sanderson-Windmeijer *F* stat	17.94
Cragg-Donald Wald *F* stat	296.87
Kleibergen-Paap Wald *rk F* stat	17.94

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. We define instrumental variable (IV) as the product of the subsidy rate at 75% coverage level and the ratio of insured acres over harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.

Table 3.A2. Robustness: Alternative Instrumental Variable and State-specific Time Trends

Variables	Total Water (1)	Ground water (2)	Surface Water (3)	Total Water (4)	Ground water (5)	Surface Water (6)
Subsidy Per Dollar of	1,263.282†	-452.051	1,715.334**	907.254**	-87.143	994.398†
Liability (PSPDL)	(782.729)	(358.406)	(754.363)	(458.863)	(295.78)	(617.364)
Temperature in April	1.581	7.677**	-6.097	5.317	10.10***	-4.792
	(5.451)	(2.995)	(5.684)	(4.027)	(3.523)	(5.136)
Temperature in May	1.608	0.531	1.076	-1.264	1.030	-2.295
	(1.889)	(1.149)	(1.671)	(1.412)	(0.885)	(1.409)
Temperature in June	4.214*	-0.687	4.902**	1.637	-2.271	3.909
	(2.293)	(1.810)	(2.272)	(2.946)	(2.346)	(2.845)
Temperature in July	0.930	-6.026	6.956*	0.041	-8.019*	8.060*
	(2.727)	(3.827)	(4.096)	(3.325)	(4.809)	(4.806)
Precipitation in April	0.463***	0.081	0.382***	0.756***	0.159	0.596***
	(0.152)	(0.096)	(0.115)	(0.234)	(0.109)	(0.191)
Precipitation in May	-0.027	-0.085	0.058	-0.095	-0.142**	0.047
	(0.102)	(0.058)	(0.107)	(0.103)	(0.069)	(0.105)
Precipitation in June	-0.072	-0.029	-0.042	-0.120	-0.085	-0.035
	(0.064)	(0.044)	(0.065)	(0.082)	(0.063)	(0.086)
Precipitation in July	-0.180*	-0.250**	0.069	-0.075	-0.270**	0.195
	(0.098)	(0.100)	(0.103)	(0.127)	(0.115)	(0.123)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,205	2,205	2,205	2,002	2,002	2,002
Number of Counties	443	443	443	381	381	381

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, † p<0.11. Results in columns (1)-(3) are based on regressions using only the premium subsidy rate of insurance policies with 75% coverage level as the instrumental variable. Results in columns (4)-(6) are based on regressions with state-specific time trends and with the same instrumental variable as that under the preferred models in Table 3.3 (i.e., the interact term between subsidy rate and 1989 insured acreage share).

Table 3.A3. Robustness: Excluding Observations in 1990 and 1995

	All Types of Crop Insurance			Yield Insurance			Revenue Insurance		
	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PSPDL	1486.03**	34.666	1,451.368**	1649.7***	47.258	1,602.463**	1866.56**	-29.268	1,895.827*
	(590.754)	(292.417)	(738.088)	(594.662)	(324.099)	(697.887)	(807.230)	(315.906)	(970.016)
Temp. in April	-4.606	10.470**	-15.076*	-0.840	10.560**	-11.401	-1.010	13.025**	-14.034*
	(7.014)	(4.687)	(8.518)	(6.200)	(4.262)	(7.350)	(6.153)	(5.084)	(8.377)
Temp. in May	9.581***	6.463***	3.118	7.493**	6.460***	1.033	12.797***	6.866***	5.931
	(3.099)	(1.815)	(2.566)	(3.065)	(1.804)	(2.633)	(4.697)	(2.042)	(4.075)
Temp. in June	5.128	-5.753**	10.881**	4.173	-5.794**	9.967**	6.639	-5.950*	12.589*
	(4.423)	(2.768)	(4.448)	(4.562)	(2.678)	(4.741)	(6.257)	(3.430)	(6.642)
Temp. in July	-7.068*	-13.938***	6.870	-1.296	-13.827***	12.531**	-7.536	-16.967***	9.431**
	(4.208)	(5.208)	(4.858)	(4.802)	(5.196)	(6.125)	(5.230)	(5.964)	(4.751)
Precip. in April	0.338**	0.196*	0.142	0.359*	0.198*	0.162	0.499*	0.137	0.361
	(0.156)	(0.117)	(0.128)	(0.210)	(0.117)	(0.200)	(0.280)	(0.118)	(0.267)
Precip. in May	0.169	-0.226**	0.395**	0.245	-0.224*	0.469***	0.270	-0.221*	0.491**
	(0.154)	(0.111)	(0.171)	(0.175)	(0.115)	(0.177)	(0.215)	(0.125)	(0.226)
Precip. in June	0.030	-0.134*	0.164	-0.017	-0.136*	0.119	0.172	-0.131	0.303*
	(0.104)	(0.071)	(0.106)	(0.112)	(0.070)	(0.103)	(0.175)	(0.088)	(0.160)
Precip. in July	-0.053	-0.305***	0.252*	-0.048	-0.303***	0.254	0.001	-0.312***	0.313**
	(0.124)	(0.094)	(0.130)	(0.204)	(0.093)	(0.216)	(0.153)	(0.101)	(0.146)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,387	1,387	1,387	1,381	1,381	1,381	1,284	1,284	1,284
Number of Counties	373	373	373	371	371	371	354	354	354

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** p<0.01, ** p<0.05, * p<0.1. We define instrumental variable (IV) as the interaction between the subsidy rate at 75% coverage level, and the ratio of insured acres and harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.

Table 3.A4. Robustness: Excluding Data for California

	All Types of Crop Insurance			Yield Insurance			Revenue Insurance		
	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subsidy Per Dollar of	819.796**	292.984*	526.812**	798.27***	283.786**	514.486***	864.76***	293.049***	571.718*
Liability (PSPDL)	(325.275)	(162.589)	(215.094)	(268.627)	(142.604)	(185.147)	(299.700)	(105.543)	(313.433)
Temperature in April	3.575	-0.209	3.784	4.186*	0.007	4.179*	6.914***	-0.009	6.923***
	(2.616)	(1.930)	(2.342)	(2.155)	(1.758)	(2.232)	(2.543)	(1.739)	(2.115)
Temperature in May	0.079	0.896	-0.817	0.011	0.864	-0.854	8.075***	5.053***	3.022
	(1.369)	(0.810)	(1.244)	(1.292)	(0.766)	(1.250)	(2.165)	(1.149)	(2.101)
Temperature in June	2.330	1.468	0.862	1.497	1.170	0.327	-2.749	-1.077	-1.672
	(2.199)	(1.060)	(1.717)	(2.120)	(0.958)	(1.708)	(2.482)	(1.120)	(2.341)
Temperature in July	1.730	1.470	0.260	3.492	2.122	1.369	-0.568	-3.726*	3.157
	(3.302)	(1.371)	(2.997)	(3.374)	(1.352)	(3.046)	(4.419)	(2.137)	(4.240)
Precipitation in April	0.270*	0.037	0.233**	0.273*	0.038	0.235**	0.134	-0.003	0.137
	(0.152)	(0.095)	(0.105)	(0.150)	(0.089)	(0.111)	(0.107)	(0.064)	(0.103)
Precipitation in May	-0.110	-0.040	-0.071	-0.066	-0.024	-0.042	-0.047	-0.027	-0.020
	(0.071)	(0.034)	(0.070)	(0.073)	(0.037)	(0.067)	(0.069)	(0.049)	(0.046)
Precipitation in June	-0.078	-0.009	-0.069	-0.095*	-0.015	-0.080*	-0.077	-0.034	-0.043
	(0.051)	(0.026)	(0.046)	(0.055)	(0.027)	(0.047)	(0.070)	(0.038)	(0.066)
Precipitation in July	-0.073	-0.124**	0.050	-0.037	-0.111**	0.074	0.118	-0.122*	0.239*
	(0.080)	(0.055)	(0.074)	(0.099)	(0.055)	(0.088)	(0.144)	(0.068)	(0.124)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,840	1,840	1,840	1,834	1,834	1,834	1,213	1,213	1,213
No. of Counties	352	352	352	350	350	350	331	331	331

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** p<0.01, ** p<0.05, * p<0.1. We define instrumental variable (IV) as the interaction between the subsidy rate at 75% coverage level, and the ratio of insured acres and harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.

Table 3.A5. Robustness: Replacing Year Fixed Effects with Time Trend

	All Types of Crop Insurance			Yield Insurance			Revenue Insurance		
	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PSPDL	899.8***	-17.082	916.97***	904.9***	-15.604	920.53***	1018***	71.902	946.3***
	(277.80)	(132.23)	(321.82)	(265.93)	(132.08)	(305.94)	(276.10)	(143.85)	(335.66)
Temp. in April	4.181**	4.173**	0.007	5.095***	4.153**	0.942	4.501	10.874**	-6.373
	(1.967)	(1.955)	(2.295)	(1.971)	(1.916)	(2.148)	(4.079)	(4.307)	(5.943)
Temp. in May	7.159***	1.472	5.686**	5.947**	1.503	4.445**	15.39***	7.950***	7.449**
	(2.706)	(1.721)	(2.243)	(2.508)	(1.682)	(2.016)	(4.223)	(2.235)	(3.266)
Temp. in June	2.23	1.278	0.952	2.669	1.274	1.395	4.14	-2.763	6.903
	(2.089)	(1.279)	(1.784)	(2.033)	(1.304)	(1.79)	(4.167)	(2.336)	(4.236)
Temp. in July	-2.684	-6.63	3.946	-1.564	-6.66	5.096	-9.033	-12.77***	3.744
	(3.754)	(4.167)	(3.839)	(3.796)	(4.21)	(4.012)	(5.724)	(4.666)	(3.521)
Precip. in April	0.368**	-0.007	0.376**	0.397**	-0.007	0.404**	0.257	0.006	0.251*
	(0.188)	(0.111)	(0.157)	(0.189)	(0.112)	(0.168)	(0.183)	(0.111)	(0.142)
Precip. in May	0.150*	-0.026	0.176**	0.207**	-0.027	0.234***	0.405**	-0.065	0.470**
	(0.082)	(0.05)	(0.075)	(0.086)	(0.053)	(0.081)	(0.193)	(0.088)	(0.184)
Precip. in June	-0.069	0.002	-0.07	-0.068	0.001	-0.069	0.005	-0.04	0.044
	(0.066)	(0.037)	(0.058)	(0.062)	(0.037)	(0.051)	(0.095)	(0.065)	(0.093)
Precip. in July	-0.243**	-0.270***	0.027	-0.211	-0.271***	0.06	-0.061	-0.321***	0.260**
	(0.123)	(0.099)	(0.099)	(0.141)	(0.099)	(0.13)	(0.145)	(0.103)	(0.117)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** p<0.01, ** p<0.05, * p<0.1. We define instrumental variable (IV) as the interaction between the subsidy rate at 75% coverage level, and the ratio of insured acres and harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.

Table 3.A6. Robustness: Including PSPDL Square Term

	All Types of Crop Insurance			Yield Insurance			Revenue Insurance		
	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water	Total Water	Ground water	Surface Water
Variables	(1)	(2)	(3)	(4)	(5))	(6)	(7)	(8)	(9)
PSPDL	2709.95***	-437.486	3147.437***	3541.679***	-467.268	4008.947***	5776.99**	-413.323	6190.315**
	(931.699)	(523.648)	(1001.389)	(1095.348)	(681.167)	(1232.616)	(2382.731)	(815.352)	(2548.228)
PSPDL-Squared	-4341.78**	1251.759	-5593.54***	-6877.23***	1352.055	-8229.28***	-8739.91**	858.554	-9598.465**
	(1776.646)	(1001.96)	(1922.807)	(2428.467)	(1,508.247)	(2844.061)	(4103.441)	(1261.917)	(4261.775)
Temp. in April	-0.466	7.005**	-7.472	0.874	6.674**	-5.800	-6.195	13.531**	-19.726*
	(4.285)	(3.321)	(5.141)	(3.866)	(3.153)	(4.748)	(8.419)	(5.385)	(10.865)
Temp. in May	1.990	0.406	1.584	1.264	0.542	0.722	16.529**	6.497***	10.032*
	(1.917)	(1.111)	(1.852)	(1.890)	(1.158)	(2.012)	(6.450)	(2.315)	(6.021)
Temp. in June	5.290**	-0.348	5.638**	6.241**	-0.672	6.913**	10.299	-6.308*	16.607*
	(2.554)	(1.965)	(2.543)	(2.748)	(2.119)	(2.953)	(8.481)	(3.790)	(9.145)
Temp. in July	0.080	-7.714*	7.794	2.531	-7.798*	10.328**	-4.201	-17.291***	13.090**
	(3.116)	(4.603)	(4.775)	(3.394)	(4.727)	(5.208)	(5.526)	(6.043)	(6.620)
Precipit. in April	0.474***	0.102	0.372***	0.587***	0.084	0.503***	0.693*	0.118	0.575
	(0.179)	(0.104)	(0.134)	(0.193)	(0.111)	(0.161)	(0.399)	(0.135)	(0.405)
Precipit. in May	0.028	-0.148*	0.176	0.084	-0.148*	0.233*	0.331	-0.227*	0.558**
	(0.125)	(0.077)	(0.122)	(0.122)	(0.082)	(0.126)	(0.277)	(0.128)	(0.282)
Precipit. in June	-0.090	-0.039	-0.051	-0.095	-0.046	-0.049	0.175	-0.132	0.307
	(0.075)	(0.050)	(0.063)	(0.085)	(0.050)	(0.076)	(0.209)	(0.087)	(0.195)
Precipit. in July	-0.190*	-0.285***	0.095	-0.009	-0.314***	0.305**	0.103	-0.322***	0.425**
	(0.105)	(0.097)	(0.096)	(0.132)	(0.111)	(0.152)	(0.188)	(0.101)	(0.195)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,002	2,002	2,002	1,996	1,996	1,996	1,286	1,286	1,286
Number of Counties	381	381	381	379	379	379	354	354	354

Notes: Robust standard errors in parentheses. Standard errors are clustered by climate division. *** p<0.01, ** p<0.05, * p<0.1. We define instrumental variable (IV) as the interaction between the subsidy rate at 75% coverage level, and the ratio of insured acres and harvested acres in the year 1989. We calculate subsidy rate for insurance policies with 75% coverage as premium subsidy divided by total premium of these policies for each county.