ILLINOIS

COLLEGE OF AGRICULTURAL, CONSUMER
& ENVIRONMENTAL SCIENCES
Department of Agricultural & Consumer Economics
326 Mumford Hall, MC-710
1301 W. Gregory Drive
Urbana, IL 61801-3605

September 19, 2019

Dr. Mark L. Waller
Professor and Acting Department Head
Department of Agricultural Economics
2124 TAMU
College Station, Texas 77843-2124

Dear Dr. Waller,

I am writing to apply for the position of Assistant Professor in Agricultural Marketing and Quantitative Analysis in the Department of Agricultural Economics at Texas A&M University. I expect to complete my Ph.D. in Agricultural and Applied Economics from the University of Illinois at Urbana-Champaign in May 2020. I believe that my solid economics trainings, policy-relevant research interests, multidisciplinary background, and extensive teaching and service experience make me an excellent match for this position.

My research interests span the fields of environmental and energy economics and agricultural economics. My job market paper investigates the net impacts of the development of wind energy on local crop yields and farm operations. This study brings a new, policy-relevant perspective on the interactions among wind energy, crop yields, and farm returns and expenses, specifically, and generally on the relationship between renewable energy policy and agricultural production. Understanding these relationships can lead to better economic and environmental outcomes by taking potential externalities and spatial spillovers of wind energy into consideration. To deal with threats to causal identification, I develop an instrumental variables approach which exploits local wind potential and aviation safety restrictions as sources of exogenous variations in the development of wind turbines. I find positive effects of wind energy on neighboring crop yields, and then explore possible mechanisms. Using farm-level data, I find no measurable increases in production inputs after wind turbines are installed, and most of the benefits from the yield increases are realized through higher labor and management returns. I also estimate the causal effects of wind turbines on local meteorological variables and find significant impacts, suggesting that the induced microclimate changes are likely the factors that lead to the higher yields. As another example, since wind turbines kill lots of bats and birds, my in-progress follow-up studies with coauthors investigate the increase in insecticide usage near new wind farms and its sequential impacts on local ecosystems and human health.

Besides empirical studies, I have a strong theoretical background and conduct applied research with analytic general equilibrium models. For example, my coauthor and I investigate the welfare effects of environmental taxes to correct a pollution externality given imperfect competition with price discrimination in the energy sector. It is common for energy firms charge significantly different prices across residential and industrial users for identical products, but this effect has been overlooked in prior models exploring pollution externalities. Our results bring a new perspective that policymakers need to balance the tradeoffs of environmental tax changes among the gain from negative externality correction against the price discrimination distortion and the cost from enlarged distortion for the underproduction of goods due to market power.

With previous educational backgrounds in engineering, I maintain professional networks with many engineers and scientists, especially in the field of agricultural and environmental engineering. My unique background enhances my ability to engage in multidisciplinary communication and research. For instance, I am recently involved in an initial research project with my previous colleagues to decompose factors that drive the expansion of the U.S. Corn Belt to the north by utilizing high-quality remote sensing data.

In addition to research, I am excited at the prospect of teaching in your department and I am well-prepared to teach both theoretical (e.g., microeconomics) and applied (e.g., agricultural marketing) courses at the introductory level, and advanced courses in environmental, energy, natural resource economics, as well as program evaluation and general equilibrium models. I have gained rich teaching experience from serving as a teaching assistant for six semesters, with many courses of more than 150 students. I often take full advantage of figures and real-life examples to inspire students, and use modern technologies like voting apps or even write simple program myself to improve teaching efficiency and quality. Paul Stoddard, a top-ranked senior lecturer, is willing to provide a reference letter specifically on my teaching performance under separate cover. Furthermore, as a graduate mentor, I have also worked one-on-one with summer exchange students from different countries on their short-term research projects for many years.

An experience, which can contribute a lot to your diversity and international cooperation, is that I have developed deep networks with partner foreign institutes through my work experience as an assistant coordinator for the Office of International Programs/Affairs at the University of Chicago and the University of Illinois since 2012. I contribute significantly to building revenue-raising summer programs and fostering further long-term international collaboration, such as “3+2” joint degree programs. During the years when I served as the graduate supervisor, in total 114 international college students graduated from our summer programs. Roughly two-thirds of them chose to pursue graduate degrees abroad, and a quarter of them came back to the same university as master’s or Ph.D. students. I am confident that my experience in international programs can be especially valuable to your department.

I have enclosed my curriculum vitae, my job market paper, and my transcripts. Three letters of reference will arrive under separate cover. Thank you in advance for your consideration. I look forward to hearing from you.

Sincerely,

Tengjiao Chen

Ph.D. Candidate
Department of Agricultural and Consumer Economics
University of Illinois at Urbana-Champaign
Tel: (217) 778-3537
Email: tchen41@illinois.edu

Chen, Tengjiao

414 Mumford Hall, 1301 W Gregory Drive, Urbana, IL 61801 • (217)778-3537 • tchen41@illinois.edu

EDUCATION

University of Illinois at Urbana-Champaign Urbana, IL

- *Ph.D. Candidate*, Agricultural and Applied Economics Expected 2020

  Committee: Erica Myers (*Advisor*), Eyal Frank, Don Fullerton, Daniel H. Karney, Madhu Khanna

  Research Fields: Environmental and Energy Economics, Agricultural Economics, Public Economics

Harris School of Public Policy, The University of Chicago Chicago, IL

- *Master of Public Policy with Honors* 2015

University of Illinois at Urbana-Champaign Urbana, IL

- *M.S.*, Agricultural and Biological Engineering 2013

Zhejiang University Hangzhou, China

- *B.Eng.*, Biosystems (Agricultural) Engineering. First-class scholarship (top 3%). Ranking: 1/22 2011
- Honors Undergraduate Program of Public Administration, Chu Kochen Honors College

WORKING PAPERS

- "Wind Energy and Agricultural Production: Evidence from Farm-Level Data" (Job Market Paper)

  Abstract: This study investigates the impacts of sizable wind farms on neighboring crop yields and farm operations. I develop an instrumental variables approach which exploits local wind potential and aviation safety restrictions as sources of exogenous variation in the development of wind turbines. I find positive effects of wind energy on nearby crop yields. In particular, my preferred estimates indicate that soybean and corn yields increase by roughly 1.3 and 2.4 percent, respectively, given an additional 50 MW of wind capacity installed in the same county. I then probe two possible mechanisms. First, using farm-level data, I explore changes in farm operations and find no measurable increases in production inputs after wind turbines are installed despite the fact that landowners might be receiving royalties. My results further reveal that most of the benefits from the yield increases are realized through higher labor and management returns. Second, I estimate the causal effects of wind turbines on local meteorological variables and find significant impacts, suggesting that the induced microclimate changes are likely important contributors to higher yields.
- "Environmental Taxes in General Equilibrium under Market Power" (with Daniel H. Karney)
- "The Anticipation Effect of the Earnings Test Reform on Younger Cohorts" (with Yajie Sheng and Yu Xu, first and corresponding author, honors paper for *M.P.P.* degree. Revise and resubmit, *Public Finance Review*)

RESEARCH IN PROGRESS

- "The Impact of Wind Turbines on Infant Mortality – through Low-Frequency Noise or Pesticide Usage" (with Eyal Frank)
- "Impacts of Wind Energy on Pesticide Usage and Bird Biodiversity" (with Luoye Chen, Yijia Li)
- "Investigating the Reasons that Shift the U.S. Corn Belt to the North: Evidence from High-quality Remote Sensing Data" (with Tao Lin, Hao Jiang)
- "Effects of Tax Policy on Technology in General Equilibrium" (with Luoye Chen)

PUBLICATION

- Qian, X., **Chen, T.**, Sheng, K., & Shen, Y. (2011). Quality characteristics of bamboo charcoal briquette based on corn and cassava starch adhesive. *Transactions of the Chinese Society of Agricultural Engineering*, *27*(1), 157-161.

OTHER RESEARCH EXPERIENCE

Research Assistant **Dept. of Agricultural and Consumer Economics, University of Illinois** 2018 - present

- Conduct an RCT project that attempts to systematically evaluate the relationship between projected and realized savings from the Weatherization Assistance Program with Dr. Erica Myers and Dr. Peter Christensen.

Research Assistant **The National Bureau of Economic Research** 2017

- Explored heterogeneous misperceptions of energy costs with empirical analysis based on sale data from the U.S. refrigerator market with Dr. Erica Myers and Dr. Sebastien Houde.

Research Assistant **Stigler Center, University of Chicago Booth School of Business** 2014

- Collected data and information on energy subsidy, emission policy, and carbon abatement implements of the coal industry in China for Dr. James Sallee.

Graduate Researcher **BioMASS Lab, University of Illinois** 2011 - 2013

- Developed an optimization model for maximizing the profits of rice farms in the Philippines based on crop growth simulation models and household survey data with Dr. Luis Rodriguez.

Undergraduate Researcher **Bio-energy and Bio-materials Lab, Zhejiang University** 2010 - 2011

- Completed a province granted Sci-Tech Extension Project - Parameter Optimization of Densified Biomass Fuel for Scale Production, and published an academic paper with Dr. Kuichuan Sheng.

Research Internship **Dept. of Biosystems and Agricultural Engineering, Michigan State University** 2009

- Worked with the research group of Dr. Wei Liao in a project on pretreatment selection for maximizing ethanol output from animal wastes.

TEACHING EXPERIENCE

Teaching Assistant	ACE 222	Agricultural Marketing	Fall 2017 - 2019
	ACE 231	Food and Agribusiness Management	Spring 2019
	ACE 232	Management of Farm Enterprises	Spring 2018
	ACE 449	Retirement and Benefit Planning	Spring 2017
	ACE 240	Personal Financial Planning	Fall 2016
Graduate Mentor	International Summer Immersion Program (ISIP)		Summer 2012 - 2013, 2016 - 2018

PROFESSIONAL SERVICE

Graduate Assistant **ACES Office of International Programs, University of Illinois** 2012 - 2013, 2016 - 2018

- Established networks with multiple international institutes, especially in China, for cooperation on revenue-raising study-abroad or joint-degree programs.
- Served as a graduate supervisor for the International Summer Immersion Program. Assisted other office programs like Global Academy, Fulbright programs, and Food Security Symposium. Helped arrange meetings with international guests and scholars from organizations like USAID, USDA, World Bank, and IRRI.

Office Assistant **Office of International Affairs, The University of Chicago** 2014 - 2015

- Coordinated various programs for international students. Maintained office website and arranged working schedules for all student assistants in the office.

CONFERENCE AND WORKSHOP

- 2019 Agricultural and Applied Economics Association (AAEA) Annual Meeting, Atlanta, GA (07/2019)
- 2019 Association of Environmental and Resource Economists (AERE) Summer Conference, Lake Tahoe, NV (05/2019)
- 2019 Midwest Energy Fest, Chicago, IL (04/2019)
- The program in Environmental and Resource Economics (pERE) seminar, Urbana, IL (02/2019)
- 2017 Berkeley/Sloan Summer School in Environmental and Energy Economics, Berkeley, CA (08/2017)

SKILLS

- Computer skills: Stata, R, ArcGIS, Python, GAMS, Geoda, SAS, MATLAB, LaTeX, Mathematica, Photoshop
- Language: native speaker in Mandarin and fluent in English

REFERENCES

Erica Myers (*Chair*), Assistant Professor
Dept. of Agricultural and Consumer Economics
University of Illinois at Urbana-Champaign
(217) 300-2023 • ecmyers@illinois.edu

Eyal Frank, Assistant Professor
Harris School of Public Policy
The University of Chicago
(646) 581-7308 • eyalfrank@uchicago.edu

Don Fullerton, Gutgsell Professor of Finance
Dept. of Finance
University of Illinois at Urbana-Champaign
(217) 244-3621 • dfullert@illinois.edu

Daniel H. Karney, Assistant Professor
Dept. of Economics
Ohio University
(740) 597-1239 • karney@ohio.edu

(For Professional Service)
Suzana Palaska-Nicholson, Associate Director
Office of International Programs, College of ACES
University of Illinois at Urbana-Champaign
(217) 244-2295 • spalaska@illinois.edu

(For Teaching Experience)
Paul Stoddard, Lecturer in Agribusiness
Dept. of Agricultural and Consumer Economics
University of Illinois at Urbana-Champaign
(217) 333-8507 • pstoddrd@illinois.edu

OFFICIAL TRANSCRIPT

Student Name	Student Number
TENGJIAO CHEN	434351

DEGREES CONFERRED:

M.P.P. MASTER OF PUBLIC POLICY WITH HONORS
HARRIS SCHOOL OF PUBLIC POLICY STUDIES
JUNE 13, 2015
M.P.P. PAPER: THE ANTICIPATION EFFECT OF THE EARNINGS TEST REFORM ON YOUNGER COHORTS

PROGRAM START QUARTERS:

AUTUMN 2013 M.P.P. PUBLIC POLICY STUDIES

PREVIOUS INSTITUTIONS:

B.ENG., ZHEJIANG UNIVERSITY
HANG ZHOU, CHINA 2011
M.S., UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN
URBANA, ILLINOIS 2013

AUTUMN 2013 — **PUBLIC POLICY STUDIES**

PPHA 39201	ENERGY & ENERGY POLICY	100	A
PPHA 41101	POLITICAL ECONOMY 1: INTRODUCTION TO APPLIED GAME THEORY	100	B+
PPHA 44100	ADV MICROECON FOR POL ANALYSIS	100	A

TOTAL UNITS TAKEN: 300

WINTER 2014 — **PUBLIC POLICY STUDIES**

PPHA 41102	POLITICAL ECONOMY II: INTERMEDIATE APPLIED THEORY	100	A
PPHA 42000	APPLIED ECONOMETRICS-1	100	B-
PPHA 44200	ADVANCED MICROECONOMICS	100	A-

TOTAL UNITS TAKEN: 300

SPRING 2014 — **PUBLIC POLICY STUDIES**

PPHA 32000	FINANCE	100	A
PPHA 41210	PHYSICS AND TECHNOLOGY FOR FUTURE POLICY WORKS	100	A-
PPHA 42100	APPLIED ECONOMETRICS-II	100	B+
PPHA 50400	SCIENCE, TECHNOLOGY AND POLICY	000	P

TOTAL UNITS TAKEN: 300

AUTUMN 2014 — **PUBLIC POLICY STUDIES**

BUSF 36900	LINEAR PROGRAMMING	100	R
PPHA 34600	PROGRAM EVALUATION	100	A
PPHA 36930	ENVIRONMENTAL ECONOMICS: THEORY AND APPLICATIONS	100	A
PPHA 39111	INTRO TO GEOGRAPHIC INFORMATION SYSTEMS	100	A

TOTAL UNITS TAKEN: 400

WINTER 2015 — **PUBLIC POLICY STUDIES**

BUSF 36901	STOCHASTIC PROGRAMMING	100	A-
GEOG 38400	INTERMEDIATE GIS/CARTOGRAPHY	100	A
PPHA 34500	MACROECONOMICS FOR PBPL	100	A

TOTAL UNITS TAKEN: 300

SPRING 2015 — **PUBLIC POLICY STUDIES**

ENROLLED HALF-TIME

GEOG 38600	ADVANCED GIS ANALYSIS	100	A
PPHA 31920	DECISIONS AND ORGANIZATIONS	100	A
PPHA 51700	ENERGY POLICY LAB: ALTERNATIVE TRANSPORTATION FUELS	100	A-

TOTAL UNITS TAKEN: 300

*** END OF OFFICIAL TRANSCRIPT ***

ISSUED TO: TENGJIAO CHEN

07/19/2015 **1 OF 1**

SCOTT C. CAMPBELL
UNIVERSITY REGISTRAR

THE UNIVERSITY OF CHICAGO

This document is official in electronic form when digitally signed.
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UNIVERSITY OF ILLINOIS AT URBANA - CHAMPAIGN

Urbana, Illinois 61801

Student Name: Chen, Tengjiao

University ID: 660496456 **Issue Date:** 29 - Jun - 19

Level: Graduate - Urbana-Champaign **Day - Month of Birth:** 22 - May

Most Recent Program(s)
College : Graduate College
Major : Agricultural & Applied Econ

Degree Awarded Master of Science 23-DEC-2013
Degree Information
College : Graduate College
Campus : Urbana-Champaign
Major : Agricultural & Biological Engr

SUBJ	NO.	COURSE TITLE	CRED	GRD	PTS	R
INSTITUTION CREDIT:						
Fall 2011 - Urbana-Champaign						
Graduate College						
Agricultural & Biological Engr						
ABE	476	Indoor Air Quality Engineering	4.00	A	16.00	
ABE	501	Graduate Research I	1.00	A	4.00	
ABE	594	Graduate Seminar	0.00	S	0.00	
ESL	500	Oral and Written Communication	0.00	S	0.00	
NRES	427	Modeling Natural Resources	4.00	A+	16.00	
STAT	410	Statistics and Probability II	4.00	A+	16.00	
		Ehrs: 13.00 GPA-Hrs: 13.00 QPts:	52.00	GPA:	4.00	
Spring 2012 - Urbana-Champaign						
Graduate College						
Agricultural & Biological Engr						
ABE	502	Graduate Research II	1.00	B	3.00	
ABE	594	Graduate Seminar	0.00	S	0.00	
ABE	599	Thesis Research	3.00	DFR	0.00	
ACE	563	Math Program App Econ I	2.00	A+	8.00	
ACE	567	Math Program App Econ II	2.00	A+	8.00	
ESL	501	Intro to Academic Writing	0.00	S	0.00	
		Ehrs: 5.00 GPA-Hrs: 5.00 QPts:	19.00	GPA:	3.80	
Fall 2012 - Urbana-Champaign						
Graduate College						
Agricultural & Biological Engr						
ABE	594	Graduate Seminar	0.00	S	0.00	
ABE	599	Thesis Research	9.00	DFR	0.00	

******************* CONTINUED ON NEXT COLUMN *******************

SUBJ	NO.	COURSE TITLE	CRED	GRD	PTS	R
Institution Information continued:						
CS	450	Numerical Analysis	3.00	A	12.00	
		Ehrs: 3.00 GPA-Hrs: 3.00 QPts:	12.00	GPA:	4.00	
Spring 2013 - Urbana-Champaign						
Graduate College						
Agricultural & Biological Engr						
ABE	425	Engrg Measurement Systems	4.00	A	16.00	
ABE	594	Graduate Seminar	0.00	S	0.00	
ABE	599	Thesis Research	8.00	DFR	0.00	
		Ehrs: 4.00 GPA-Hrs: 4.00 QPts:	16.00	GPA:	4.00	
Summer 2013 - Urbana-Champaign						
Graduate College						
Agricultural & Biological Engr						
ABE	597	Independent Study	3.00	A+	12.00	
MATH	461	Probability Theory	4.00	A	16.00	
STAT	440	Statistical Data Management	4.00	A	16.00	
		Ehrs: 11.00 GPA-Hrs: 11.00 QPts:	44.00	GPA:	4.00	
Fall 2015 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ACE	501	Risk and Info: Theory and App	4.00	A-	14.68	
ACE	592	Microeconomics	4.00	A	16.00	
ACE	594	Environmental & Resource Econ	1.00	S	0.00	
ECON	580	Industrial Organization	4.00	A	16.00	
		Ehrs: 13.00 GPA-Hrs: 12.00 QPts:	46.68	GPA:	3.89	
Spring 2016 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ACE	502	Demand/Supply/Firms/Households	4.00	A+	16.00	
ACE	503	Equilibrium and Welfare Econ	4.00	A	16.00	
ECON	535	Econometric Analysis II	4.00	A-	14.68	

******************** CONTINUED ON PAGE 2 ********************

Recipient: TENGJIAO CHEN

Student email: tchen41@illinois.edu

Issued to: REFNUM: 20011160788

Meghan Hazen, Registrar

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UNIVERSITY OF ILLINOIS AT URBANA - CHAMPAIGN

Urbana, Illinois 61801

Student Name: Chen, Tengjiao

University ID: 660496456   **Issue Date:** 29 - Jun - 19

Level: Graduate - Urbana-Champaign   **Day - Month of Birth:** 22 - May

SUBJ	NO.	COURSE TITLE	CRED	GRD	PTS	R
Institution Information continued:						
		Ehrs: 12.00 GPA-Hrs: 12.00 QPts:	46.68	GPA:	3.89	
Summer 2016 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ESL	504	English Pronunciation for ITAs	0.00	S	0.00	
		Ehrs: 0.00 GPA-Hrs: 0.00 QPts:	0.00	GPA:	0.00	
Fall 2016 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ECON	536	Applied Econometrics	4.00	B+	13.32	
ECON	546	Gen Equ Env Tax Policy	4.00	A	16.00	
ESL	510	Engl Pronun for Acad Purposes	0.00	S	0.00	
		Ehrs: 8.00 GPA-Hrs: 8.00 QPts:	29.32	GPA:	3.66	
Spring 2017 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ACE	516	Environmental Economics	4.00	A	16.00	
ACE	561	Adv Res and Scholarly Comm	4.00	A	16.00	
ACE	592	Spatial Econometrics	4.00	A+	16.00	
		Ehrs: 12.00 GPA-Hrs: 12.00 QPts:	48.00	GPA:	4.00	
Fall 2017 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ACE	531	Impact Evaluation	2.00	A	8.00	
ACE	592	Empirical Methods	2.00	A-	7.34	
ACE	599	Thesis Research	4.00	DFR	0.00	
		Ehrs: 4.00 GPA-Hrs: 4.00 QPts:	15.34	GPA:	3.83	
Spring 2018 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						

******************* CONTINUED ON NEXT COLUMN *******************

SUBJ	NO.	COURSE TITLE	CRED	GRD	PTS	R
Institution Information continued:						
ACE	599	Thesis Research	8.00	DFR	0.00	
		Ehrs: 0.00 GPA-Hrs: 0.00 QPts:	0.00	GPA:	0.00	
Fall 2018 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ACE	599	Thesis Research	12.00	DFR	0.00	
		Ehrs: 0.00 GPA-Hrs: 0.00 QPts:	0.00	GPA:	0.00	
Spring 2019 - Urbana-Champaign						
Graduate College						
Agricultural & Applied Econ						
ACE	599	Thesis Research	12.00	DFR	0.00	
		Ehrs: 0.00 GPA-Hrs: 0.00 QPts:	0.00	GPA:	0.00	

********************* TRANSCRIPT TOTALS **********************

	Earned Hrs	GPA Hrs	Points	GPA
TOTAL INSTITUTION	85.00	84.00	329.02	3.91
TOTAL TRANSFER	0.00	0.00	0.00	0.00
OVERALL	85.00	84.00	329.02	3.91

********************* END OF TRANSCRIPT **********************

Meghan Hazen, Registrar

This electronic transcript, as delivered in PDF form, has a transcript explanation at the end of the document which details authentication information.

ZHEJIANG UNIVERSITY
Student's Academic Records

Registration No:Z2327

Name:Chen Tengjiao	College/Dept.:College of Biosystems Eng. & Food Science		Speciality:Biosystems Engineering		Student ID:3071315026
Sex:Male	Birthday:05/22/1988	Birth Place:Zhejiang	Entrance Date:09/01/2007	Graduation Date:06/30/2011	Years of Program:4Years

Academic Year 2007-2008			College English Band III	3.0	74	Plant Physiology & Experiment (B)	3.0	84	Introduction to the Principle of Marxism	2.5	85	Leadership Science & Skills	2.0	86
Courses(1st Term)	*Cr	*Sc	Situation and Policy	2.0	92	Macroeconomics (A)	3.0	80	Biosystem Detection & Control	2.0	82			
Military Training	2.0	B	Calculus III	1.5	82	Engineering Mechanics	3.5	90	Engineering Surveying (B)	1.5	86			
The 10-year History of the Great Proletarian Cultural Revolution	1.5	90	Physics & Its Lab	5.0	96	Academic Year 2009-2010			Courses(2nd Term)	*Cr	*Sc			
Modern Wars and Defense Technology	1.5	92	Lab. & Fundamentals of C Programming	3.0	86	Courses(1st Term)	*Cr	*Sc	Biosystem Engineering Specialized Practice	2.0	B			
Experiments of Introduction to Life Science & Biotechnology	1.0	95	Modern Chinese History	2.5	90	Biosystem Engineering Acquaintanceship Practice	1.0	80	Thesis	8.0	95			
Freshmen Seminar:Deve. & Problems in Intelligent Transport. Sys.	1.0	95	Organic Chemistry Experiment	1.5	A	Experimental Design and Data Analysis	2.0	98	Practice Ability & Quality Development	4	A			
Tennis (Basic Level)	1.0	86	Academic Year 2008-2009			Biosystem Transmission Process	3.0	96	Introduction to Subject	1.5	P			
General Chemical Experiment	2.0	89	Courses(1st Term)	*Cr	*Sc	Principles of Biosystems Engineering	1.5	86	Physical test	1	P			
College English Band II	3.0	69	Ordinary Differential Equations	1.0	84	Applied Electronics & Experiment	4.5	93	Minor Courses	*Cr	*Sc			
Calculus I	4.5	90	Appreciation of World Fiction	1.5	95	Physical Propeties of Bio-Materials	2.0	80	Finance	3.0	92			
Linear Algebra	2.5	80	College English Band IV	3.0	73	Courses(2nd Term)	*Cr	*Sc	International Finance	3.0	78			
Inorganic Chemistry (B)	2.0	90	Botany and Experiments (B)	3.0	81	Design technique of Biosystems	1.5	88	Commercial Bank Management	3.0	90			
Mental Education and Foundation of Law	2.5	86	Introduction to Marketing	1.5	86	Biosystem Simulation	2.0	92	Insurance	3.0	78			
Fundamentals of Computer Science and Technology	2.0	87	Table Tennis (Mid Level)	1.0	81	Principle of Automatic Control	2.0	93	Securities Investment	3.0	87			
Engineering Graphics	2.5	95	Mao Zedong Thought, Deng Xiaoping Theory & "Three Represents"	4.0	84	Bio-environmental Engineering	2.0	94	Public and the Third Sectors Strategy Management	2.0	93			
Courses(2nd Term)	*Cr	*Sc	Career Planning	1.5	A	Biosensor and Instrumentation	2.0	89	Public Economics	3.0	81			
Calculus II	2.0	80	Biochemistry and Experiment (C)	4.0	96	Water Resources Engineering	2.0	90	Analysis of Public Policy	3.0	85			
Probability Theory	1.5	70	Courses(2nd Term)	*Cr	*Sc	Academic Year 2010-2011			Principles of Public Administration	2.0	90			
Jewellery Culture and Gem Identification	1.5	90	Astronomy	1.5	92	Courses(1st Term)	*Cr	*Sc	Science of Politics	3.0	80			
Mechanical Graphing and CAD Fundamentals	1.5	87	History of World Civilization	1.5	91	The Synthetical Design of the Robotics for Bioproduction Systems	2.0	86	DECISION MAKING	2.0	95			
Table Tennis (Basic Level)	1.0	90	Microbiology and Experiments (B)	3.0	91	Robotics for Bioproduction Systems	2.0	89	Government & Politics of China	2.0	93			
Studies on Song Iambic Verse	1.5	85	Football (Basic Level)	1.0	86	Biomaterials Processing Engineering	1.5	94	Critical and Creative Thinking	2.0	91	Overall GPA:3.82/4.0(87.11/100)		
Mathematical Statistics	1.5	92	Engineering Mechanics Experiment	0.5	85	3S Technology and Precision Agriculture	2.0	85	Ethics	2.0	85	The last two years GPA:3.89/4.0 (89.06/100)		
Organic Chemistry (C)	4.0	90	Military Theory	1.5	87	Engineering Training	1.5	82	Administrative Law	3.0	78			

Credits Required for Graduation:160+4+5	Credits Obtained:199	Degree Granted:Bachelor of Engineering

*Cr=Credits;*Sc=Score;
Three grade systems are used simultaneously in Zhejiang University, specifically as follows:
1. The percentage system:Above 60 is passing, 100 is full mark;
2. Five degree grading:Excellent(A), Good(B), Fair(C), Passing(D), Failed(E);
3. Two degree grading:Passing(P), Failed(F).
4. Courses identified with "*" are transferred from partner universities.

Associate Provost: 陆国栋 Registrar: Date Issued:09/09/2013

RECOGNITION INSTRUCTION: 1."ZHEJIANG UNIVERSITY" is microprinted on the lower right corner as a line, they can be seen under the magnifying glass. 2.The fluorescent school badge of ZHEJIANG University on the higher left corner will appear under the UV light. 3.The words "ZJU" on the center of the report will turn purple under the sunlight. 4.This style transcript has been formally in use since September 1,1999.

Eyal Frank
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07/24/2019

Dear Members of the Recruitment Committee,

I am writing this letter in support or Tengjiao Chen's application to your department. While I am not a formal member of Tengjiao's dissertation committee, I have been discussing his work with him and collaborating with him on a project since 2018. Throughout this time, I have been very impressed with his ability to come up with interesting research questions at the intersection of agriculture, environment, and energy economics. Tengjiao has also demonstrated that he can skillfully execute his ideas and produce high quality research. In the following, I will describe the papers in his research agenda with which I am most familiar, his contributions to our collaborative project, and my overall impression regarding his potential to generate solid research papers in the near future. Briefly, Tengjiao has a promising career ahead of him and I highly recommend that you interview him for the position.

Tengjiao broadly works on estimating externalities and unintended consequences in agricultural, environmental, and energy economics. He has one earlier publication from his time as an undergraduate, and a current *Revise and Resubmit* at the *Public Finance Review*, which is a paper from his MPP degree. These papers demonstrate that he has worked hard to be productive, and has gained valuable exposure and experience with the publication process. His current work focuses on the potential spillovers of wind energy, which he studies using several data sets. Covering an important and emerging renewable energy sector positions him to become a leading scholar on the subject of wind energy impacts across a wide array of outcomes.

In his solo-authored job market paper, Tengjiao studies the degree to which wind energy production can have positive spillovers on crop yields. This is an important question to quantify and answer, as it can shape future policy which aims to direct the development of wind energy using different subsidies. If wind turbines do have a large positive impact on yields, policy could choose to incentivize their construction around farms. The main mechanism, as documented in the natural sciences literature, which connects wind turbines and crop yields has to do with mixing the air. To keep this brief, the wind turbines mix air from around the surface with that above the surface. This helps to better smooth out temperatures throughout the day, as well as increase CO_2 concentrations, enabling faster growth of the crop.

Studying this requires granular spatial data on the location of wind farms and economic activity. While previous papers, such as the work by Daniel Kaffine from the University of Colorado Boulder, have used county-level data, Tengjiao is able to use farm-level data for the state of Illinois. Accessing the data was the result of his independent work and tenacity. The high granularity of the data allows him to exploit the geocoded data on the location of wind turbines, and to include farm-level fixed effects in his analysis, while also controlling for time-varying farm inputs. In his JMP, the main outcome of interest is yields. However, instead of simply regressing farm crop yield on wind energy capacity, he utilizes an instrumental variable approach to account for the potential endogeneity of wind farm location. Because wind energy potential is an important determinant in the decision on where to construct a farm, it offers a potentially strong shifter of installed capacity, the variable of interest.

After instrumenting for wind energy capacity, he finds large positive effects on corn and soy yields. While these results are based on one state, they offer the most granular results to date on this relationship. Tengjiao goes one step further and validates the local micro-climate impact that wind turbines have. This provides additional evidence in support of the main mechanism. As this paper makes an important contribution to our understanding of the spillovers from wind energy production to agriculture, I am confident that this paper will publish well in either JEEM, JAERE, AJAE or an equivalent quality journal.

In my work with Tengjiao, we are interested in studying the health impacts of wind farms. The literature currently suggests that wind farms might have a direct impact through infrasound, such as in the work of Eric Zou from the University of Oregon, or that there might be an indirect effect on the use of pesticides through the negative impact wind turbines have on bat populations (which I study in a different paper). These offer two important, yet different, channels through which wind energy development could have an impact on human health for those living in the vicinity of such farms. With wind energy growing rapidly across the U.S. and the world, it is important we identify what is the magnitude of these effects, and if there is sufficient evidence that supports their existence. This again demonstrates that Tengjiao is working on large and important questions at the intersection of agriculture, environment, and energy economics.

As such, we have collected data on infant and fetal health, as well as the universe of mortality in the U.S. Using the data Tengjiao has put together on the location of wind farms, the different wind potential scores, and the ways to construct installed capacity density variables across multiple scales, we aim to study how the development of wind energy relates to these outcomes. We are still in the early stages of the project, yet Tengjiao has already managed to impress me with his hard-working drive and ingenuity. His contributions to the project have been vital with getting the data together, thinking carefully on how it should be merged, and developing the testable hypotheses. A key challenge in this study it the assignment of treatment. Tengjiao has thought about this topic carefully, and how we stand to trade-off different elements when choosing among a set of treatment assignment rules. Our preliminary results already find evidence connecting wind energy development with an increase in the use of insecticides. This works through the channel of reducing bat populations, who often suffer death around wind farms. Bats offer a free source of pest control, and when they decline, farmers compensate by using more insecticides.

To conclude, I find that Tengjiao is already a great colleague to work and interact with. I think he has found an important and understudied topic of research which covers several often-overlapping areas of research, such that there will be a large community ready to discuss and engage with his type of work. I am delighted to recommend Mr. Chen for the position, and will be more than happy to answer any additional questions.

Sincerely,

Eyal Frank

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Dear Search Committee:

It is my pleasure to provide a reference for **Tengjiao Chen**, who is an environmental economist completing his Ph.D. in the Department of Agricultural and Consumer Economics at the University of Illinois. His primary research interests are in the intersection of agricultural and energy economics. He has extraordinary technical skills and careful approach to research. The ACE department has a long tradition of producing well-trained economics researchers, many of whom go on to work in government policy offices, international NGO's, the World Bank, and in private sector employment. Tengjiao stands out from this group as one of the best students technically that I have interacted with in my 5 years in the department, and particularly, as someone who could excel in academic research.

Of our previous students, I believe his research potential is most comparable to Andres Ham (2017), who received academic offers both inside the U.S. and internationally, ultimately choosing a position at Universidad de los Andes in his home country, Columbia. Like Hamm, Tengjiao has been unusually entrepreneurial in developing his graduate research agenda independently. His job market paper, "Wind Energy and Agricultural Production: Evidence from Farm-Level Data," is sole-authored. In addition, he developed his other two dissertation chapters by reaching out to researchers at other institutions, (Eyal Frank, U Chicago and Daniel Karney, Ohio University) and initiating collaborations.

As I will describe below, Tengjiao also stands out in his mastery of different methodological approaches, which he applies in his dissertation. In his work on the impacts of wind farms on agricultural output and ecosystem services, he has implemented modern reduced form empirical strategies to uncover causal relationships. However, he also has an aptitude for math and theoretical analysis and has a dissertation chapter using an analytical general equilibrium model to investigate the welfare effects of Pigouvian pollution taxes under imperfect competition with price discrimination in energy sector.

Tengjiao's job market paper investigates the impact of wind farm operations on crop yields. He uses an instrumental variables approach which exploits exogenous variation in installations due to two factors: 1) wind capacity and 2) citing restrictions caused by Federal Aviation Authority (FAA) aeronautical requirements. Like previous work in this area (Kaffine, JEEM 2019), he finds that wind farms increase crop yields.

The major contribution of his work is that he is then able to explore two mechanisms that might lead to this finding, one operational and one environmental. The first hypothesis he explores for the increase in yield from wind farms is that farmers are using lease payments from the installations to invest in more inputs. Using farm-level panel data from Illinois, he estimates the effect of wind farm installations on different aspects of farm operations including input costs and labor costs, and management returns to name a few. He finds that wind installations cause higher income and returns on a per acre basis. However, he does not find support that they lead to expansion of operating acres or purchase of more inputs.

The second hypothesis he explores is that wind turbines increase yields through changing the microclimate. He finds that windfarms increase the incidence of growing degree days (degree days between 10 and 30 degrees Celsius) and decrease the incidence of extreme degree days (degree days above 30 degrees Celsius). He links this finding to literature from other disciplines, which suggest that wind farms can improve growing conditions by cooling air during the day and warming it slightly at night.

These results suggest that changes in microclimates are likely a significant contributor to the higher yields on cropland as a result of nearby windfarms. As far as I am aware, this positive externality is not widely discussed in renewable energy policy. Given that climate change is projected to lead to an increased incidence of extreme degree days in the Corn Belt, the positive effects of windfarms on microclimates may become increasingly relevant. Given its contribution I believe this paper has the potential to publish in a top field journal like JEEM or AJAE.

Tengjiao's second chapter, joint with Eyal Frank, aims to identify the effects of wind farms on infant mortality. They use a difference-in-differences approach comparing counties in years before and after nearby wind farms were built relative to counties that are otherwise similar but not close to wind turbines. Using the confidential infant health and mortality data from the National Association for Public Health Statistics and Information Systems, their preliminary results imply that sizable wind farms lead to higher infant mortality nearby. They also find that wind farms are associated with higher pesticide usage. Since low-frequency noise generated by wind turbines may also negatively impact human health, their main contribution will be to distinguish whether it is the pesticides or the presence of turbines themselves that lead to the mortality result. They will shed light on this by exploring whether the health effects are more concentrated in counties with large agricultural land area as compared to counties with little agricultural activity.

The third chapter of Tengjiao's dissertation, joint with Daniel Karney, demonstrates his methodological versatility. They use a general equilibrium model to investigate the welfare effects of Pigouvian pollution taxation in settings, like some energy production markets, with imperfect competition and price discrimination. They show that the welfare effects of environmental taxation under these conditions can be ambiguous. Taxing energy to correct for negative pollution externalities enlarges the underproduction distortion under market power and has ambiguous consequences on the price discrimination distortion.

Tengjiao has a variety of other projects in progress as well. I expect his working moving forward to continue to draw from different methodologies to explore policy relevant questions in environmental and agricultural economics. I am aware of a project joint with another graduate student, Luoye Chen, investigating the externality effects of subsidies on technology in general equilibrium. In addition, he is part of an interdisciplinary team that is using remote sensing data to try to decompose the factors driving the northern expansion of the U.S. Corn Belt.

Since I am writing letter for two students this year who are applying for many of the same jobs, I think it is important to emphasize that these are both exceptional students. Either of them would have easily been the strongest environment student with skills in modern causal inference out of the ACE department in a normal year, if not over several normal years. I strongly believe that either of them have potential to excel in economics research environments, including academic environments. Tengjiao stands out with his impressive independence in developing a productive research agenda from early on in the program.

In sum, I believe Tengjiao has the skills to excel in a research environment. He has incredible technical proficiency and a careful approach to research. This combined with his passion for the subject matter and his ability to develop collaborations with other researchers make me believe that he will continue to be productive.

Please don’t hesitate to contact me if I can provide any further information.

Sincerely,

Erica Myers

Prof. Don Fullerton
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To whom it may concern: September 21, 2019

Tengjiao Chen will finish a PhD by August 2020 in the Department of Agricultural and Consumer Economics (ACE) at the University of Illinois at Urbana-Champaign. I am writing to recommend him for an assistant professor position at a good college or university, or for a research position. My own appointment is 100% in the Finance Department of the Gies College of Business, but I have courtesy appointments in the IGPA, the Economics Department, and in ACE (in the College of Agriculture). Tengjiao took a class from me, and I am on his dissertation committee. He is very smart, and he is well trained. He will work very hard, and he will be able to publish his dissertation chapters successfully. I believe he will be a success in academia and in research.

Tengjiao was in Agricultural Engineering here at UIUC in 2011-13, but he left to get a M.P.P. degree from the Harris School of Public Policy at the University of Chicago in 2013-15. While there, he co-authored a paper that has been revised for resubmission to the *Public Finance Review* called "The Anticipation Effect of the Earnings Test Reform on Younger Cohorts." He then came back to UIUC in 2015 to enter the PhD program in ACE, so he is now in his fifth year of this program. During his first year in 2015, he took all the required economic theory and econometrics courses, followed by field courses in environmental and energy economics, plus industrial organization and impact evaluation.

In the fall of 2016 during his second year, he took my course called "General Equilibrium Analysis of Environmental Tax Policy". This course is not for reading all the published papers in the field; instead it's more of a "modelling methods" course. All students work to replicate all the math in several prior published papers, while learning how to build their own analytical G.E. model. Each comes up with their own idea for a term paper, and designs a model complete with production functions and resource constraints, consumer utility, and budget constraints. Then they differentiate all those equations to linearize the model, and solve the N linear equations for N unknown outcomes, effects of a small exogenous change in some policy variable or other shock.

Within the one semester of this course, Tengjiao designed an excellent model, solved it, wrote an original research paper, and presented it to the class. Prior research had used partial equilibrium models to find that a pollution tax in a monopolized industry can lead to output reductions that exacerbate the distorting effects of monopoly and thus reduce welfare. Tengjiao extended that research to a general equilibrium setting and wrote an excellent term paper. Moreover, he pursued it after the course ended, by working with Prof. Dan Karney of Ohio University to produce an even more polished co-authored research paper that will be a chapter of his dissertation and can be submitted soon to a refereed journal. This paper now includes oligopolistic firms producing electricity for final demand by households but also sold to industry to use as an intermediate input. Because the consumer demand elasticity can differ from industry's electricity input demand elasticity, electricity producers can engage in price discrimination.

All these equations are linearized, including production functions, resource constraints, consumer behavior, and industrial electricity input demands. The linearized equations are solved for the effects of a pollution tax not only on pollution, but on all industry factor inputs, intermediate inputs, outputs, prices, and consumer welfare. The model includes multiple market imperfections: pre-existing taxes, externalities, market power, and price discrimination. Thus, the second-best effects of a pollution tax are entirely ambiguous. Given the linearization with these existing distortions, the paper solves for welfare effects of small changes in the pollution tax rate, and explains the analytical results intuitively by decomposing the change in overall welfare into three effects: an externality correction effect, a production distortion effect, and a price discrimination effect. It then illustrates numerical magnitudes by inserting plausible parameter values for the U.S. economy into the analytical expressions, and finds that an environmental tax still typically leads to higher welfare in this setting with multiple distortions. This analysis is particularly applicable today, as electricity market power is changing amid carbon policy debates.

His dissertation will also include a paper co-authored with Prof. Eyal Frank of the University of Chicago, called "The Impact of Wind Turbines on Infant Mortality – through Low-Frequency Noise or Pesticide Usage." I have not read that paper yet, and so cannot comment on it until the next version of this letter.

Finally, Tengjiao is also working on a single-authored job market paper called "Wind Energy and Agricultural Production: Evidence from Farm-Level Data." It is an empirical paper that improves in several ways upon previous efforts to measure the effect of multiple wind turbines in "wind farms" that are located on agricultural land. These wind farms have some effect on the wind, and therefore on local weather. That in turn may have some positive or negative effect on crop yields. He finds a significant positive effect: using his estimates, he calculates that an additional 50 MW of wind capacity raises yields in the same county for soybeans by 1.3% and for corn by 2.4%. To make these estimates more credible, he undertakes multiple additional steps and robustness checks.

First, he assembles a large and comprehensive farm-level dataset for 2003 to 2017 that allows him to improve upon prior studies that are only at the county level. These data include farm labor and other inputs, and so they allow him to consider the possibility that royalty payments from the wind-energy companies to the farmers allow them to increase other farm inputs that could explain the increased crop yields. He finds no effect of the new wind turbines on farmers' inputs. The increase in crop yields and revenues are thus attributable to increased yields from the same inputs.

Second, he captures the spillover effects from one farm to another. He does not have specific farm locations, only their county, and so he must aggregate the development of wind turbines to the county level for his main estimates of the effects of wind turbines on crop yields, but he still captures external spillovers from the turbines on one farm to productivity at other farms within the county. That is, he finds the effect of all new wind farms in the county on productivity at all firms within the county.

Third, he uses others' research on how changes in wind *can* affect crop yields. He cites research that demonstrates the effects of wind turbines on microclimates up to 20 km downwind. Turbines mix the air vertically, which changes air moisture, carbon dioxide, and air temperatures – particularly warmer temperatures at night and cooler temperatures during the summer days. It makes the microclimate endogenous, biasing OLS results.

Fourth, while his main goal is to estimate the effects of wind turbines on crop yields, using an IV approach, he also estimates the significant effects of wind turbines on local meteorological variables. This result also helps confirm evidence that wind turbines are significant contributors to higher yields.

Fifth, he deals with potential endogeneity from measurement error (e.g. spillover effects) and omitted variables (e.g., technological changes that may influence both agricultural technology and wind power technology). To do so, he constructs an entirely new instrument from data on *potential* wind power (wind power class) interacted with the aviation authority's determination of where wind turbines can safely and legally be built. These instruments are plausibly related to the establishment of new wind turbines but are not a determinant of crop yields. All these steps demonstrate Tengjiao Chen's careful and thorough approach to demonstrating causation in his econometric strategies.

Tengjiao Chen is a hardworking and experienced research economist who will be a good academic researcher and teacher in the right kind of job where he can excel. You should consider him carefully, interview him at the meetings, and give him a chance to present his research. Thank you for your consideration, and please let me know if you have any other questions.

Yours,

Don Fullerton

Don Fullerton

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July 29, 2019

To Whom It May Concern,

This letter is in support of Tengjiao Chen in his application for an academic position at an agricultural economics department or energy/environmental position at an economics department. He is an energetic and highly-motivated economist using his diverse background to conduct policy-relevant research and provide effective teaching. Tengjiao's research agenda lies at the intersection of agricultural economics and energy/environmental economics with a focus on externalities and spillovers. He has a number of interesting research projects in various stages of development with a few of those soon to be under review at well-placed academic journals.

To be clear, I am not one of Tengjiao's advisors on his dissertation committee but I have provided feedback on his job market paper and I am a co-author with Tengjiao on a separate research project.

Tengjiao and I met approximately three years ago in Fall 2016 when I was an external co-instructor for an elective course in analytical general equilibrium modeling at the University of Illinois. The primary instructor for that course was Prof. Don Fullerton and the purpose of the course was to provide students experience using a specific modeling technique and then have them develop an original research paper. The class presented their research at a mini-symposium and I acted as an external reviewer for all of the papers by providing detailed comments. Tengjiao had one of the best papers in the class and approximately one year later we began work as co-authors expanding the main idea and writing a journal-ready manuscript that is nearly ready for submission and review. I will expand on this specific research next.

Again, Tengjiao has a variety of research projects at various stages of development. Here, I will describe the two projects that I am familiar with in terms of completeness, importance, and publishing potential. To start, our co-authored paper titled "Environmental Taxes in General Equilibrium under Market Power and Price Discrimination" analyzes the policy-relevant setting of a pollution producing energy sector (e.g. electricity sector) that has market power and engages in price discrimination across industrial and residential customers. It is generally known that taxing pollution in similar settings makes the market power distortion worse, but we show that a pollution tax increase actually helps mitigate some of the price discrimination distortion. This paper is will be submitted shortly to a top field journal in environmental economics such as The Journal of Environmental Economics and Management (JEEM).

The other research project of Tengjiao's that I am familiar with is his job market paper titled "Wind Energy and Agricultural Production – Evidence from Farm-Level Data". The motivation for that paper is to identify and measure the net externality of wind farms on nearby agricultural production. A previous paper looks at this question using county-level data, but this analysis uses detailed farm-level data. Furthermore, Tengjiao employs a new instrumental variable (IV) to plausibly identify the causal impact due to the potentially endogenous natural of wind farm location. The main finding is that wind energy provides a net positive externality to nearby agricultural production, and specifically "corn and soybean yields increase by roughly 2.9 bushels and 0.89 bushels per acre, respectively, given an additional 50 MW wind capacity installed in the same county." These estimated effects are economically meaningful and potentially generated by known micro-climate impacts of wind farms. Therefore, policies that limit the siting of wind farms should consider this positive externality on agricultural production when consider such regulations. Thus, this paper could fit in either a top energy economics field journal or similarly regarded agricultural economics journal.

While I do not have direct knowledge of Tengjiao's teaching abilities, we have discussed Tengjiao's teaching philosophy and style (so that he could write an accurate Teaching Statement). My impression from these discussions is that Tengjiao actively seeks to improve his teaching. However, I know from my own work with Tengjiao that he is quite enthusiastic about economics, and that is a great foundation from which to teach.

One of the unique aspects of Tengjiao's background that makes him particularly suited to employment at an agricultural economics department is that he has a Master's Degree in Agricultural and Biological Engineering. This enables Tengjiao to engage in interdisciplinary research due to his familiarity of across disciplines of jargon, topics, theories, and methods.

I would like to digress a moment in my letter to note that I am not going to rank of department or institution to which I would recommend Tengjiao as I believe this leads to unnecessary, artificial pigeonholing. I know my practice is in contrast to that other Letter of Recommendation writers. Rather, when I am submitting a Letter then I am implicitly stating that Tengjiao is a feasible fit for the given job opening. I then leave it up to your

Search Committee (or equivalent process) to evaluate his application and quality of fit based on your own criteria.

Regarding Tengjiao's English language proficiency both his written and verbal skills have vastly improved since I met him three years ago. His spoken language is quite good and he communicates clearly. He does speak quickly sometimes but that is his enthusiasm for the ideas being discussed. In terms of technical writing, Tengjiao again clearly communicates but for journal-level publications he employs professional copy editors. However, I have seen his unedited slides for class presentations and there are no issues of concern in that context.

In summary, Tengjiao is a conscientious, new academic economist with a great deal of motivation and potential, and thus I support Tengjiao's application to your open academic position. Please call or email if you have any questions.

Sincerely,

Daniel H. Karney
Ohio University

Wind Energy and Agricultural Production: Evidence from Farm-Level Data

By TENGJIAO CHEN*

August, 2019

Abstract

This study investigates the impacts of sizable wind farms on neighboring crop yields and farm operations. I develop an instrumental variables (IV) approach which exploits local wind potential and aviation safety restrictions as sources of exogenous variation in the development of wind turbines. I find positive effects of wind energy on nearby crop yields, and then probe two possible mechanisms. First, using farm-level data, I explore changes in farm operations and find no measurable increases in production inputs after wind turbines are installed despite the fact that landowners might be receiving royalties. My results further reveal that most of the benefits from the yield increases are realized through higher labor and management returns. Second, I estimate the causal effects of wind turbines on local meteorological variables and find significant impacts, suggesting that the induced microclimate changes are likely important contributors to higher yields.

JEL Codes: Q12, Q42, Q48, Q51, Q54
Keywords: wind energy, crop yields, microclimates, farm operations, farm returns

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* Chen: Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. tchen41@illinois.edu. This work is not based on any financial support. I wish to thank Erica Myers in particular for her advice and support. I am grateful for the dataset provided by the Illinois Farm Business Farm Management Association and help from Gary Schnitkey, Yilan Xu and Bradley Zwilling. I appreciate the helpful comments from Luoye Chen, Benjamin Crost, Tatyana Deryugina, Eyal Frank, Don Fullerton, Benjamin Gramig, Daniel Kaffine, Daniel Karney, Madhu Khanna, Rebecca Martin, Sarah Sellars, Mateus Souza, Juo-Han Tsay, and Eric Zou, as well as seminar participants at University of Illinois Program in Environmental and Resource Economics seminar, Midwest Energy Fest, AERE summer conference, and AAEA annual meeting. I also thank my department for providing student research travel awards. There are no conflicts of interest to report. All errors are mine.

1. Introduction

Wind energy is important for climate goals and has been developing rapidly over the last 15 years in the U.S., with growing annual generation from 11,187 GWh in 2003 to 254,303 GWh in 2017. Wind generators currently provide roughly 6.3 percent of total U.S. utility-scale electricity generation, and the U.S. Department of Energy (DOE, 2017) envisions that wind power could grow to 20 percent in 2030 and 35 percent in 2050. A unique feature of wind energy is that the footprints of wind farms often overlap with croplands, especially in the Midwest. Wind turbine arrays can impact local agricultural production through several possible channels. Landowners could possibly plant more acreage or purchase additional production inputs with royalties from leasing the airspace to wind developers (Kaffine 2019). Scientific literature also suggests that wind farms may affect agricultural production through microclimate effects or impacts on local ecosystems (Dai et al. 2015; Rajewski et al. 2013; 2014). What is more complicated is that these effects can easily expand beyond farm or even county borders and thus present an externality. Landlords could bargain with wind energy companies through the leasing process, but they would not be concerned about effects beyond their own lands, even if they were fully aware of the impacts of wind turbines at the time of negotiation. Therefore, well-identified estimates of the net impacts of wind energy on agricultural production and outcomes on nearby farms would be helpful to quantify farmers' welfare and to design better future renewable energy or agricultural policies.

In this paper, I provide estimates of the net effects of the development of wind energy on neighboring crop yields, as well as operating expenses and returns, based on highly localized data at the farm level. My primary outcome variables are from certified longitudinal data collected by the Illinois Farm Business Farm Management Association (FBFM) and the University of Illinois from 2003 to 2017. To the best of my knowledge, this is the first study in the area that uses farm-level data with the ability to control for farm fixed-effects and inputs. I exploit variation in the timing and spatial densities of sizable wind farm operations to study how they affect farm-level outcomes. This study builds on prior work that uses county-level data in the U.S. and finds positive effects of wind farms on neighboring crop yields (Kaffine 2019), but provides several innovations. First, I develop an instrumental variables (IV) approach based on local wind potential and airspace feasibility to deal with threats to causal identification. Second, I further investigate two possible mechanisms: 1) my farm-level dataset allows me to directly examine whether operating expenses increase or not after wind turbines are installed nearby; and 2) I know the exact location of every wind turbine and can verify microclimate effects at a fine grid level. Third, I also attempt to quantify the net effects of the development of wind energy on farm returns.

To identify the causal effects, I need to address measurement error and omitted-variable bias as two main sources of endogeneity. The measurement error may come from the spatial spillover effects. Many wind turbines are located near county borders. In particular, some of them are concentrated on one side of the borders, with their footprints clearly truncated by administrative boundaries. However, the local impacts of these wind turbines can easily extend to adjacent counties but may not be able to reach the other side of the same county. Wind development indicators that do not take this into account, such as county-level *wind capacity density* used in existing literature, could result in an underestimate of the true impact due to the fact that they only increase in the county where the wind turbines are installed but remain unchanged in the adjacent counties.

The potential omitted-variable bias problem may occur if the development of wind turbines is associated with local time-varying unobservables that can also affect agricultural production. For instance, many scientific studies indicate that wind turbines can affect carbon dioxide, heat, and moisture exchange between the surface and the atmosphere by enhancing vertical mixing of air when extracting kinetic energy (Baidya Roy 2011; Moravec et al. 2018). Therefore, local meteorological variables are potentially endogenous, while on the other hand, dropping them from the regression analysis could result in an omitted-variable bias. As another example, the adoption rate of genetically engineered (GE) seeds, which is only available at the state level, has increased remarkably during the same study period in Illinois. Farmers' adoption decisions might be correlated with many factors, especially their attitudes toward new technology including wind energy.

To deal with these challenges to identification, I develop an innovative instrumental variables (IV) approach. As a natural endowment, local wind energy potential measured by *wind power class* is a key driver for the development of wind energy. It is also exogenous and time-invariant (at least in the short term) in a given location, which implies that farm fixed-effects can largely capture its impacts on agricultural production in general. Therefore, given that the wind energy technology advancement and state-wide renewable energy policy changes across years are exogenous to crop yields, *wind power class* by year dummies could work as instruments for the cumulative development of local wind energy, theoretically; however, I find they suffer from the weak IV problem. To enhance the correlation in the first stage, I take airspace feasibility into consideration and construct *feasible wind class (FWC)* by year dummies as my new instruments. *FWC* is a simple function of multiplying *wind power class* by *non-air-hazard ratio*. I define the *non-air-hazard ratio* as the percentage of proposed wind turbine locations that receive determinations of "No Hazard to Air Navigation" based on the information provided by the Federal Aviation Administration (FAA). The development of wind energy will be largely restricted in areas with high likelihood to receive determinations of "Hazard to Air Navigation", even though these areas may also have high wind potential. The basis for all determinations is aeronautical study findings. The airspace feasibility considers conditions far above the ground level and therefore provides plausibly exogenous variation with respect to agricultural activities.

I find strong evidence that the growth of wind energy has significant positive effects on nearby soybean and corn yields, and moreover, the marginal effects tend to diminish as the density of wind generators becomes higher. In particular, given an additional 50 MW of wind capacity installed in the same county, my preferred estimates from the IV approach indicate that soybean and corn yields increase by roughly 0.89 and 2.9 bushels per acre, respectively, based on the level analyses, or by 1.3 and 2.4 percent, respectively, from the log-linear models. These estimated effects on crop yields are robust to different specifications and moderately larger than the estimates from previous literature (e.g., Kaffine 2019) based on county-level data and reduced-form strategies without addressing potential endogenous threats.

I then investigate possible mechanisms that could lead to the increases in neighboring crop yields. One possible channel is through changes in local climate induced by the operation of sizable wind farms. Using fine-scale weather data conducted by Schlenker and Roberts (2009), I implement a simple difference-in-differences analysis to test the microclimate effects of wind turbines at the 2.5-by-2.5-mile grid level. Another possible explanation is from the perspective of farm input or operation changes. One potential concern is that farmers may adjust agricultural practices based on their own observations, like crop growth level or pest damages, even without knowing any possible causal connections with wind turbines. Another concern is that landowners receive lease payments from wind farms, and thus may expand production or purchase additional farm inputs. FBFM data have detailed information on farm operating expenses, which provide a unique opportunity for me to directly test whether farmers change their operations after the installation of a wind farm nearby.

With the help of farm-level observations, I find that crop acreage and per acre farm operating expenses do not significantly change on farms located close to installed wind turbines. On the other hand, I find evidence that sizable wind farms have significant effects on the local climate, and therefore these local meteorological variables that are commonly used as right-hand-side control variables in existing literature, including growing degree days, extreme degree days, and precipitations, are endogenous. In particular, the growing season extreme degree days in grids close to a sizable wind farm after its installation decrease by about 2.2 to 2.6 percent. In summary, my results suggest that the microclimate effects induced by the operation of wind turbines are likely resulting in higher neighboring crop yields.

In addition, I further explore the net impacts of nearby wind turbine arrays on farm returns. My results indicate that 50 MW of new wind capacity built in the same county raises crop returns by $12.0 per acre or 1.7 percent equivalently, which is right in between the estimated yield effects on soybeans and corn.[1] Furthermore, it is likely that farmers are expanding production and using more inputs, if the net farm incomes, which is defined as the value of farm production less total operating expenses and depreciation, do not change when yields and crop returns go up after the installation of wind turbines nearby. However, my results suggest that most of the benefits from the yield increases are realized through higher labor and management returns, though the effects of wind energy on crop yields seem modest. These findings are consistent with the insignificant estimates on operating expenses and further point to the induced microclimate effects. In

[1] Crop returns are defined by FBFM (Krapf et al., 2017) as:
Crop returns are the sum of grain, seed, and feed sales; the value of homegrown seed used; the value of all feed fed (except milk); government farm program payments received and accrued; crop insurance payments received and accrued; and the change in value for feed and grain inventories, less the value of feed and grain purchased.

particular, under the same conditions as above, my estimates show that net farm income increases by \$6.84 per acre or 3.7 percent, management income increases by \$6.23 per acre or 12.5 percent, and annual per operator labor and management income increases by \$23,858 or 26.0 percent.[2] These estimates strongly imply that the induced positive effects of wind energy can improve farmers' welfare.

Given the corn and soybean price and harvested acreage in 2017, these estimates imply an annual increase of \$50.5 million in total crop returns or \$28.8 million in total net farm income in Illinois alone with an additional well-dispersed 1,000 MW of wind capacity, or equivalent to a 23 percent increase, installed within the state. Even with these non-negligible aggregate effects, the policy implications can be subtle. On one hand, landowners and wind energy companies can fully internalize the local impacts on the croplands where turbines are standing through the bargaining and leasing process, as long as both parties are fully aware of all possible positive and negative externalities. On the other hand, the microclimate effects of wind turbines and their positive impacts on crop yields can extend far beyond farm boundaries or even county borders. Therefore, policymakers may want to consider these positive spillovers to neighboring areas, along with other possible externalities of wind energy, when updating both agricultural and renewable energy policies.

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[2] Farm returns are defined by FBFM (Krapf et al., 2017) as:
Net farm income is the value of farm production, less total operating expenses and depreciation, plus gain or loss on machinery or buildings sold. Net farm income includes the return to the farm and family for unpaid labor, the interest on all invested capital, and the returns to management.
Management return is the residual surplus after a charge for unpaid labor and the interest or land charge on capital are deducted from net farm income.
Labor and management income per operator is total net farm income, less the value of family labor and the interest, including net rent, charged on all capital invested. This figure, as the residual return to all unpaid operators' labor and management efforts, is divided by the months of unpaid operator labor and multiplied by 12 to reflect income for one operator on multiple-operator farms.

This paper contributes to a large and growing literature on the externalities of wind energy, and even renewable energy more broadly.[3] The economic literature has studied emission and pollution abatement from renewable energy (e.g., Chiang et al. 2016; Cullen 2013; Kaffine, McBee, and Lieskovsky 2013; Novan 2015), and other papers estimate the external effects of wind turbines on the value of nearby properties since wind turbines generate visual disamenities and noise (e.g., Dröes and Koster 2016; Gibbons 2015; Jensen, Panduro, and Lundhede 2014; Lang, Opaluch, and Sfinarolakis 2014; Vyn and McCullough 2014). Moreover, recent studies investigate the externalities of wind energy on various outcomes, for instance, costs of wake effects from uncoordinated wind energy development (Lundquist et al. 2019), impacts of low-frequency noise on human health (Zou 2018), and net effects on crop yields (Kaffine 2019). In addition, this paper brings a new perspective, from wind energy, on the interactions among farm operations, agricultural policy, and renewable energy policy, which traditionally largely concentrate on the impacts of bioenergy and ethanol production on crop production, farmland value, land-use changes, and Conservation Reserve Program (CRP) enrollment decisions (e.g., Blomendahl, Perrin, and Johnson 2011; Henderson and Gloy 2009; Miao 2013; Motamed, McPhail, and Williams 2016; Peckham and Kropp 2015).

2. Background

This section briefly introduces the basic scientific mechanism underlying the microclimate effects of wind turbines. I then discuss reasons why scientific literature has not achieved a consensus

[3] For further reference, Dai et al (2015) and Zerrahn (2017) provide comprehensive literature reviews with more details on wind power and externalities from multiple perspectives, not limited to economic papers.

regarding the net effects of wind farms on agricultural production, and the advantage of using an econometric approach.

Existing scientific literature has revealed the impacts of large wind farms on meteorology and possibly on climate, especially at local and regional scales. An array of wind turbines reduces wind speed and creates turbulence, which can enhance vertical mixing and exchanges of heat, moisture, and carbon dioxide in the wake of rotors when harvesting energy from the atmosphere (Adkins and Sescu 2018; Baidya Roy, Pacala, and Walko 2004; Rajewski et al. 2014). A typical scale of the length of wind turbine wakes can reach around 20 km and is not sensitive to the size of the wind farms or to the local climate conditions (Abbasi and Abbasi 2016). Analyses based on model simulations also show that the impacts of wind turbines can extend to the scale of 10 km or even up to more than 50 km downwind (Abbasi and Abbasi 2016; Fitch et al. 2012; Fitch, Lundquist, and Olson 2013; Lundquist et al. 2019; Rajewski et al. 2013).

Many studies have tried to examine the regional climate impacts of wind turbines via numerical simulation models, though enormous uncertainties are unavoidable when modeling interactions between wind turbines and the atmospheric boundary layer (Adams and Keith 2007; Adams and Keith 2013; Baidya Roy, Pacala, and Walko 2004; Baidya Roy 2011; Barrie and Kirk-Davidoff 2010; Cervarich, Roy, and Zhou 2013; Fitch, Lundquist, and Olson 2013; Keith et al. 2004; Wang and Prinn 2010). Remote sensing based on data from satellites or drones is an effective alternative approach to detect and quantify the local or mesoscale meteorological changes due to wind farm operations (Adkins and Sescu 2018; Harris, Zhou, and Xia 2014; Slawsky et al. 2015; Walsh-Thomas et al. 2012; Zhou et al. 2012; 2013). For instance, Zhou et al. (2013) find a consistent warming effect of 0.31-0.70 K at nighttime in all seasons during the study period based on Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) data. Only a few field experiments have measured air temperature, surface fluxes, and other variables from on-shore wind plants. Baidya Roy and Traiteur (2010) use observations from a wind farm in California and indicate that the wind farm warms near-surface air temperatures downwind during the night and early morning hours, but also leads to a cooling effect during the day. Smith et al. (2013) collect in situ data from a wind farm in the Midwest and find a strong warming effect at night and significant impacts on downwind wind speed and turbulence intensity. Similar phenomena have also been discovered by a comprehensive field campaign in Iowa called Crop Wind Energy Experiment (CWEX), which attempts to understand the impacts of wind turbines on the microclimate over cropland (Rajewski et al. 2013; 2014; 2016; Rhodes and Lundquist 2013).

Since wind farms are often located on agricultural lands in the Midwest, large wind plants can potentially affect crop growth through their microclimate effects (Adkins and Sescu 2018; Armstrong et al. 2014; Baidya Roy and Traiteur 2010; Harris, Zhou, and Xia 2014; Rajewski et al. 2013; Xia et al. 2016; Zhou et al. 2012). Unfortunately, current scientific literature has not achieved a consensus regarding the net effects of wind farms on crop or vegetation growth, while some studies even find a limited or inhibiting effect (Tang et al. 2017; Xia and Zhou 2017). There are three major challenges. First, changes in heat, moisture flux, and carbon dioxide caused by large wind farms may have both positive and negative effects on crop growth, and the direction of the overall effect can vary across specific locations or weather conditions. Reports from the CWEX indicate that the warming effect at night may increase plants' respiration, while the enhanced fluxes of carbon dioxide and water contribute to transpiration and photosynthesis in the daytime (Rajewski et al. 2014). Second, the signs and magnitudes of local climate changes due to wind turbines depend on many specific and complicated factors and conditions, not to mention the interactions between the characteristics of turbines and the crop surface (Rajewski et al. 2014; 2016).[4] Along with uncertainties from cultivar, soil texture, and management techniques, short-term observations from a limited number of observation points in these expensive field experiments may not obtain enough statistical power to distinguish true effects from the noisy background. Third, large wind farms may affect local ecosystems and productivity through other direct or indict channels besides microclimate effects, such as low-frequency noise, bird and bat mortality or disturbance, soil erosion, visual pollution, and path planning for tractors (Boyles et al. 2011; Dai et al. 2015; Moravec et al. 2018; Zerrahn 2017). More interestingly, another study shows that wind-farm energy output increases by 14 percent when the crop underneath is switched from corn to soybeans (Vanderwende and Lundquist 2016).

To deal with these challenges, Kaffine's (2019) paper uses a reduced-form, econometric approach to identify the net impact of wind farms on neighboring crop yields, and takes advantage of the large number of observations to overcome the lack of representativeness issue. That study employs county-level crop and wind capacity data in the U.S. and finds that corn yields increase by about 1 percent with an additional 100 MW of wind capacity installed in the same county.

3. Data

This study assembles a unique and comprehensive dataset by combining FBFM farm-level production and expenses data, geographic locations and characteristics of wind turbines mainly from the American Wind Energy Association (AWEA), airspace obstruction determinations from the FAA, wind potential information from the National Renewable Energy Laboratory of the U.S.

[4] Rajewski et al. (2014, 2016) indicate that the magnitude and locations of local climate changes are affected by the turbine characteristics (hub height, rotor diameter, blade style, blade pitch angle, and model-specific thrust and power coefficients) and the ambient conditions (atmospheric stability, wind direction, wind speed, and moisture conditions).

DOE, and meteorological variables conducted by Schlenker and Roberts (2009) based on the PRISM climate data.

3.1 Farm data

My primary farm-level variables are from certified longitudinal data collected by the FBFM Association and the University of Illinois from 2003 to 2017. FBFM data include more than 90 years of farm business records and have long been used in many studies in the field of agricultural economics (e.g., Barry, Bierlen, and Sotomayor 2000; Franken, Pennings, and Garcia 2014; Garcia, Sonka, and Yoo 1982; Garcia et al. 1986; Woodard and Verteramo-Chiu 2017). The dataset used in this study includes annual corn and soybean yields, farm returns, farm operating expenses, total operating acres, share of land-use for each crop, land ownership (owned, crop shared, and cash rented), farm types, percentage of land irrigated, percentage of feed fed, and soil productivity rate for each farm. Unfortunately, FBFM data only have the geographic location information of farms available at the county level, but do not reveal further details of farms' specific locations.

The FBFM data contain annual accounting and production records for more than 5,000 participating farms in recent years, which is about one out of every five Illinois commercial farms with over 500 acres or total farm sales over $100,000 (Franken, Pennings, and Garcia 2014). About half of the total FBFM samples are qualified as certified data and released for this study. The FBFM educational service is available to all agricultural producers in Illinois for a fee, and farmers participate in this business analysis program voluntarily (Krapf, Raab, and Zwilling 2017).

Since producers voluntarily choose to participate in the FBFM service every year, one might be concerned about the selection effects on enrollment related to the installation of wind turbines. Appendix table A1 lists the retention rates, defined as the percentage of this year's farms that also took the survey last year. The overall average retention rate is about 80 percent for all farms, and 81 percent for farms in counties with installed wind capacity as of the end of 2017.[5] The retention rate differences between farms in panel A and B are relatively small compared to yearly changes. I do not find evidence that implies systematic selection in FBFM enrollments due to the development of wind energy.

3.2 Wind turbine data

The wind turbine data mainly come from the database managed by the AWEA, which provides specific geographic location, turbine model, capacity, and online year and month for each commercial wind turbine. I then merge the AWEA dataset with two other datasets, the United States Wind Turbine Database (USWTDB) from the U.S. Geological Survey (USGS) and the U.S. DOE and the Wind Turbine Location Data from the FAA, based on the spatial location of each turbine to provide complementary information.

Since the FBFM data do not reveal the location information of farms below the county level, the wind development variables need to be constructed as a county-by-year panel so that both datasets can be merged. One of the primary explanatory variables generated in this study is *wind capacity density* (MW/square mile), which equals the total capacity of all installed wind turbines in each county divided by the county's area, the same as in Kaffine's (2019) paper. However, since many wind farms are located near county borders, the local impacts of wind farms can easily extend to neighboring counties, and therefore cannot be captured by *wind capacity density*. To deal with this spatial spillover effect, I develop another explanatory variable for wind energy

[5] Note that an 80 percent retention rate does not mean that only 64 percent of farms would remain after two years or 51 percent after three years. Although only 454 farms have complete records for all years from 2003 to 2017, most farms occasionally skip one or two years but reenter the FBFM system later.

development, *wind area ratio*, which is defined as the percentage of the county area that is within a certain distance (e.g., 10 km or 25 km) of a sizable wind farm in a given year. To avoid including isolated wind turbines, here "sizable" means at least 10 wind turbines.[6] In figure 1, the dark dots are existing wind turbines in and around the state of Illinois at the end of 2017; the inner buffer areas are within 10 km of a sizable wind farm, while the outer buffer areas are within 25 km of a sizable wind farm. Ideally, the buffer areas should be on the downwind side of wind farms if the impacts come from microclimate effects exclusively. However, the differences are likely attenuated, since 1) modern large wind turbines can rotate actively to face the wind direction; 2) both wind development variables *wind capacity density* and *wind area ratio* are aggregated at the county level and therefore not that sensitive to shifts of buffer areas; and 3) wind turbines may affect agricultural activities through other channels, which may not necessarily be on the downwind side.

The Wind Turbine Location Data from the FAA also provide determination and status information of proposed wind turbine locations from Obstruction Analysis/Airport Airspace Analysis (OE/AAA). As shown in appendix figure A1, FAA decides whether a potential location of wind turbine is hazardous to air navigation. If so, then further construction is not allowed. I calculate simple *non-air-hazard ratios* as essential components in my instruments, which equal the number of applications that receive determinations of "No Hazard to Air Navigation" divided by the total number of completed applications in each county before any given year. Details of my IV approach are described in the empirical strategy section.

[6] Although I have to arbitrarily choose a threshold number of wind turbines to define what a sizable wind farm is, it turns out that the corresponding buffer areas are not at all sensitive to any threshold number from 5 to 16.

3.3 Weather and wind potential data

I use the Fine-Scale Daily Weather Data for the Contiguous United States conducted by Schlenker and Roberts (2009) based on the PRISM climate data from 1998 to 2017. The raw data files provide daily minimum and maximum temperature and precipitation at the 2.5-by-2.5-mile grid level. Following previous literature, I construct growing season precipitation as the cumulative depth in mm of water from April 1 to September 30. Similarly, growing degree days (GDD) are the number of degree days between 10°C and 30°C, and extreme degree days (XDD) are the number of degree days above 30°C, during the same agricultural growing period every year.

Wind power class data are from the National Renewable Energy Laboratory of the U.S. DOE. All areas are designated into seven classes, as illustrated in appendix figure A2. Generally speaking, Class 1 areas have the least potential for the development of wind energy, while areas designated Class 3 or higher have adequate wind resources for utility-scale wind turbine applications. Class 2 areas are marginal for commercial wind turbines. Note that wind power class is a time-invariant variable, and county-level averages of wind power class have been calculated for further application.

3.4 Summary statistics

Table 1 provides summary statistics for selected important variables in odd years at the farm level with simple identical weights. Panel A includes all farms, while panel B only includes farms from counties with wind capacity installed by the end of 2017. Both crop yields and wind energy have achieved remarkable growth during the same period from 2003 to 2017. Meanwhile, the number of farms participating in the FBFM declines in general, which is consistent with the decrease of the total number of farms in Illinois, but with a very similar trend in counties with or without wind energy development. As a natural consequence, the average acreage of farms increases in both panels.

Another interesting fact reflected by the summary table is that farms located close to wind turbines have relatively higher soil productivity rates than the state average, and therefore, higher yields on both corn and soybeans as well. Figures 2(a) and 2(b) provide box plots for the soybean and corn yields of farms located in counties with different exposure to wind energy by the end of 2017, marked as "no exposure" if the *wind area ratio (25 km)* in 2017 is 0 percent, "less exposure" if between 0 and 60 percent, and "more exposure" if above 60 percent. Despite the fact that crop yield data are almost always full of noise, figures 2(a) and 2(b) illustrate roughly a parallel movement pattern of the yield trends among farms in all three wind energy exposure categories. Although the gap in soil productivity rate between farms in panels A and B remains roughly the same throughout the study period and it is hard to believe that energy companies intend to build wind turbines on better agricultural fields, any analysis that attempts to estimate the effects of wind farms on crop yields will need to address potential challenges from spatial spillovers, unobservable time-varying factors or unknown channels along with the existing trends of yield increase and farm expansion, especially when the wind-energy-affected buffer areas, as shown in figure 1, are obviously geographically clustered in Illinois.

4. Empirical Strategy

This section introduces a typical ordinary least squares (OLS) strategy first. Next, I discuss two threats to identification from measurement error and omitted-variable bias and then suggest an innovative IV approach to identify the net effects of wind energy on neighboring farm outcomes.

4.1 OLS approach

The econometric strategy in this study is a fixed-effects model, which follows Kaffine (2019) and Deschênes and Greenstone (2007). The empirical regression model used to estimate the effects of wind farms on crop yields is:

$$y_{ict} = \alpha_i + \beta W_{ct} + \theta X_{ict} + \gamma_t + \epsilon_{ict}, \qquad (1)$$

where y_{ict} is the per acre soybean or corn yield on farm i in county c in year t. Since the farm location is only available at the county level, my primary explanatory variable indicating the development of wind energy, W_{ct}, needs to be aggregated at the county level rather than the farm level. W_{ct} can be either *wind capacity density* as megawatts of wind capacity installed per square mile in the county or *wind area ratio* defined as the percentage of area that is within a certain distance (10 or 25 km) of a sizable wind farm in county c in year t. Farm fixed-effects are α_i, which control time-invariant farm characteristics, such as topographic and geographic conditions. Year fixed-effects γ_t absorb common annual shocks to yields over time, such as technology improvement. Besides fixed-effects controls, the vector of time-variant control variables at the farm level X_{ict} includes percentage of land irrigated, percentage of feed fed, share of land ownership (owned, crop shared, and cash rented), as well as farm size and soil productivity rates and their quadratic terms. All regression analyses are weighted based on the number of operating acres of the corresponding crop. Also, I only use farms that were in the system at least once before the installation of wind turbines nearby.

The identifying assumptions of the OLS approach are: 1) crop yields on farms from wind-energy-affected counties would have parallel trends as those that are far away from sizable wind farms in a counterfactual world with no wind turbines installed, and 2) there are no unobservable or uncontrolled for variables that affect agricultural production and are correlated with wind energy development.

One might be concerned about the aggregation error when county averages of *wind capacity density* and *wind area ratio* are used since the truth of these variables at the farm level is not available. Unlike the classical measurement error that is uncorrelated with the truth, here the error is uncorrelated with the aggregated averages but necessarily correlated with the true values (Kirwan and Roberts 2016). Therefore, supposing there is no other source of endogeneity, within estimators using county averages will still be consistent in panel data.[7]

4.2 Threats to identification

To identify the effects of the development of wind energy on local crop yields and farm operation activities consistently, I need to address two threats to identification: omitted-variable bias and measurement error.

Some obvious control variables, such as farm operating expenses and local meteorological variables, are potentially endogenous, even though they have important explanatory power for agricultural outcomes. Farm operation costs may be endogenous through two possible channels. First, farmers may use the lease payments from wind energy companies to purchase additional production inputs like land, labor, capital, or fertilizer (Kaffine 2019). Second, farmers may change

[7] To see this, we have $W_{ct} = W_{ict} + u_{ict}$, where W_{ict} is the true wind development variable on farm i in county c in year t, and u_{ict} is the measurement error. Unlike the classical measurement error assumption that $cov(W_{ict}, u_{ict}) = 0$, here the measurement error u_{ict} is correlated with W_{ict} but uncorrelated with the average W_{ct}, that is, $cov(W_{ct}, u_{ict}) = 0$. Assuming no other endogeneity and the distribution of ϵ_{ict} is i.i.d with mean zero and variance σ_{ϵ}^2, we can rewrite the model as $y_{ict} = \alpha_i + \beta W_{ict} + \gamma_t + \epsilon_{ict} = \alpha_i + \beta W_{ct} + \gamma_t + \epsilon_{ict} - \beta u_{ict}$. Therefore, in panel data, within estimators using county average W_{ct} will be consistent since $cov(W_{ct}, \epsilon_{ict} - \beta u_{ict})$ is zero and controlling individual and time fixed-effects can eliminate biases from the nonzero correlations $cov(W_{ct}, \alpha_i)$ and $cov(W_{ct}, \gamma_t)$.

their behaviors based on their own observations, like crop growth level or pest damages, though farmers may not establish causal links between wind turbine installation and certain changes they have observed. [8] Moreover, since wind turbines can affect local climate, as discussed in the background section, they may also change common weather control variables used in agricultural models like GDD, XDD, or precipitation during the growing season. However, dropping these controls in farm operations and local climates may bring omitted-variable bias.

In addition, as mentioned in the data section, areas with higher wind capacity density in Illinois happen to have better soil quality and higher average yields, and the wind-energy-affected areas are geographically clustered. One possible concern is that the location selection of wind farms may be correlated with unobservable time-varying local characteristics that can affect agricultural activities. For instance, during the same study period from 2003 to 2017, the adoption of genetically engineered (GE) seeds has expanded from 77 to 93 percent for soybeans and from 28 to 92 percent for corn in Illinois. Additionally, there have been shifts among different types of GE technology. If the GE adoption decision of farmers were correlated with factors that might affect wind development such as soil type, local climate, and/or local farmers' attitudes to new technology, it would bias the estimates.

Another source of bias is measurement error. An ideal indicator for the development of wind energy should reflect both the density of installed capacity and the distance from a sizable wind farm at the local level. Unfortunately, neither *wind capacity density* nor *wind area ratio* is perfect. As shown in figure 1, many wind farms are located near county borders and only on one side in particular, but the effects of wind turbines will not be blocked by the administrative boundaries. By definition, *wind capacity density* only increases in the county where the wind farm is post-

[8] Mill (2015) indicates that landowners generally do not think that wind energy changes local weather patterns based on a survey.

installation but remains unchanged in the adjacent counties. As a result, failing to deal with the measurement error from spatial spillovers could result in a significant underestimate of the true impact of wind farms. On the other hand, *wind area ratio* takes the spatial spillovers into consideration roughly by allowing adjacent counties to be affected. However, it cannot effectively reflect the increase of wind capacity in nearby locations as long as the total number of wind turbines is above the threshold used to define “sizable” wind farms (10 turbines here).[9] Moreover, the effects of wind turbines on local climate are probably not evenly distributed within a perfectly round buffer area, which creates another type of measurement error.

4.3 IV approach

In order to address these potential threats to identification discussed above, I need an IV approach designed to leverage exogenous variation that is essential to the development of wind farms but does not affect agricultural production. As a natural endowment, wind potential measured by *wind power class* is a key driver for the development of wind energy. It is also exogenous and time-invariant, at least in the short term, in a given location, which implies that the farm fixed-effects can largely capture its impacts on agricultural production in general. In theory, I could use interactions of *wind power class* and year dummies as instruments for cumulative local wind development, given that the wind energy technology advancement and state-wide renewable energy policy changes across years are exogenous to agricultural production. However, I find these instruments suffer from the weak IV problem. There is another concern that the effects of windy conditions on crop growth could possibly vary year by year. For instance, wind can reduce the

[9] Since the associated buffer areas with 25 km or 10 km are much larger than the footprints of the wind farms, the buffer area of a dense array of 40 wind turbines is only slightly larger than that of a wind farm with 20 turbines. Note that this problem has nothing to do with the choice of the threshold used to define “sizable wind farms”.

chances of disease by drying out plants faster in a wet season, or can remove water too quickly for plants to replace in a particularly hot season.

To enhance the correlation in the first stage and eliminate potential confounding effects of *wind power class* from alternative channels mentioned above as much as possible, I take the airspace feasibility into consideration. According to the FAA, all air-hazard decisions are based on the aeronautical study findings "as to the extent of adverse physical or electromagnetic interference effect upon navigable airspace or air navigation facilities" before any real construction or adjustment, and therefore, provide plausibly exogenous variation with respect to agricultural activities. [10] FAA determinations can prevent wind turbines from standing in certain areas, even if they have high local wind potential. Therefore, integrating *non-air-hazard ratio* with *wind power class* can largely strengthen the instruments in the first stage.

I construct the *feasible wind class*, defined as $FWC_{ct} \equiv \textit{wind power class}_c * \textit{non-air-hazard ratio}_{ct}$, where $\textit{wind power class}_c$ is the area weighted average of *wind power class*, which measures available wind resources for the development of wind energy, in county c. Another component, $\textit{non-air-hazard ratio}_{ct}$, which measures the restriction on wind turbine construction due to airspace feasibility, is defined as the ratio of the number of projects that receive determinations of "No Hazard to Air Navigation" divided by the total number of proposed wind turbine locations that have completed the aeronautical studies by FAA in county c before year t.

[10] FAA Order JO 7400.2M - Procedures for Handling Airspace Matters: Chapter 7, 7-1-1: "The basis for all determinations must be on the aeronautical study findings as to the extent of adverse physical or electromagnetic interference effect upon navigable airspace or air navigation facilities."
Also, Chapter 7, 7-1-3: "Issue a 'Determination of Hazard' (DOH) if the structure would have or has a substantial adverse effect; negotiations with the sponsor have been unsuccessful in eliminating the substantial adverse effect; and the affected aeronautical operations and/or procedures cannot be adjusted to accommodate the structure without resulting in a substantial adverse effect."
Available at (on 06/26/2019): https://www.faa.gov/documentLibrary/media/Order/7400.2M_Bsc_dtd_2-28-19.pdf

To account for cumulative development of wind energy, the first-stage regression uses FWC by year dummies as the instruments to estimate the wind development variables as:

$$W_{ict} = \alpha_i^1 + \sum_{year} \rho_t FWC_{ct} * 1(t = year) + \theta^1 X_{ict} + \gamma_t^1 + \epsilon_{ict}^1, \quad \text{(2a)}$$

and then uses the predicted values of W_{ict} in the second-stage regression as:

$$y_{ict} = \alpha_i + \beta \widehat{W}_{ict} + \theta X_{ict} + \gamma_t + \epsilon_{ict}. \quad \text{(2b)}$$

Using this strategy, the local average treatment effect will come from the differences in the difficulty of developing wind energy among counties due to local wind potential and airspace feasibility across years, given the same technology advancement level and overall renewable energy policy environment in any particular year. The identifying assumption is that my instruments can largely determine the installed capacity of wind turbines and exclusively affect agricultural activities through the channel of wind energy, and also requires parallel trends of the reduced form and no other confounding factors.

In my main specification, I include farm characteristic variables, like farm size, percentage of land irrigated, and share of land ownership, which could be affected through the potential income channel from royalties received from wind energy companies. As a robustness check, I use only year and farm fixed-effects in addition to the wind development variables in one specification, which eliminates the chance of having any endogenous control variables. Next, I allow for more flexible controls with the interactions between farm characteristics and year dummies, which provides a robustness test of parallel trends, because if there is anything time-varying between farms in observable ways, that might also imply changes in unobservable ways.

4.4 Mechanism investigation

Following the discussion in the background section with existing scientific literature, large wind farms could affect local meteorological variables. Using the weather dataset conducted by Schlenker and Roberts (2009) based on the PRISM data, I implement a simple panel regression model to test the microclimate effects of wind turbines at the 2.5-by-2.5-mile grid level:

$$y_{gt} = \alpha_g + \beta W_{gt} + \gamma_t + \epsilon_{gt}, \tag{3}$$

where y_{gt} can be GDD, XDD, or precipitation during the growing season of grid g in year t. W_{gt} indicates whether the centroid of grid g in year t is within a certain distance (10km or 25km) of a sizable wind farm that has been built. Since the weather data provide exact geographic location information for each grid, here the primary explanatory variable W_{gt} does not need to be adjusted at the county level. Location and year fixed-effects are controlled by α_g and γ_t, respectively. To prevent misinterpretation, note that the grid-level observations are actually weighted averages from the closest 10 weather stations rather than direct local measurements due to the nature of the PRISM data files. The coefficients estimated from the above regression analysis are very likely to be underestimated, and therefore, the magnitudes of my results cannot be directly interpreted.[11] However, if results do reveal an effect, it is strong evidence that wind farms affect local climate. The purpose of this analysis is to test if sizable wind farms can affect weather variables, like GDD, XDD, and precipitation during the growing season. If so, these meteorological variables are endogenous and would confound the estimated effects of wind farm operations on crop yields if these control variables were included.

[11] Note that the measurement error from using the weighted average of observations from closest 10 weather stations does not satisfy the classical measurement error assumption as an *i.i.d.*, since it is probably correlated with the wind development variable W_{gt}. Therefore, it is endogenous, even though it comes from the left-hand side of the regression.

Since farmers might use their land lease payments to increase operating acreage or purchase additional inputs, my farm-level dataset provides a unique opportunity to directly test whether farm operation outcomes are affected by the development of wind farms. For this, I use the same 2SLS approach as described in equations (2a) and (2b). The wind energy development variable, as well as farm and year fixed-effects, remain unchanged. However, now the dependent variable y_{ict} can be total nonfeed costs, fertilizer costs, crop costs (sum of fertilizer, pesticide, and seed costs), power and equipment costs, building costs, labor costs, crop returns, net farm incomes, and management returns from farm i in county c in year t. Since typical farms rotate crops yearly, farm time-variant control variables X_{ict} also include the percentage share of land used for each crop on farm i in county c in year t in addition to other control variables used for the analysis on crop yields.

5. Results

This section begins with results from the baseline specification, and then provides robustness checks. Next, I test the validity of my IV approach and perform a falsification test. I further investigate two possible mechanisms that could lead to my findings. Finally, I estimate the effects of wind energy development on farm returns.

5.1 Effects on crop yields

Table 2 reports the primary results of the effects of wind farms on neighboring crop yields. As soybeans and corn are two major crops in Illinois, panel A summarizes the results for soybeans and panel B for corn. OLS estimates based on equation (1) are in the first four columns, and 2SLS estimates outlined by equations (2a) and (2b) are in the last four columns. Moreover, odd-numbered columns (1a), (1b), (3a), and (3b) report estimates from regressions on per acre yields of corn and soybeans, while the rest of the columns are based on log-linear models.

All the specifications in table 2 control for year fixed-effects, farm fixed-effects, and farm characteristics. Farm observations from different years are probably serially correlated, even after controlling for the fixed-effects. Moreover, agricultural activities on farms close to each other could have spatial autocorrelation due to unobservable spatial or social factors and policy similarities. The typical approach is to use the biggest or most aggregated clusters if possible (Abadie et al. 2017; Cameron and Miller 2015). Therefore, the standard errors are clustered at the county level in table 2.

My results show that all OLS and 2SLS coefficients of both *wind capacity density* and *wind area ratio (25 km)* are positive. Central estimates from 2SLS are larger than those from OLS and all are significant at the 5 percent level or below. In panel A, these estimated effects of wind energy on soybean yields are positive and significant at the 1 percent level regardless of the level or log-linear models. In panel B, only 2SLS coefficients on wind development variables for corn yields are significant at the 5 percent level, while OLS estimates are positive and within the 95 percent intervals of the 2SLS estimates, though not significant.

Note that the unit of *wind capacity density* is megawatts per square mile, as defined in Kaffine (2019). However, this unit is actually very large, since the overall *wind capacity density* in Illinois as of the end of 2017 is only 0.078 MW per square mile with 4,332 MW of wind capacity installed. The county with the highest *wind capacity density* reaches 0.526 MW per square mile, with 548 MW of installed wind capacity. To interpret the coefficients of all column (a)s, I transfer the unit to a more reasonable marginal magnitude. Since the average county area in IL is 544.3 square miles, an additional 50 MW of wind capacity installed within a county means a 0.092 MW per square mile increase in wind density.[12] Given this relationship, a new wind farm with 50 MW of wind power capacity increases soybean yields by 0.89 bushels per acre and corn yields by 2.9 bushels per acre based on column (3a), or raises soybean and corn yields by 1.3 and 2.4 percent, respectively, according to column (4a), within the same county. The estimates on *wind area ratio (25 km)* provide another perspective to look at the effects. From column (4b), we can observe that, with an additional 1 percent of county area located within 25 km of a sizable wind farm, average soybean yield increases by roughly 0.07 percent, and corn yield increases by about 0.11 percent. I should emphasize that the main estimates in table 2 are only valid at the margin, and I will test the concavity of the effects in the next section to help with interpretation and extrapolation.

An essential identifying assumption underlying both the OLS and the IV approaches is that crop yields on farms located either close to or away from sizable wind farms have common yield trends before the installations of wind turbines. As mentioned above, areas that experience wind energy development happen to have relatively better soil quality and therefore relatively higher average yields, though it is hard to believe that energy companies intend to select better agricultural lands to build wind turbines. However, the obvious geographic cluster pattern of areas affected by wind energy causes a concern that they might be on a different long-run trend of crop yields than other areas apart from the effects induced by wind energy. Although figures 2(a) and 2(b) illustrate parallel movements of crop yields in general, I test the common pre-trends assumption formally with a flexible difference-in-differences specification:

$$y_{ict} = \alpha_i + \sum_{\tau=-6}^{-1} \beta^{\tau} \omega_{ct}^{\tau} + \sum_{\tau=1}^{6} \beta^{\tau} \omega_{ct}^{\tau} + \theta X_{ict} + \gamma_t + \epsilon_{ict}, \quad (4)$$

[12] Kaffine (2019) uses the county-level data in the U.S. and does the calculation with an additional 100 MW of wind capacity. However, the average county land area in the lower 48 states of the U.S. is 997.6 square miles, and about 800 square miles for those with corn production according to Kaffine (2019), but only 544.3 square miles in Illinois. To be roughly consistent regarding the magnitudes, I use an additional 50 MW of wind capacity instead.

where $\omega_{ct}^{\tau} = 1(t - T_c = \tau)$ is a dummy variable taking the value of one when the county c is τ years away from the initial wind development in year t.[13] I estimate relative effects for a reasonably wide range of six years prior to and six years post the initial installation of wind turbines, and top and bottom code seven years and above prior to and away from the initial exposure.

I plot the estimated coefficients $\hat{\beta}^{\tau}$ and corresponding confidence intervals based on robust errors clustered at the county level in figure 3. As one can expect if the parallel trends assumption holds, all coefficients for both soybean and corn yields prior to the first wind development remain small and insignificant. The positive effects become more obvious after a few years from the initial development mainly because there is a time gap between the installation of the first wind turbine and the proper operation of the whole wind farm. The estimates of soybean yield are consistently large and roughly significant from the second year after the first wind turbine was installed, while the coefficients on corn yield vary a little bit, though most of them also become highly positive, which could possibly be due to the unbalanced and noisy panel data. These results also partially explain why the difference between the OLS and 2SLS estimates for corn yields are larger than those for soybean yields.

5.2 Robustness checks

The 2SLS estimates from table 2 provide suggestive evidence of a positive net effect of sizable wind farms on crop yields. Table 3 further checks the robustness of the 2SLS estimates with different specifications and controls. The estimates in columns (1a) and (1b) of table 3 only control

[13] Here the initial wind development is defined as the year when the first non-isolated wind turbine was installed, or the wind area ratio (25 km) became larger than 25 percent even if no single wind turbine was built in the county, since I want to get rid of isolated one or two wind turbines and also want to take the spatial spillover effects into consideration more or less.

for farm and year fixed-effects. The estimates for both soybeans and corn from both columns are still significant at the 5 percent level or lower, which show that these results are not being driven by potentially endogenous controls. Next, columns (2a) and (2b) in table 3 allow more flexible controls for farm characteristics by multiplying them with year dummy variables. Again, the estimates from this specification remain almost unchanged, which imply the parallel trends hold since unobservable variations between farms are often reflected in observable ways as well.

Columns (3a) and (3b) then have farm operations controlled for. Farm inputs are essential to crop yields, and controlling them would largely help identify the true impacts of wind farms on crop yields through the microclimate or ecosystem effects. However, landowners might expand farm production after receiving royalties from wind energy companies. Farmers might also change their agricultural practices based on observed changes resulting from the induced effects through microclimate or ecosystems without even knowing the causal relationship. The point estimates from columns (3a) and (3b) are almost identical to those in the previous columns correspondingly, which implies that the farm input channel may only explain the yield increases to a limited extent.

People may also argue that growing-season GDD and precipitation are important factors that can largely determine crop yields. In particular, prior literature often controls both of them, along with their quadratic terms, in preferred specifications, and even involves interaction terms of weather variables with multiple fixed-effects in some specifications. The remaining two columns in table 3 include these meteorological variables as controls. The coefficients on wind development variables estimated in these specifications remain in the same direction and are still significant at the 5 percent level or lower. The point estimates have modest changes compared to the rest of the columns in table 3. However, these weather variables could be endogenous, and therefore, should not be included as right-hand side control variables if the microclimate effects caused by wind turbines were the primary mechanism that lead to yield increases. Therefore, in the mechanism investigation section later, I will directly examine the effects of wind energy on farm operations and meteorological variables.

As an alternative robustness check, appendix table A2 summarizes the results using the dummy indicator $1(W_{c0})$ for the wind development, which takes value one after the first installation of wind turbines in county *c*. Similarly, panel A is for soybeans and panel B is for corn. Column (1) only includes year and farm fixed-effects, column (2) further controls for farm characteristics, and column (3) adds farm operations on the right-hand side. To absorb any potential alternative local trends, I allow each county to have its own linear time trend in column (4). The 2SLS coefficients of the dummy wind indicators are positive and significant in all these specifications for both crops. The magnitudes of the coefficients remain almost the same in the first three columns and even have a modest increase with county-specific linear time trends controlled.

If sizable wind farms actually cause the crop yield increases in neighboring areas, the effects should be larger in closer areas. To see this, I use a different threshold distance, 10 km, to calculate *wind area ratio* besides the 25 km threshold used in previous tables. Note that *wind capacity density*, *wind area ratio (25 km)*, and *wind area ratio (10 km)* are actually very different in terms of determining which counties have been affected by wind energy. By the end of 2017, 31 counties have installed wind capacity but only 19 of them have sizable wind farms. There are 35 counties with a positive *wind area ratio (25 km)* varying from 0.1 to 100 percent, but only 24 counties are defined as affected by wind energy based on *wind area ratio (10 km)*, with values varying from 2 to 50 percent. Although none of these variables measure the impacts of wind energy perfectly, estimates from using different wind development variables provide another robustness check. If the development of wind farms has causal effects on the crop yields of nearby farms, the estimated effects of *wind area ratio (10 km)* should be larger than those of *wind area ratio (25 km)*. As shown in table 4, the coefficients of *wind area ratio (10 km)* in column (3) are about double the magnitude of those of *wind area ratio (25 km)* in column (2) for both soybeans and corn, and significant at the 1 percent and 5 percent levels, respectively.

Finally, to allow for non-linear effects of wind farms on crop yields, columns (4), (5), and (6) in table 4 include a corresponding quadratic term of *wind capacity density*, *wind area ratio (25 km)*, and *wind area ratio (10 km)*, respectively. All coefficients of the squared terms of wind energy variables are negative in both panels for soybean and corn yields, which suggests a concave relationship between the wind energy development level and its effects on crop yields. Because of the diminishing marginal effects, central estimates are only valid at the marginal extent. In particular, we must be cautious about projecting the potential effects on agricultural production too far away in areas with intensive growth of wind power capacity.

5.3 Validity of instrumental variables and falsification test

The above analyses rely heavily on the validity of the instrumental variables. The first condition is that *FWC* needs to be correlated with the development of wind farms, which is seemingly plausible. Of the two components that construct the instrumental variables, *wind power class* measures wind resources available for commercial wind turbines, and *non-air-hazard ratio* determines the share of potential wind turbine projects that can move forward to construction. By using *FWC* rather than raw *wind power class*, the first-stage predictions have been largely enhanced, since some windy areas receive low scores for the possibility of wind energy development due to aviation safety restrictions. The results from the first-stage regression are illustrated in figures 4(a) and 4(b) for *wind capacity density* and *wind area ratio (25 km)*, respectively. Since only a few wind farms were built before 2010, the coefficients of these earlier years are not significant. After that, the coefficients of *FWC* become positive, large and significant. The general increasing trends of the first-stage coefficients over the years fit the reality well. Appendix figures A3(a) and A3(b) illustrate the corresponding first-stage coefficients when using *wind power class* only. Although they are positive in later years as well, the standard errors are much larger than those with *FWC*, so most of the coefficients are at the edge of being significant or insignificant at the 5 percent level.

Another key condition of any IV approach is the exclusion restriction assumption, which requires that *FWC* can affect crop yields solely through the development of wind farms. A simple and straightforward test of the exclusion restriction assumption is to see if the set of *FWC* has any explanatory power in the regression on crop yields directly before the installation of wind turbines nearby. Figures 5(a) and 5(b) use a subsample of farms located in counties that had not been affected by wind farms by 2012 for soybeans and corn, respectively. Since wind energy has been developed dramatically in recent years, I would lose too many observations, especially those in areas with high *FWC*, if I push the threshold year to later than 2012. Note that none of the 18 estimates except one are significant at the 5 percent level. Moreover, these coefficients have both positive and negative signs across the years from 2003 to 2011. These results support the claim that *FWC* does not significantly affect crop yields before the installation of wind turbines, which implies that the exclusion restriction assumption holds for the IV approach.

Another concern of this study is that other time-varying unobservables that have similar trends as the development of wind energy may result in spurious effects. A bootstrap-based permutation test is used to rule out any possible spurious effects. There are 102 counties in Illinois, each of which has a complete profile with *FWC*, *wind capacity density*, and *wind area ratio (25 km and*

10 km) from 2003 to 2017. To maintain the correlation between IVs and wind energy development variables in the first-stage as well as the development trends of wind energy in Illinois, the time series of these variables remain unchanged within a county's profile. The permutation process then randomly assigns county wind profiles across farms. The results from 10,000 permutation repeats are reported in panel A of table 5, and show that my estimates are extremely unlikely to appear by randomly assigning wind development profiles. In panel B, I further restrict the permutation. The random assignments are now based on counties rather than farms, so farms originally from the same county receive the same random profile in each repeat. Note that there are only 102 counties in Illinois, and many of them share very similar wind energy development paths. Again, my preferred estimates are robust, especially considering the effects on both corn and soybean yields simultaneously.

5.4 Mechanism investigation

To investigate potential mechanisms that could lead to these findings, I directly examine the effects of wind energy on meteorological variables and farm operations. I find significant effects on local climate but do not detect measurable changes on farm operations after wind turbines are installed nearby. Therefore, my results suggest that the microclimate effects induced by the operation of wind turbines are likely resulting in the higher neighboring crop yields.

Table 6 presents results from a simple panel regression based on equation (3). The wind energy development indicator is time-variant, and shifts from 0 to 1 if a sizable wind farm has been installed within 25 km of the centroid of a grid. The "donut" regressions reported in columns (2), (4), and (6) do not include grids with centroids located between 25 km and 40 km from any sizable wind farm built before the end of 2017. The estimates of the wind energy indicator within

25 km clearly show that the development of wind farms has significant effects on local meteorological variables. In particular, growing-season XDDs in grids within 25 km of a wind farm after its installation decrease by about 2.2 to 2.6 percent. Due to the nature of the PRISM data with weighted average observations from the closest 10 weather stations, the results presented in table 6 tend to be underestimated, and therefore, cannot be interpreted as rigorous scientific evidence of microclimate effects resulting from the development of wind farms. However, these estimates are strong enough to show that all three weather variables, GDD, XDD, and precipitation, are endogenous as right-hand-side explanatory variables in regression analyses for crop yields or farm operations.

The FBFM farm-level data provides a unique opportunity to further investigate possible effects of wind energy on farm operations through two possible channels. First, crop growth conditions may more or less reflect the microclimate changes or ecosystem impacts due to sizable wind farms being nearby. Farmers, therefore, change their operations correspondingly based on their own observations without even knowing the causal link to wind energy. Another possible explanation is through the associated lease payments for land use to run wind turbines. Landlords may use the royalties to expand operating acres or purchase more inputs (Kaffine 2019). However, the results in table 7 suggest that wind farms do not change farm operations in general, or at least, most effects are too minimal to be statistically detected with the currently available dataset. The coefficients of *wind capacity density* in panel A or *wind area ratio (25 km)* in panel B are all insignificant, except one, on both corn and soybean acreage and different operating expenses.[14]

[14] Several operating expenses are defined by FBFM (Krapf et al., 2017) as:
Power and equipment includes depreciation, repairs, machine hire and lease, fuel and oil, and the farm share of expenses for electricity, telephone, and light vehicles.
Labor includes hired labor plus family and operator's labor, charged in 2016 at $3,800 per month.

Therefore, involving these farm operating expenses as control variables in the regression analysis above seems acceptable.

5.5 Effects on farm returns

The next question is what these findings mean to farmers and policymakers. To answer this question, a proper accounting of the effects of wind turbines on net farm returns is of importance.

Table 8 reports estimates on total nonfeed costs and farm returns based on different definitions.[15] Not surprisingly, the estimates of both *wind capacity density* in panel A and *wind area ratio (25 km)* in panel B suggest positive effects on per acre crop returns, per acre net farm income, per acre management returns, and labor and management income per operator, as shown in columns (2) to (5). On the other hand, the effects on total nonfeed costs, reported in column (1), are not significant, though they are positive. Similar to the interpretation of the results from table 2, I multiply the coefficients by 0.092 MW of wind capacity per square mile, which is derived from an additional 50 MW of wind energy capacity built within a county. The estimate from column (2) in panel A of table 8 implies a $12.0 per acre, or 1.7 percent equivalently, increase in crop returns, which is right in between the preferred estimates of the yield effects on soybeans and corn as 1.3 and 2.4 percent, respectively.

Although the net effects of wind energy on crop yields are modest, I find that most of the benefits from the yield increases are realized through higher labor and management returns since total operating expenses do not increase accordingly. Under the same conditions as above, the

[15] Dependent variables in Table 9 are defined by FBFM (Krapf et al., 2017) as:
Total nonfeed costs include cash operating expenses, adjustments for accrued expenses and farm produced inputs, depreciation, and charges for unpaid labor and interest including land charge.
For others, please see footnotes 1 and 2.

coefficients from columns (3) to (5) in panel A suggest that net farm income increases by \$6.84 or 3.7 percent, management income increases by \$6.23 or 12.5 percent, and annual per operator labor and management income increases by \$23,858 or 26.0 percent, respectively. These results provide further support to the conclusion in the last section that the crop yield increases are not likely due to higher production inputs. Supposing farmers use royalties received from energy companies to expand farm production or purchase additional inputs after the installation of wind turbines, we would observe increases in crop yields along with higher operating expenses, and as a result, the net farm income or labor and management returns should not change significantly.

Using a simple back-of-envelope calculation here, an additional 1,000 MW of wind power capacity installed in Illinois, which is about a 23 percent increase based on 4,332 MW installed by the end of 2017, and assuming the incremental capacity spreads evenly across the whole state, can increase wind capacity density by about 0.018 MW per square mile. Therefore, the estimated crop return increase is about \$2.35 per acre based on the coefficient of column (2) in panel A, table 8. Considering only the areas cultivated with soybeans and corn in Illinois, which is 21.5 million acres in 2017, the total potential increase in crop returns is about \$50.5 million per year. Similarly, the estimated annual increase in net farm income is about \$28.8 million under the same condition.

6. Conclusion

This paper investigates the net impacts of sizable wind farms on local crop yields and agricultural activities at the farm level by using an innovative IV approach. I find that soybean and corn yields increase by roughly 1.3 and 2.4 percent, respectively, given an additional 50 MW of wind capacity installed in the same county. The induced microclimate changes are likely main contributors to these increases, as my results also show that the development of wind energy has significant impacts on local meteorological variables but does not measurably change farm operations. Moreover, I also find that farms can obtain most benefits gained from the higher crop yields as labor and management returns. The aggregate benefits from this unanticipated positive externality of wind energy on agricultural production are fairly large in Illinois.

The primary caveat of this study is that the specific location information of each farm below the county level is not available, though most observations are at the farm level. As a result, wind development variables have to be aggregated at the county level, which inevitably brings extra measurement error. Nonetheless, the techniques and the IV approach developed by this study can be easily transferred to a much finer level as long as the location details of farms are revealed. Another caveat is from the perspective of external validity. Since the microclimate effects of wind energy vary with local geographical and climate characteristics, spatial heterogeneity must exist. Kaffine's (2019) estimates provide complementary evidence to my results that the direction of the net impacts should be consistent in general nationwide. However, more field experiments, like the CWEX project, are necessary to further explore more specific details of the impacts of wind turbines on crop growth.

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Figures and Tables:

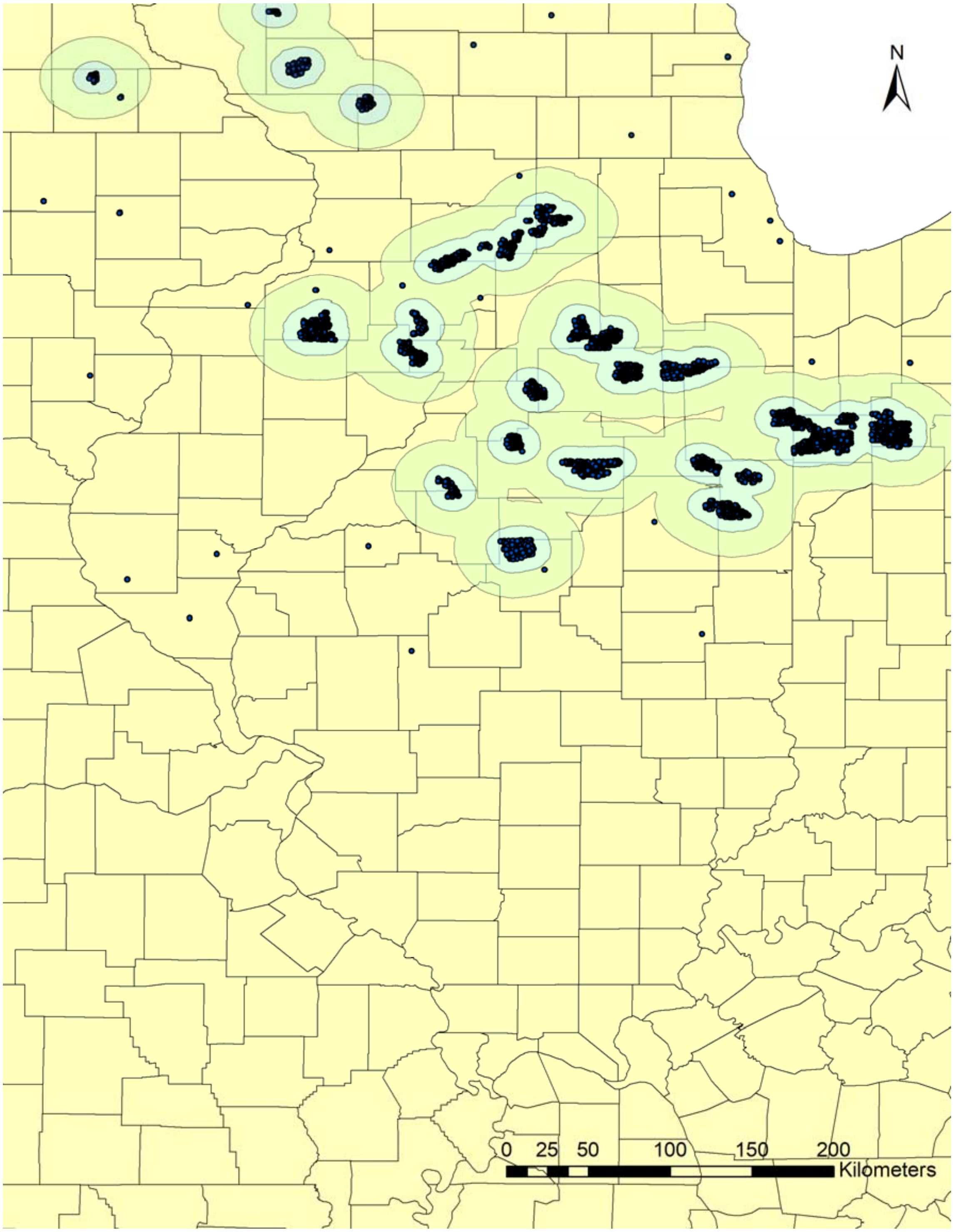
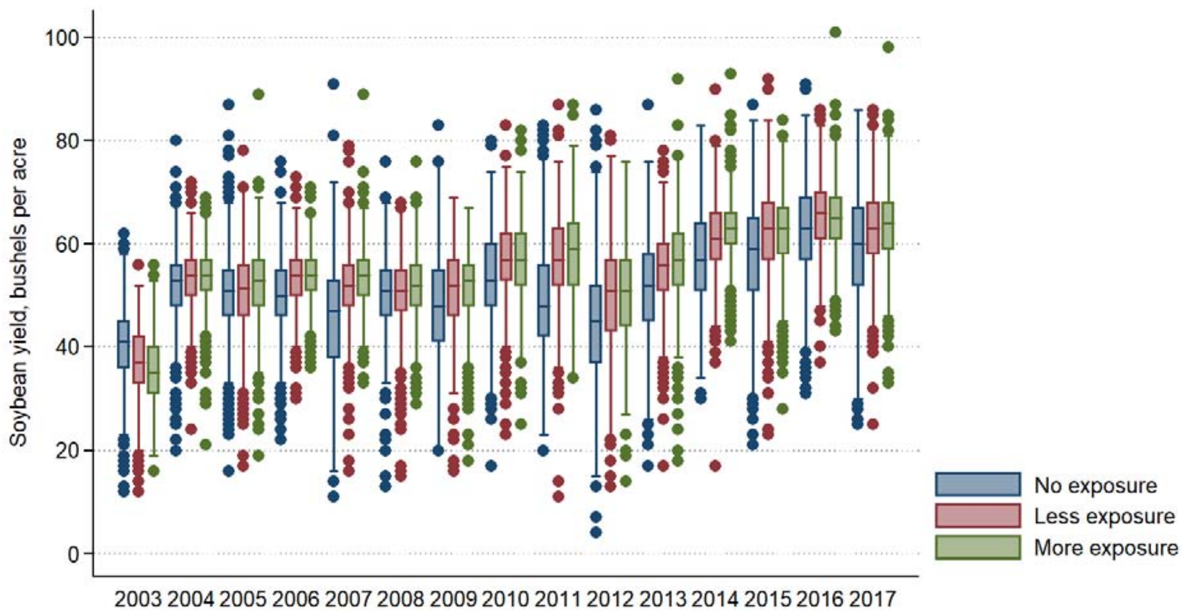
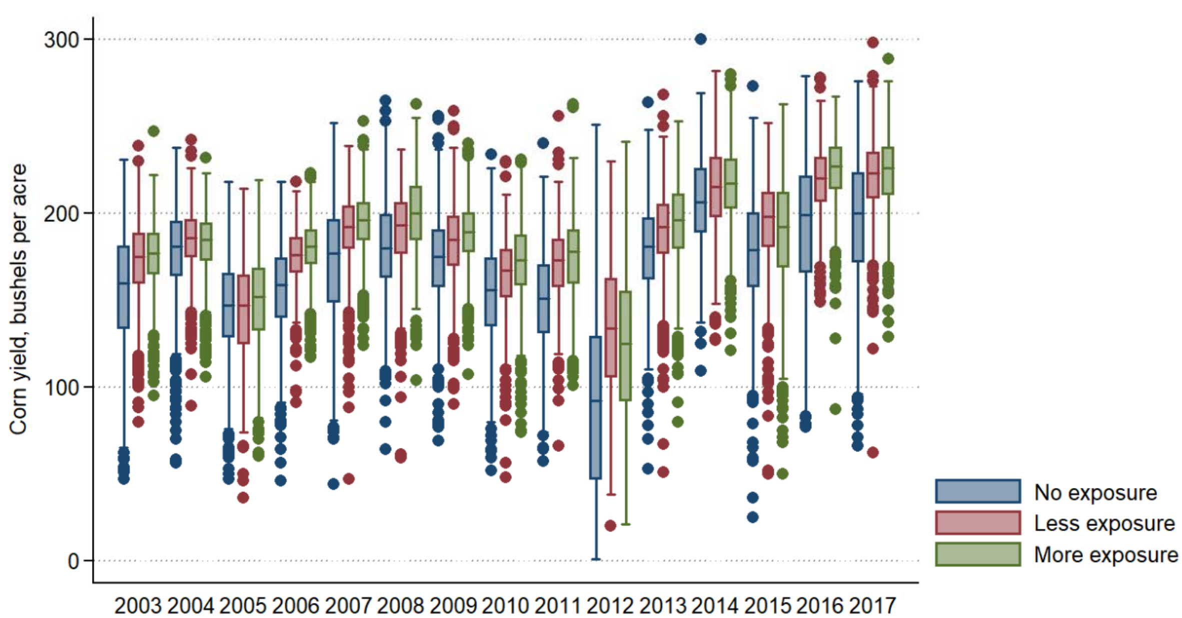


Figure 1. Installed wind turbines and 10 or 25 km buffer areas to sizable wind farms, by the end of 2017

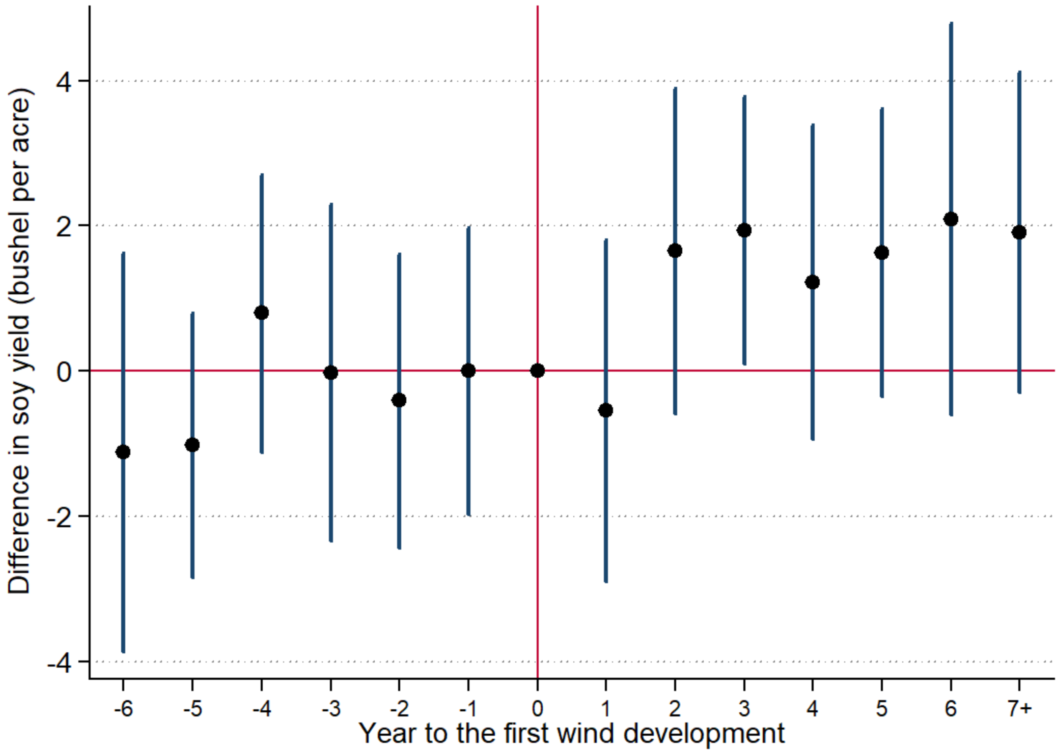


(a) Soybeans

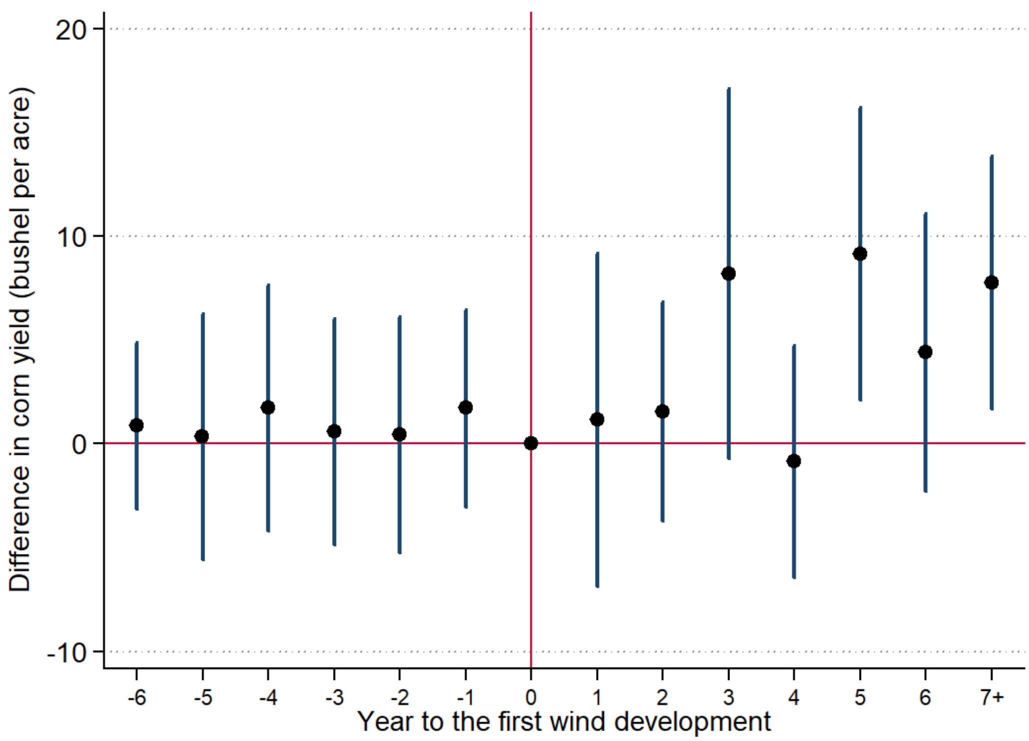


(b) Corn

Figure 2. Box plots of FBFM soybean and corn yield observations, 2003-2017

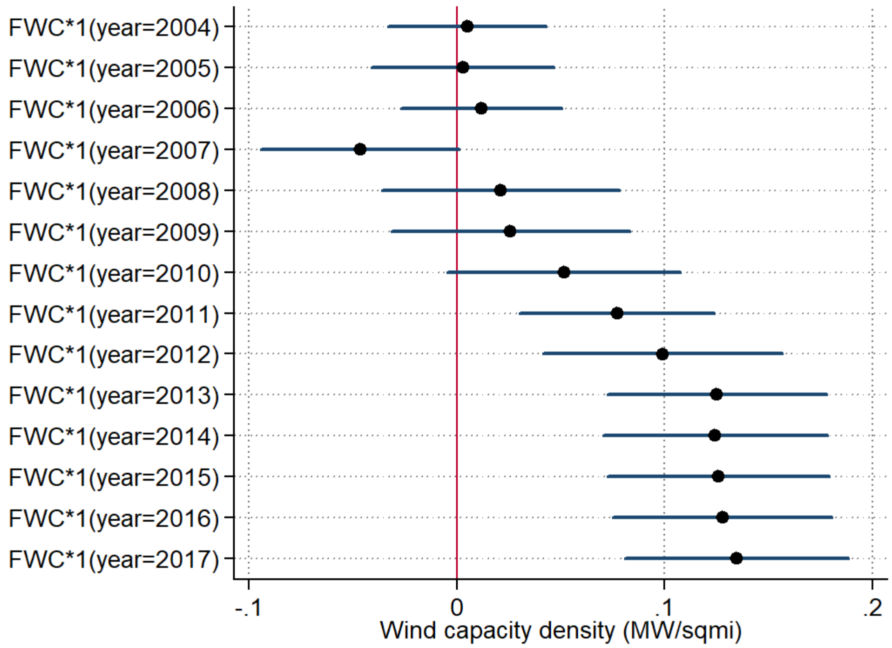


(a) Soybeans

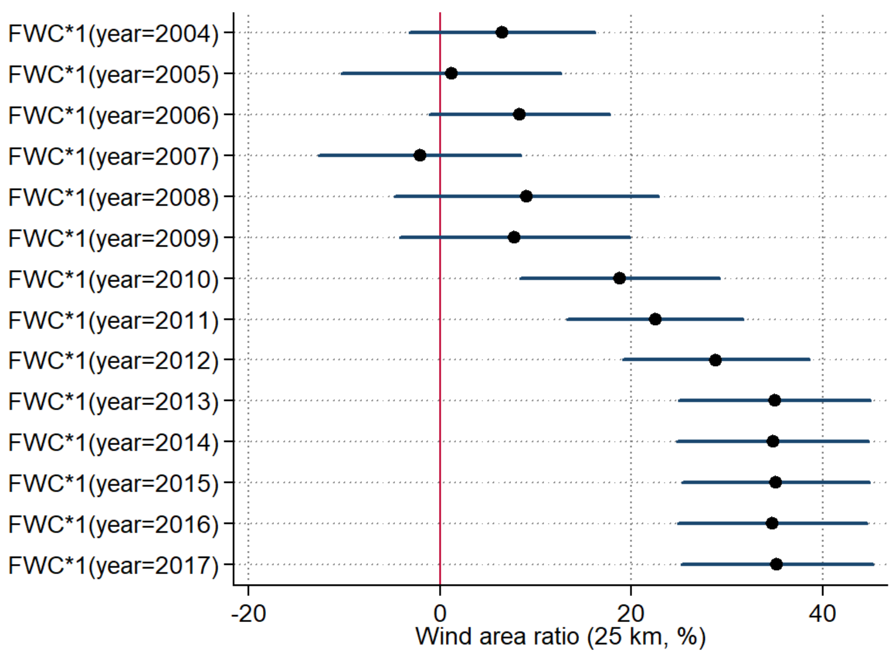


(b) Corn

Figure 3. Yield differences in years before and after the first wind development

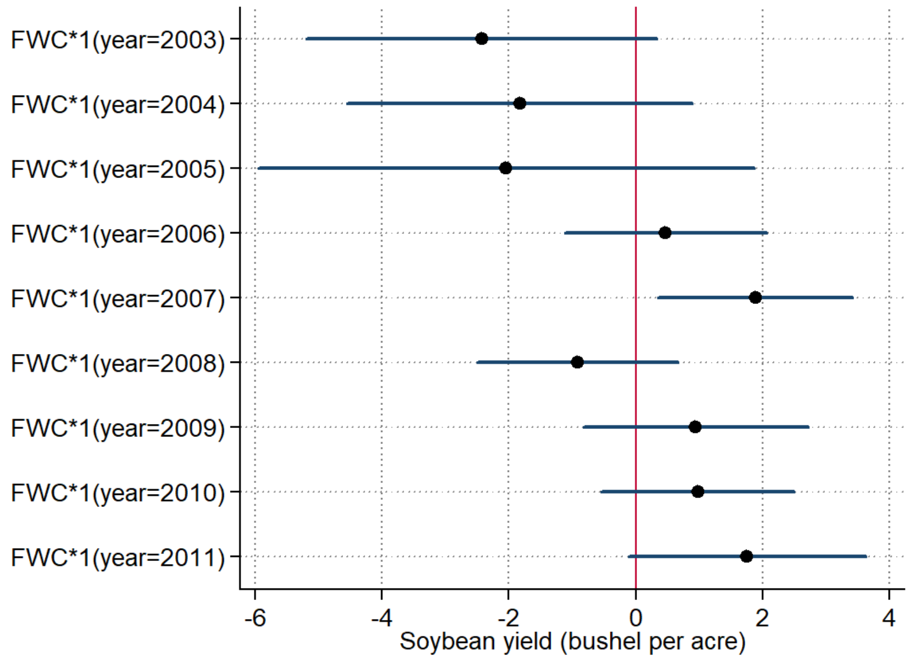


(a) Wind capacity density

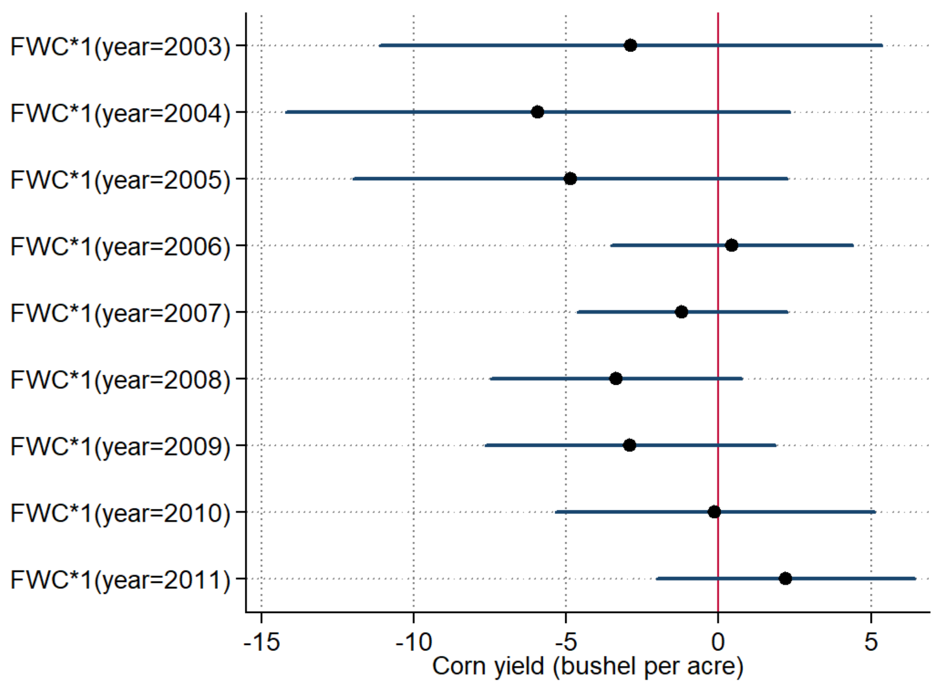


(b) Wind area ratio (25 km)

Figure 4. First-stage results with feasible wind class by year dummies as the instruments



(a) Soybeans



(b) Corn

Figure 5. Exclusion restriction test of the instruments on soybean and corn yields

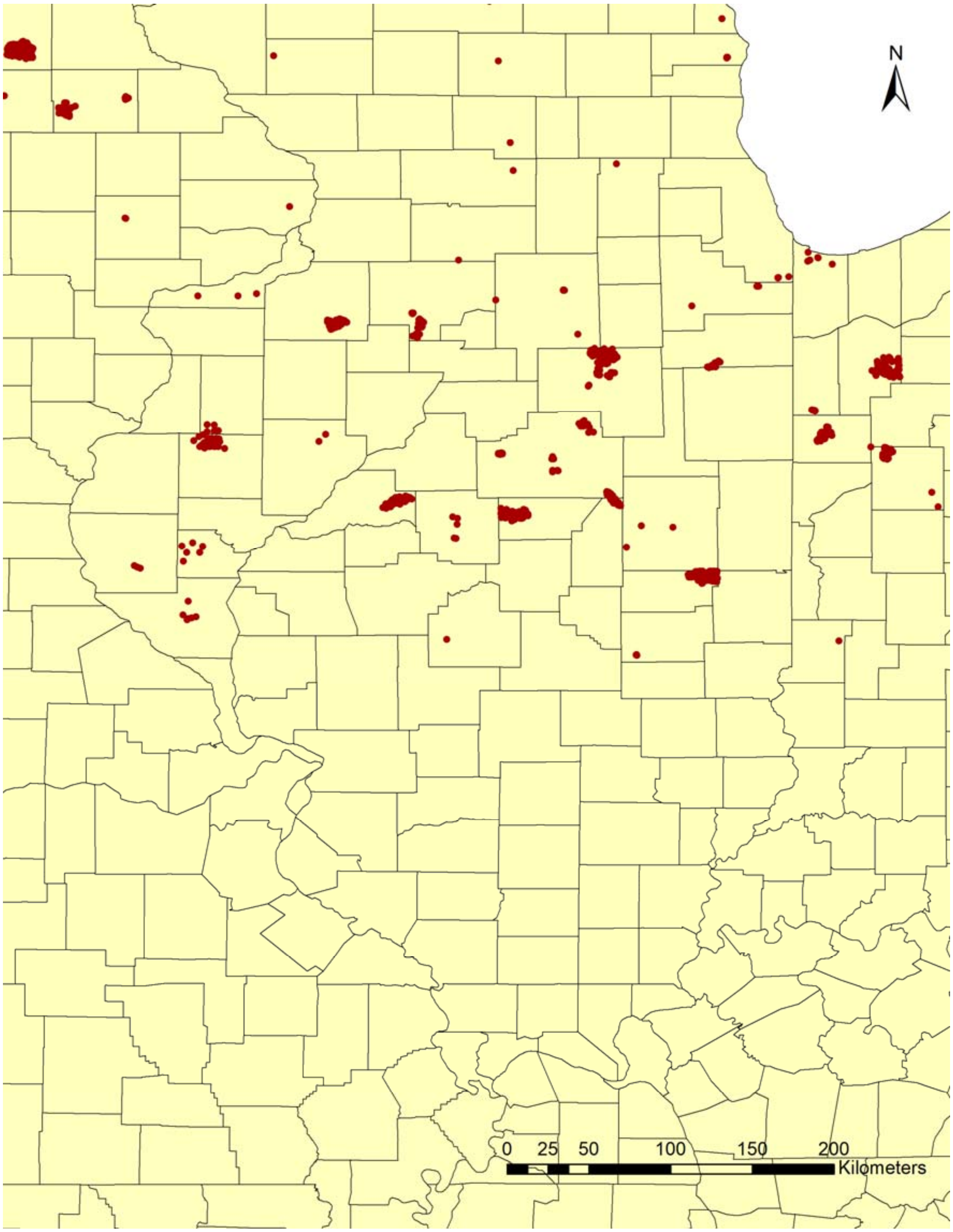


Figure A1. Proposed wind turbine locations with determinations of "Hazard to Air Navigation"

Source: Wind Turbine Location Data (updated 10/2018), Federal Aviation Administration

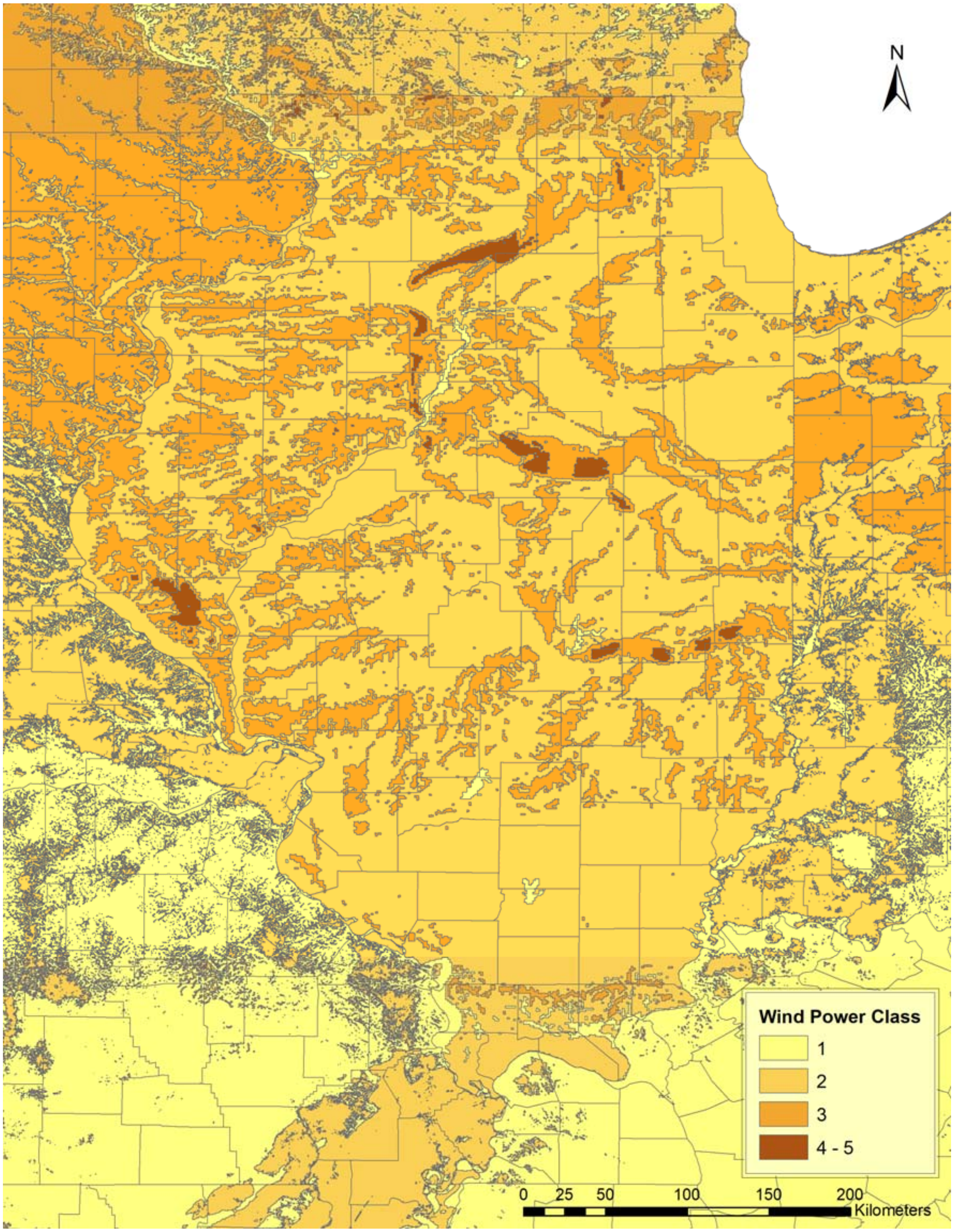
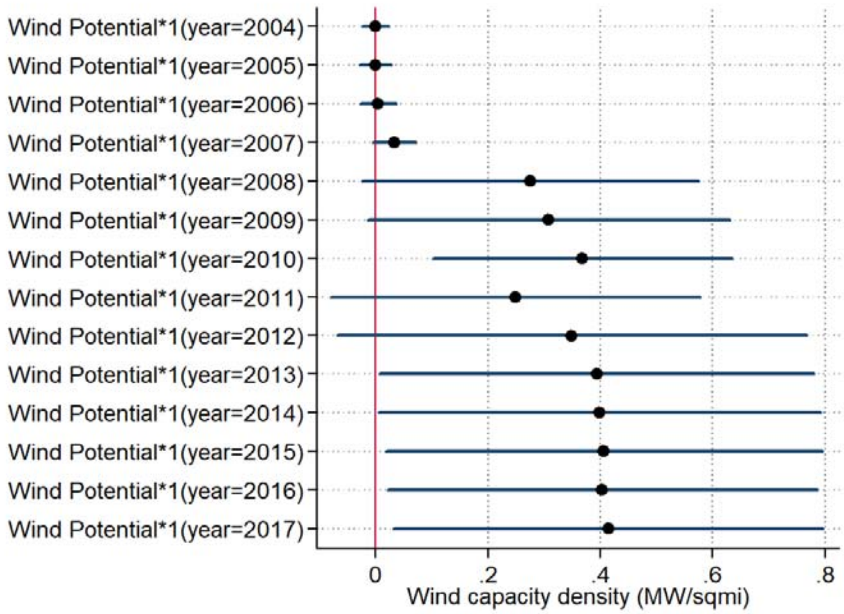
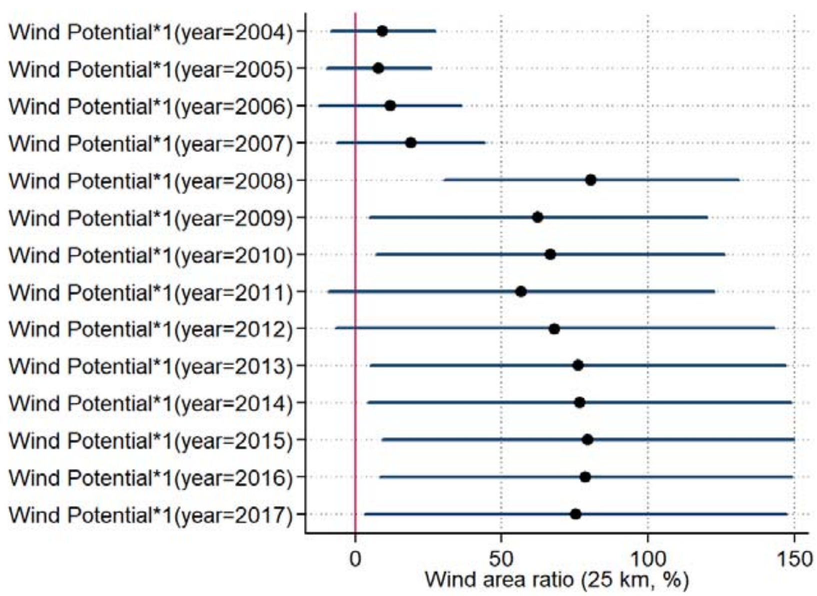


Figure A2. Wind power class map

Source: National Renewable Energy Laboratory, U.S. Department of Energy



(a) Soybeans



(b) Corn

Figure A3. First-stage results with wind power class by year dummies as the instruments

Table 1. Summary statistics

	2003	2005	2007	2009	2011	2013	2015	2017
Panel A: All farms								
Corn yield (bushel per acre)	168.01	146.47	185.49	181.94	165.75	188.17	186.70	213.66
	(27.43)	(27.03)	(26.90)	(22.94)	(26.34)	(25.96)	(31.75)	(31.12)
Soybean yield (bushel per acre)	37.35	51.32	50.40	50.31	54.78	54.87	61.01	61.89
	(7.22)	(7.73)	(8.60)	(8.14)	(9.91)	(8.78)	(8.94)	(8.69)
Soil productivity rate	79.77	80.54	80.70	80.63	80.82	80.79	81.15	81.34
	(12.57)	(12.45)	(12.24)	(12.39)	(12.37)	(12.29)	(12.06)	(11.94)
Operating acres	720.13	774.89	816.51	834.97	891.93	889.35	947.86	997.58
	(587.64)	(608.53)	(652.21)	(669.48)	(930.76)	(823.32)	(889.63)	(1119.42)
Percent land owned	27.56	26.61	25.96	25.42	25.76	26.59	26.28	26.55
	(29.69)	(29.09)	(28.51)	(28.15)	(27.90)	(27.94)	(27.68)	(27.63)
Wind area ratio (25 km, percent)	0.00	2.28	4.50	17.74	30.46	44.00	44.19	44.54
		(8.21)	(12.18)	(26.32)	(33.79)	(39.15)	(38.97)	(39.36)
Wind capacity density (MW/sqml)	0.000	0.001	0.002	0.038	0.089	0.133	0.133	0.140
		(0.008)	(0.010)	(0.092)	(0.134)	(0.160)	(0.160)	(0.167)
N	3042	2987	2826	2767	2788	2719	2737	2449
Panel B: Farms in counties with wind farms installed by the end of 2017								
Corn yield (bushel per acre)	174.39	148.46	191.71	186.21	172.26	192.49	189.60	220.69
	(20.82)	(26.50)	(20.07)	(20.45)	(23.53)	(24.46)	(30.77)	(22.10)
Soybean yield (bushel per acre)	35.89	51.84	52.89	51.72	56.91	56.50	62.42	63.13
	(6.56)	(7.39)	(6.24)	(7.35)	(8.76)	(8.07)	(7.99)	(7.80)
Soil productivity rate	83.87	84.41	84.43	84.57	84.83	84.84	84.99	85.17
	(9.09)	(8.89)	(8.82)	(8.75)	(8.69)	(8.48)	(8.46)	(8.23)
Operating acres	659.37	716.20	751.56	770.01	845.14	838.76	884.71	959.60
	(506.32)	(555.80)	(592.95)	(621.17)	(1028.25)	(859.53)	(825.66)	(1259.80)
Percent land owned	26.38	25.71	24.88	24.51	24.54	25.51	25.19	26.06
	(29.78)	(28.83)	(28.18)	(28.00)	(27.47)	(27.34)	(27.08)	(27.59)
Wind area ratio (25 km, percent)	0.00	3.65	7.29	27.15	46.98	67.50	68.13	69.71
		(10.15)	(14.84)	(29.07)	(32.98)	(30.62)	(29.90)	(29.58)
Wind capacity density (MW/sqml)	0.000	0.002	0.002	0.062	0.145	0.215	0.217	0.232
		(0.010)	(0.013)	(0.110)	(0.145)	(0.154)	(0.153)	(0.157)
N	1835	1862	1743	1721	1715	1684	1681	1476

Note: Standard deviations appear in parenthesis.

Table 2. Effects of wind farms on soybean and corn yields, 2003-2017

	yield - OLS		ln(yield) - OLS		yield - 2SLS		ln(yield) - 2SLS	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Panel A: Soybeans								
Wind capacity density	5.434***		0.0979***		9.668***		0.137***	
(MW/sqmi)	(1.733)		(0.0319)		(3.079)		(0.0502)	
Wind area ratio		0.0229***		0.000403***		0.0441***		0.000716***
(25 km, %)		(0.00701)		(0.000130)		(0.0112)		(0.000193)
Observations	37924	36333	37924	36333	37924	36333	37924	36333
Adjusted R^2	0.669	0.667	0.646	0.644	0.668	0.665	0.646	0.644
Panel B: Corn								
Wind capacity density	4.200		0.0323		31.88**		0.266**	
(MW/sqmi)	(5.973)		(0.0476)		(15.93)		(0.124)	
Wind area ratio		0.0265		0.000190		0.123**		0.00110**
(25 km, %)		(0.0279)		(0.000207)		(0.0567)		(0.000460)
Observations	38853	37211	38853	37211	38853	37211	38853	37211
Adjusted R^2	0.726	0.727	0.629	0.630	0.723	0.725	0.624	0.626
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Farm characteristics include farm size (w/ quadratic term), soil productivity rate (w/ quadratic term), farm type, percentage of land irrigated, percentage of feed fed, share of land ownership (owned, crop shared, and cash rented). Robust standard errors (in parentheses) are clustered at the county level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Robustness checks of effects of wind farms on soybean and corn yields, 2003-2017

	ln(yield) – 2SLS							
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Panel A: Soybeans								
Wind capacity density	0.138***		0.132***		0.139***		0.137***	
(MW/sqmi)	(0.0500)		(0.0459)		(0.0501)		(0.0515)	
Wind area ratio		0.000721***		0.000696***		0.000731***		0.000532***
(25 km, %)		(0.000194)		(0.000174)		(0.000192)		(0.000163)
GDD							0.00238***	0.00240***
							(0.000275)	(0.000279)
GDD^2							-0.000000729***	-0.000000735***
							(7.84e-08)	(7.86e-08)
Precipitation							0.00132***	0.00133***
							(0.000148)	(0.000147)
Precipitation^2							-0.000000974***	-0.000000977***
							(0.000000106)	(0.000000104)
Observations	37926	36335	37918	36327	37924	36333	37924	36333
Adjusted R^2	0.646	0.643	0.654	0.651	0.648	0.645	0.667	0.665
Panel B: Corn								
Wind capacity density	0.261**		0.263**		0.274**		0.221**	
(MW/sqmi)	(0.122)		(0.114)		(0.121)		(0.108)	
Wind area ratio		0.00109**		0.00110**		0.00114**		0.000876**
(25 km, %)		(0.000461)		(0.000422)		(0.000447)		(0.000406)
GDD							0.00328***	0.00317***
							(0.000388)	(0.000381)
GDD^2							-0.000000836***	-0.000000805***
							(9.66e-08)	(9.84e-08)
Precipitation							0.000278	0.000330
							(0.000381)	(0.000380)
Precipitation^2							-0.000000298	-0.000000326
							(0.000000283)	(0.000000281)
Observations	38855	37213	38845	37203	38853	37211	38853	37211
Adjusted R^2	0.624	0.626	0.634	0.635	0.625	0.627	0.634	0.635
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm characteristics	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year by characteristics	No	No	Yes	Yes	No	No	No	No
Operating costs	No	No	No	No	Yes	Yes	No	No

Note: Operating costs include fertilizer costs, crop costs (sum of fertilizer, pesticide, and seed), power and equipment costs, building costs, and labor costs. Robust standard errors (in parentheses) are clustered at the county level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Diminishing marginal effects of wind farms on crop yields, 2003-2017

	ln(yield) w/o quadratic terms			ln(yield) w/ quadratic terms		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Soybeans						
Wind capacity density (MW/sqmi)	0.137***			1.240		
	(0.0502)			(0.865)		
Wind area ratio (25 km, %)		0.000716***			0.00490**	
		(0.000193)			(0.00217)	
Wind area ratio (10 km, %)			0.00144***			0.0130**
			(0.000462)			(0.00605)
[Wind capacity density]^2				-3.058		
				(2.630)		
[Wind area ratio (25 km, %)]^2					-0.0000480*	
					(0.0000242)	
[Wind area ratio (10 km, %)]^2						-0.000353*
						(0.000194)
Observations	37924	36333	37143	37924	36333	37143
Adjusted R^2	0.646	0.644	0.645	0.626	0.630	0.621
Panel B: Corn						
Wind capacity density (MW/sqmi)	0.266**			0.365		
	(0.124)			(0.671)		
Wind area ratio (25 km, %)		0.00110**			0.00814*	
		(0.000460)			(0.00429)	
Wind area ratio (10 km, %)			0.00257**			0.00705
			(0.00112)			(0.00536)
[Wind capacity density]^2				-0.281		
				(1.981)		
[Wind area ratio (25 km, %)]^2					-0.0000808*	
					(0.0000475)	
[Wind area ratio (10 km, %)]^2						-0.000138
						(0.000165)
Observations	38853	37211	38076	38853	37211	38076
Adjusted R^2	0.624	0.626	0.627	0.625	0.602	0.625
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes
Farm characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors (in parentheses) are clustered at the county level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Permutation test

	Sum. of 10,000 permutation repeats Mean	Std. Dev.	Est. coef. from preferred specification	Est. coef. larger than % of repeats	Larger than % of repeats for both corn and soybeans simultaneously
Panel A: Farms are randomly assigned county wind profile					
Est. of *wind capacity density* for soybeans	-0.000526	0.0430559	0.137	99.9%	100.0%
Est. of *wind capacity density* for corn	0.000921	0.0526965	0.266	100.0%	
Est. of *wind area ratio (25 km)* for soybeans	-0.0000058	0.0001512	0.000716	100.0%	100.0%
Est. of *wind area ratio (25 km)* for corn	0.0000060	0.0001873	0.00110	100.0%	
Panel B: Farms from the same original county are randomly assigned the same county wind profile					
Est. of *wind capacity density* for soybeans	0.0048198	0.1252781	0.137	88.5%	97.5%
Est. of *wind capacity density* for corn	-0.0038088	0.1887545	0.266	94.4%	
Est. of *wind area ratio (25 km)* for soybeans	0.00000108	0.0004519	0.000716	95.9%	98.6%
Est. of *wind area ratio (25 km)* for corn	-0.00000032	0.0006548	0.00110	97.5%	

Table 6. Effects of wind farms on meteorological variables, 1998-2017

	ln(GDD)	ln(GDD)-donut	ln(XDD)	ln(XDD)-donut	ln(precip.)	ln(precip.)-donut
	(1)	(2)	(3)	(4)	(5)	(6)
If within 25 km of wind farms	0.00152***	0.00168***	-0.0223***	-0.0258***	-0.0133***	-0.0173***
	(0.000219)	(0.000229)	(0.00273)	(0.00286)	(0.00136)	(0.00144)
Observations	177660	157660	177651	157651	177660	157660
Adjusted R^2	0.997	0.997	0.992	0.992	0.975	0.975
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors (in parentheses) are clustered at the grid level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Effects of wind farms on farm operations

	Corn Acreage (1)	Soybean Acreage (2)	Fertilizer (3)	Crop Total (4)	Power and Equipment (5)	Building (6)	Labor (7)
Panel A: Wind capacity density							
Wind capacity density	-141.4	60.98	3.653	4.016	-12.39	6.013	-13.11
(MW/sqmi)	(110.2)	(100.3)	(9.275)	(16.13)	(16.93)	(9.411)	(8.027)
Observations	39248	39248	39248	39248	39248	39248	39248
Adjusted R^2	0.955	0.886	0.677	0.810	0.779	0.202	0.673
Panel B: Wind area ratio							
Wind area ratio (25 km, %)	-0.614	0.228	0.0120	0.0232	-0.0595	0.00365	-0.0555*
	(0.451)	(0.398)	(0.0351)	(0.0611)	(0.0625)	(0.0385)	(0.0310)
Observations	37590	37590	37590	37590	37590	37590	37590
Adjusted R^2	0.975	0.931	0.679	0.813	0.781	0.193	0.674
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors (in parentheses) are clustered at the county level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Effects of wind farms on farm returns

	Total nonfeed costs (per acre) (1)	Crop returns (per acre) (2)	Net farm income (per acre) (3)	Management returns (per acre) (4)	Labor and management income (per operator) (5)
Panel A: Wind capacity density					
Wind capacity density (MW/sqmi)	44.63	130.0**	74.31*	67.71*	259330.4***
	(38.31)	(59.99)	(37.79)	(37.86)	(94440.4)
Observations	36195	36195	36195	36195	36195
Adjusted R^2	0.797	0.842	0.360	0.330	0.522
Panel B: Wind area ratio					
Wind area ratio (25 km, %)	0.183	0.561***	0.324**	0.303**	991.8***
	(0.143)	(0.210)	(0.139)	(0.131)	(326.1)
Observations	34654	34654	34654	34654	34654
Adjusted R^2	0.795	0.843	0.353	0.321	0.519
Year FE	Yes	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes	Yes
Farm characteristics	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors (in parentheses) are clustered at the county level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A1. The retention rates of FBFM enrollment, 2003 - 2017

Year	Percent of farms enrolled in last year		
	All farms	Farms in counties with wind farms by the end of 2017	Difference
2003	N/A	N/A	N/A
2004	79.59	81.25	1.66
2005	78.47	81.74	3.27
2006	74.69	75.78	1.09
2007	77.7	80.39	2.69
2008	79.02	80.09	1.07
2009	81.15	82.67	1.52
2010	80.23	80.59	0.36
2011	83.35	83.03	-0.32
2012	83.32	83.91	0.59
2013	80.68	82.17	1.49
2014	82.24	83.73	1.49
2015	81.75	82.56	0.81
2016	80.12	79.18	-0.94
2017	76.67	77.38	0.71

Table A2. Robustness checks with dummy wind development indicator, 2003-2017

	(1)	(2)	(3)	(4)
Panel A: Soybeans				
1(W_{c0})	0.0717***	0.0709***	0.0715***	0.107*
	(0.0245)	(0.0244)	(0.0243)	(0.0547)
Observations	35749	35749	35749	35749
Adjusted R^2	0.641	0.642	0.644	0.645
Panel B: Corn				
1(W_{c0})	0.0692**	0.0689**	0.0708**	0.0748*
	(0.0327)	(0.0324)	(0.0321)	(0.0418)
Observations	36593	36593	36593	36593
Adjusted R^2	0.631	0.632	0.633	0.638
Year FE	Yes	Yes	Yes	Yes
Farm FE	Yes	Yes	Yes	Yes
Farm characteristics	No	Yes	Yes	Yes
Operating costs	No	No	Yes	No
County specific linear time trend	No	No	No	Yes

Note: Robust standard errors (in parentheses) are clustered at the county level. Asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.