FOUR ESSAYS ON FARMERS' BEHAVIOR WHEN MAKING INSURANCE, GRAZING, AND SEED DECISIONS IN THE FACE OF UNCERTAINTY

By

Yuyuan Che

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics—Doctor of Philosophy
Economics—Dual Major

2021

ABSTRACT

FOUR ESSAYS ON FARMERS' BEHAVIOR WHEN MAKING INSURANCE, GRAZING, AND SEED DECISIONS IN THE FACE OF UNCERTAINTY

By

Yuyuan Che

Decision-makers typically encounter at least some difficulties when making decisions about managing uncertain future outcomes. Traditional economic theory assumes that individuals seek to maximize expected profits or expected utility based on their available information. However, many studies have shown that these assumptions are violated in some cases, especially when people countenance uncertainty. Agricultural producers cannot avoid uncertainty about weather conditions, market fluctuations, and the effectiveness of technology choices when making important production decisions. A central theme of this dissertation is how agricultural producers make decisions with a particular focus on behavioral factors. The dissertation consists of four essays on farmers' decisions regarding crop insurance, rotational grazing, and seeding rates.

The first essay explores whether and how farmers' crop insurance participation decisions are influenced by recent indemnity or weather events using historic federal crop insurance program data. With parametric and non-parametric methods, we find that higher past indemnities encourage farmers to participate in insurance programs and choose a higher coverage level, while prior adverse weather shocks work indirectly. We also find that the increase in participation due to indemnities peaks in the year following a loss.

The second and third essays investigate how ranchers make decisions about whether to adopt rotational grazing practices. The second essay focuses on peer effects and subsidy impacts. With farm-level survey data, we apply a simultaneous-equations model to take account of

endogeneity issues arising from peer effects. We find that there are significant peer effects in the adoption of rotational grazing, and that incentive policies will have multiplier effects in the long run on adoption through peer networking. The third essay investigates why ranchers who view rotational grazing as a win-win practice for both profit and the environment do not use the practice.

The fourth and final essay studies how farmers' seeding rate choices respond to markets, resources, and technologies by considering a trade-off between more seeds and fewer resources allocated to each seed. Trends in seeding rates have differed between corn and soybean over the past several decades, but the underlying reasons for this have not received attention in the agronomic and economic literature. With a unique detailed U.S. farm-level market data, we find that soybean seeding rate choice is more price elastic than is that for corn, i.e., seed companies are likely to have less power in the soybean seed market. Most inputs that come with the land, and so are divided across all seeds increase corn and soybean seeding rates; while inputs that come with the seed increase corn seeding rates and decrease soybean seeding rates. As an application, we combine findings in the literature with our empirical analysis to conclude that tax or price policies that target the seed or crop will mitigate neonicotinoid-related ecological impacts.

I dedicate this dissertation to my parents, Guiping Che and Shijie Wang.
Your love, support, and encouragement always motivate me.

ACKNOWLEDGEMENTS

I would first like to express my deep appreciation to my advisors, Dr. Hongli Feng and Dr. David Hennessy, for their patient guidance, support, and encouragement throughout my Ph.D. study period. They have always been ready to help whenever I've encountered difficulties in my research. Their insights about research and life continuously inspire me.

I would like to thank my committee members, Dr. Scott Swinton, Dr. Jeffery Wooldridge, and Dr. Jinhua Zhao, for their mentorship and inspiration. Their constructive comments and suggestions have been invaluable and have improved the quality of my dissertation.

I am also grateful to my friends in the AFRE for their kind support and company. Thanks for all the great time we spent together.

Finally, I would like to thank my parents, Guiping Che and Shijie Wang. I would not have made it this far without their unconditional love, endless support, and continued encouragement.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Understanding individuals' decision-making under uncertainty is a crucial question in both theoretical and empirical economics. Decision-makers typically encounter at least some difficulties with making decisions about managing uncertain future outcomes. Traditional economic theory assumes that individuals make decisions through maximizing expected profits or expected utility based on their available information. However, many studies have shown that these assumptions are violated in some cases, and especially when people face uncertainty.

This dissertation seeks to better understand how agricultural producers make production decisions faced with risks. Agricultural production outputs are always correlated with uncertain weather conditions, market fluctuations, and technology innovations. Agricultural producers need to make important input, practice, and risk management choices at the beginning of a growing season and before knowing exact external factors. Examples include farmers' decisions regarding crop insurance, grazing practices, and seeding rates, which are studied in the four essays of this dissertation. These analyses on agricultural producers' behavior about production choices have significant implications for farm profits, the environment, and policy design.

The first essay explores whether and how farmers' crop insurance participation decisions are influenced by recent indemnity or weather experiences (i.e., recency effects). Recency effects have been studied in many important economic decisions and can influence individuals' willingness to mitigate risks through activities including purchasing insurance (Karlan et al. 2014; Kousky 2017; Bjerge and Trifkovic 2018). For crop insurance, there is evidence that insurance purchase decisions do not conform to predictions based on standard expected utility theory (Pétraud et al. 2015; Du et al. 2017). We develop a model to identify two channels through which recent adverse weather experiences may affect participation, one where weather shocks directly affect participation and the other where they affect participation through indemnity payouts. Applying both parametric and non-parametric methods to historic federal crop insurance program data, we find that higher past indemnities encourage participation at both extensive and intensive margins, and that prior adverse weather shocks work indirectly. We also find that the increase in participation due to indemnities peaks in the year following a loss.

The second and third essays investigate how ranchers make decisions to adopt grazing practices. Rotational grazing can address many environmental concerns due to extensive grazing and provides multiple potential private and social benefits (Park, Ale and Teague 2017; Searchinger et al. 2018). However, the average adoption rate among ranchers is just over 30 percent in the United States. Peer effects are increasingly recognized as an important driver of technology adoption (Foster and Rosenzweig 1995; Bandiera and Rasul 2006; Conley and Udry 2010; Sampson and Perry 2019). In the second essay, we develop a model to identify how peer networking affects ranchers' grazing practice adoption decisions, and also the impacts of subsidies on these decisions. With farm-level survey data, we apply a simultaneous-equations model to take account of endogeneity issues arising from peer effects. We find that there are significant peer effects in the adoption of rotational grazing, and incentive policies will have multiplier effects in the long run on adoption through peer networking.

In the third essay, we further explore an adoption gap between the set that could potentially adopt rotational grazing and the set that actually adopts. In contradiction to basic economic reasoning, many surveyed ranchers who viewed rotational grazing as a win-win practice for both profit and the environment did not adopt it. We find that these win-win non-adopters were a very constrained group in regard to most potential challenges to rotational grazing adoption, and were more willing to adopt rotational grazing than others when a one-time hypothetical subsidy was offered. These findings suggest that win-win non-adopters are a suitable target group for investment subsidies intended to promote adoption. Policies are likely to be more effective when they adequately address the costs and constraints that producers face.

The fourth and final essay studies how farmers' seeding rate choices respond to markets, resources, and technologies by considering a trade-off between more seeds and fewer resources allocated to each seed. Seeding rates in the United States have steadily increased over the past several decades for corn but have steadily decreased for soybean. Both trends have been accompanied by increasing crop yields (Assefa et al. 2016; Assefa et al. 2018) and environmental risks due to widely used chemical coating on seeds (Perry and Moschini 2020). With a unique detailed U.S. farm-level market dataset, we find that soybean seeding rate choice is more price elastic than is that for corn, i.e., seed companies are likely to have less power in the soybean seed market. An increase in most input endowments that come with land, and so are split over all seeds, increases corn and soybean seeding rates; while an increase in input endowments that come with the seed increases corn seeding rates and decreases soybean seeding rates. Focus group participants reveal some different ideas and they rely most heavily on their own experience when deciding on seeding rate choices. Our findings, when joined with an earlier paper on ecological effects, suggest that targeted tax or price policies on seed or crop will mitigate neonicotinoid-related ecological impacts.

REFERENCES

REFERENCES

Assefa, Y., P. Carter, M. Hinds, G. Bhalla, R. Schon, M. Jeschke, S. Paszkiewicz, S. Smith, and I.A. Ciampitti. 2018. Analysis of Long Term Study Indicates Both Agronomic Optimal Plant Density and Increase Maize Yield per Plant Contributed to Yield Gain. *Scientific Reports* 8 (1): 4937.

Assefa, Y., P.V. Vara Prasad, P. Carter, M. Hinds, G. Bhalla, R. Schon, M. Jeschke, S. Paszkiewicz, and I.A. Ciampitti. 2016. Yield Responses to Planting Density for US Modern Corn Hybrids: A Synthesis-Analysis. *Crop Science* 56 (5): 2802–2817.

Bandiera, O., and I. Rasul. 2006. Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal* 116 (514): 869–902.

Bjerge, B., and N. Trifkovic. 2018. Extreme Weather and Demand for Index Insurance in Rural India. *European Review of Agricultural Economics* 45(3): 397-431.

Conley, T.G., and C.R. Udry. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100 (1): 35–69.

Du, X., H. Feng, and D.A. Hennessy. 2017. Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics* 99(3): 732-756.

Foster, A.D., and M.R. Rosenzweig. 1995. Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy* 103 (6): 1176–1209.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. Agricultural Decisions after Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics* 129(2): 597-652.

Kousky, C. 2017. Disasters as Learning Experiences or Disasters as Policy Opportunities? Examining Flood Insurance Purchases after Hurricanes. *Risk Analysis* 37(3): 517-530.

Park, J.Y., S. Ale, and W.R. Teague. 2017. Simulated Water Quality Effects of Alternate Grazing Management Practices at the Ranch and Watershed Scales. *Ecological Modelling* 360: 1–13.

Perry, E.D., and G. Moschini. 2020. Neonicotinoids in U.S. Maize: Insecticide Substitution Effects and Environmental Risk. *Journal of Environmental Economics and Management* 102: 102320.

Pétraud, J., S. Boucher, and M. Carter. 2015. *Competing Theories of Risk Preferences and the Demand for Crop Insurance: Experimental Evidence from Peru.* Paper presented at the 2015 Conference, August 9-14, 2015, Milan, Italy 211383, International Association of Agricultural Economists.

Sampson, G.S., and E.D. Perry. 2019. The Role of Peer Effects in Natural Resource Appropriation – The Case of Groundwater. *American Journal of Agricultural Economics* 101 (1): 154–171.

Searchinger, T.D., S. Wirsenius, T. Beringer, and P. Dumas. 2018. Assessing the Efficiency of Changes in Land Use for Mitigating Climate Change. *Nature* 564 (7735): 249–253.

CHAPTER 1 Recency Effects and Participation at the Extensive and Intensive Margins in U.S. Federal Crop Insurance Programs

Abstract

Participation in U.S. Federal Crop Insurance Programs (FCIPs) has increased over time at both extensive (insured acres) and intensive (coverage levels) margins, but clear spatio-temporal variations exist in these trends. Farmers' decisions are likely influenced by recent indemnity or weather experiences (i.e., recency effects). We develop a model to identify two channels through which recent adverse weather experiences may affect participation, one where weather shocks directly affect participation and the other where they affect participation through indemnity payouts. With historic FCIP data over 2001-2017, we use parametric and non-parametric methods to estimate these effects. At both extensive and intensive margins, higher past indemnities are found to encourage participation. This provides evidence that prior adverse weather shocks work indirectly. Less evidence is found in favor of direct weather effects. We also find that the increase in participation due to indemnities peaks in the year following a loss.

Introduction

Understanding how recent experience can affect the decision-making of individuals under uncertainty is a crucial question in behavioral economics. Decision-makers typically encounter at least some difficulties with making decisions about managing uncertain future outcomes. Many important economic decisions are influenced by the utility derived from recent experiences or the occurrence of a certain event (i.e., recency effects) when facing risks. Recency effects refer to how the strength of recent information affects a decision-maker's working memory and probability judgment (Camerer and Loewenstein 2011). However, to the extent that risks materialize independently over time, these events should have limited effects on a decision-maker's choice whenever her goal is to maximize expected payouts or utility. The extant experimental economics literature in experienced utility and recency effects finds that experiences at the last moments of an experiment have privileged roles in evaluations of subsequent choices (Fredrickson and Kahneman 1993; Schreiber and Kahneman 2000).

Many studies have investigated recency effects in different types of insurance markets, and also in situations beyond insurance. Stein (2016) analyzes the dynamic nature of rainfall insurance purchasing decisions. Based on customer data from the Indian microfinance institution BASIX between 2005 and 2007, that paper shows the prior year's insurance payout to be associated with a 9 to 22 percentage point increase in participation. For the direct weather effects, the paper tests how prior year rainfall affects insurance purchases, finding evidence that previous rainfall shocks decrease purchases. Based on a nationwide panel dataset of large regional floods and flood insurance policies, Gallagher (2014) applies a flexible event study framework to show that insurance take-up spikes the year after a flood and then steadily declines back to its baseline. Kousky (2017) applies a fixed-effect model to a flood insurance policy dataset when testing for whether hurricane and tropical storm events affect flood insurance choices across all Atlantic and Gulf coast states between 2001 and 2010. The results show that a prior year hurricane increases net flood insurance purchases and also that this effect dies out after three years.

Cai and Song (2017) use a novel experimental design to ascertain any roles for experience or information in insurance take-up in rural China. In light of the finding that experience gained in a recently played insurance game has a stronger effect on actual insurance take-up, they conclude that learning from experience displays strong recency bias. In Cai et al. (2016), data from a two-year field experiment in rural China support the belief that experiencing a year one payout increases year two weather insurance demand. The study provides only an indirect channel for how exogenous shocks affect insurance demand, which is through the prior indemnity payouts. Perhaps closest to our work is that of Bjerge and Trifkovic (2018), who relate extreme weather events to a household panel data set that records weather insurance index choices in Gujarat, India. They find a positive response to excessive rainfall but no response to dry conditions, the latter effect likely being due to the presence of irrigation. The above work, and also many other lines of recent economic research, have brought attention to what is salient in the minds of decision-makers and how objective data are processed (Bakkensen et al. 2019; Royal and Walls 2019). Questions that naturally arise are whether responses to different risk sources differ and whether past indemnification matters in determining these responses.

In this paper, we examine whether and how recent experience affects insurance choices at extensive (how many acres to insure) and intensive (which coverage level to choose) margins. We are not concerned with how learning about a product through social and other interactions can affect diffusion. An extensive literature exists on the economics of product and practice diffusion, including the Cai et al. (2015) social network experiment analysis of weather insurance adoption in rural China and the Santeramo (2019) study of crop insurance uptake in Italy. Rather, we are concerned with the impact of recent events on demand. Our interest is in the U.S. Federal Crop Insurance Program (FCIP), which provides an important setting in which to examine real-world recency effects. FCIP is a large insurance market with more than $106 billion of insurance protection (i.e., liability) for over 130 different kinds of crops on about 335 million acres in 2018. The total premium from about 1.1 billion policies that year was about $9.9 billion, of which the government subsidized about 63% and farmers paid about 37% out of their own pockets for insurance protection.[1] Extensive margin participation in FCIP is high for major crops. For example, about 86% of corn and soybeans were insured in 2017, so there is limited potential for information asymmetry to affect extensive margin participation.

FCIP is also a near-ideal setting in which to examine real-world recency effects. The primary cause for payouts, being weather events, is exogenous, difficult to predict in advance, and varies spatially within a given year. Furthermore, and by contrast with private insurance markets, FCIP is not concerned about short-run solvency and adjusts premium rates according to pre-set rules such that premiums are largely unaffected by prior year indemnification. In addition, as with other insurance markets, there is evidence that crop insurance purchase decisions do not conform to predictions based on standard expected utility theory (Du et al. 2017; Pétraud et al. 2015). Our hypothesis is that recency effects can explain part of this non-conformity. For example, farmers who experienced a natural event or received a higher indemnity in a given year may overestimate the year later recurrence probability. Similarly, farmers who did not have such an experience may underestimate the probability of an indemnity.

[1] Detailed are available at https://legacy.rma.usda.gov/data/sob.html.

While recency effects have been examined extensively by psychologists and economists in general, there is limited research on how variations in participation relate to recent experience in FCIP. Chong and Ifft (2016) have regressed the share of planted acres insured on spatial and space-time interaction fixed effects as well as county mean yield deviations from trend. They show that corn acres insured increases in the year after an adverse yield shock and, to a lesser extent, decreases in the year after a good harvest. But our approach is distinct in that we work directly with weather and indemnity variable metrics. This allows us to identify how recent experiences in risks posed, rather than the yield deviations that they impact, affect participation decisions. This approach also allows us to compare two alternative channels through which recency effects can arise, where either the indemnities themselves or the underlying weather shocks may motivate the participation response to recent events.

Our paper contributes to the literature in the following ways. First, we construct a theoretical model that includes recency effects in which individuals use recent experiences to update their information on the benefits of insurance choices. This model adds to the literature by extending the updating model applied in Cai et al. (2016) to include recency effects in the experienced utility function. Second, we estimate the impacts of recently experienced indemnity payouts and a variety of weather shocks on crop insurance participation through two approaches: a two-step parametric approach and a flexible non-parametric approach. The two-step parametric model allows us to examine the direct effect of prior year indemnities' experience, and also the indirect and direct effects of prior adverse weather on crop insurance participation. The nonparametric flexible event study model (Gallagher 2014) enables us to estimate longer-run impacts of a large indemnity on participation in subsequent years. Third, our paper provides an integrated perspective on crop insurance participation at the extensive and intensive margins. To our knowledge, no study has examined crop insurance demand in terms of these two margins.

Our findings are as follows. First, in support of the Cai et al. (2016) experimental setting conclusion on extensive margin demand under higher prior period indemnity payouts, we find that actual prior year indemnities encourage higher extensive and intensive margin participation. Second, prior adverse weather events work indirectly by inducing higher participation through providing indemnities. Third, the direct effects of prior adverse weather on participation are not consistent across different weather events and are insignificant for some events. Fourth, there is an immediate but largely transient rise in participation after either a weather shock event or a large indemnities' experience. For example, consider when the indemnity ratio is 70 percent for corn (i.e., 70% of policies earning premium in a county are indemnified).[2] Then we find that the effect of a weather shock event on the logit of participation, as measured by the fraction of total corn acres that are insured, peaks at about 13.6 percent in the first year just after that event and declines steadily thereafter.

In what follows we briefly explain FCIP and how it relates to variations in participation. We then adapt the standard expected utility modeling framework to identify and decompose recency effects, including direct and indirect roles. Next, we explain the crop insurance and weather data that we analyze and also the variables that we construct. Then we apply a two-step parametric model to examine the direct and indirect effects of recent experience on participation, and we also use a nonparametric event model to test for the lasting effects of large indemnities. After reporting and analyzing the estimation results, we conclude with some brief comments.

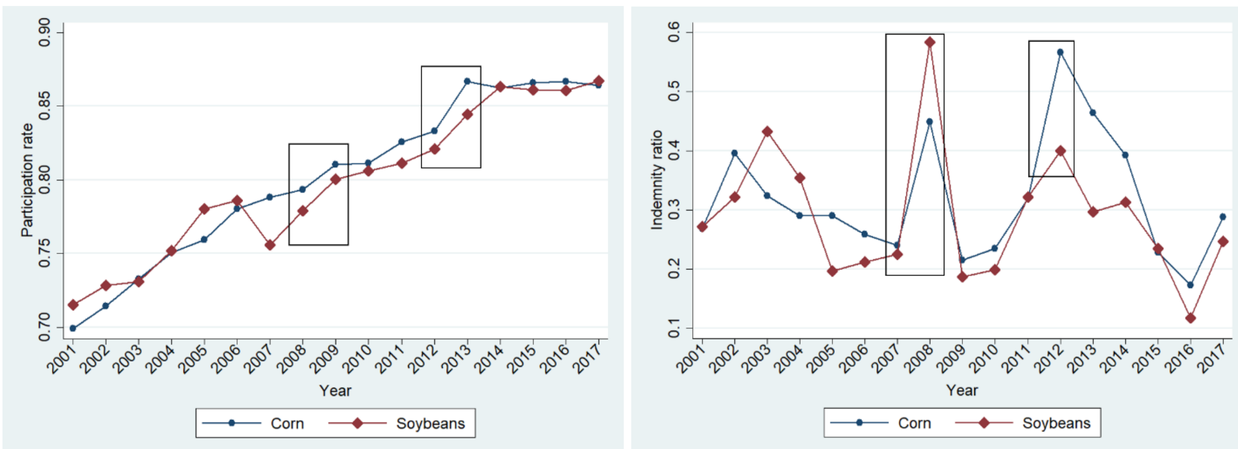
[2] Indemnity ratio, as defined above, depends on intensive margin choices. All else equal, the indemnification rate will be higher when average coverage level is higher.

U.S. Federal Crop Insurance Program Details and Participation Trends

FCIP was first authorized under the U.S. Agricultural Adjustment Act of 1938 and was run on an experimental basis for many decades. Crop and region coverage was limited and contract availability might be removed when experience called actuarially soundness into question (Kramer 1983). Even where available, participation remained low during the initial decades. Reasons for small uptake include comparatively low institutional commitment to the program, product novelty, token premium subsidy rates, grower liquidity constraints, uninformed rate-setting procedures and the prospect of federal enactments to provide region-wide ad hoc free disaster relief transfer payments or loans in the event of a general crop failure.

Participation grew in the decade after the Federal Crop Insurance Act (FCIA) of 1980, which finally provided strong federal commitment to the policy. FCIP obtained continuous authorization under FCIA while periodic revisions were written into Farm Bill and other enactments. FCIA funded premium subsidies at up to 30% and expanded program breadth to cover more crops and regions, but sign-up levels did not attain policymaker expectations (Glauber 2004). The Federal Crop Insurance Reform Act of 1994 further increased premium subsidies and added a new insurance policy, Catastrophic Risk Protection Endorsement (CAT). CAT compensates farmers for losses in excess of 50% of normal yield paid at 55% of the estimated market price of the crop. CAT is free apart from an administrative fee. It is viewed as distinctive, where contracts that provide higher coverage at a positive charge are referred to as buy-up contracts (Shields 2015).

Acreage participation expanded further after the 1994 Reform Act, and again in the late 1990s when revenue insurance contracts were introduced. Additional impetus for expansion, and especially for higher coverage levels, was provided by further premium mark-downs funded under the Agricultural Risk Protection Act of 2000 as well as Farm Bill legislation in 2008 and 2014 (O'Donoghue 2014). As is shown in Figure 1.1a, which provides average participation trend lines in a 12 state U.S. Midwestern and Great Plains Region[3] for corn and soybean, the percent of planted acres that were insured increased markedly between 2001 and 2017. For both corn and soybeans acres, average area participation increased from about 70% in 2001 to about 86% in 2017.



(a) Acreage participation (b) Indemnity ratio

Figure 1.1 Extensive margin participation, as measured by fraction of total crop acres that are insured, and also indemnity ratio for corn and soybeans in the 12 State Region for the period 2001-2017

Note: The states are Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota and Wisconsin. See Table 1.1 for formal definitions of participation rate and indemnity ratio

Throughout FCIP's history the changes in outcomes, especially regarding the fraction of total crop acres and coverage levels, have been closely related to subsidy rates and the development of new contract policy designs. Many previous studies have examined the effect of premium subsidies on either acreage participation or coverage levels choices.[4] Using data from

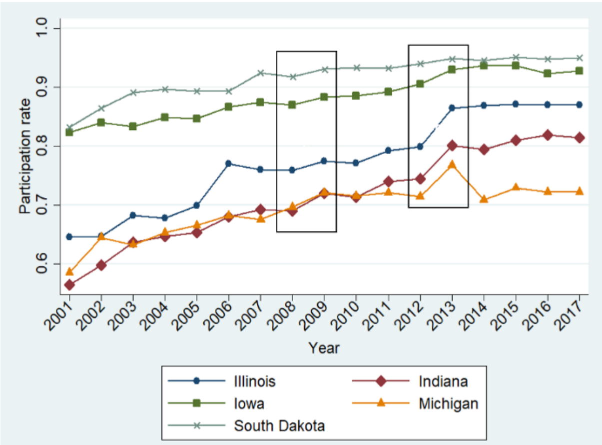
[3] The twelve states are Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota and Wisconsin.

[4] More generally insurance studies have typically covered either the intensive margin or the extensive margin, but not both. See analysis by Geruso et al. (2019), on equilibrium under adverse selection, for reasoning on why considering these margins separately may be problematic.

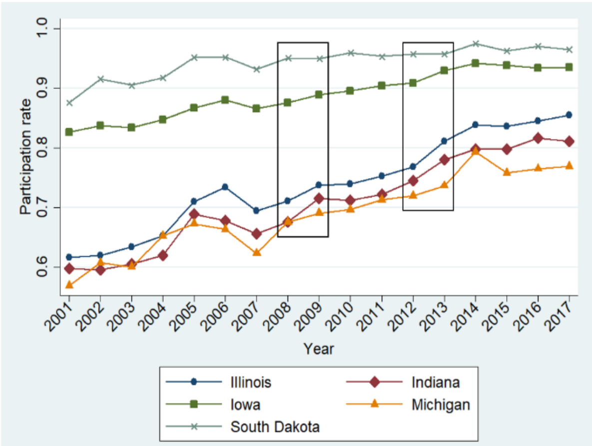
1985 to 1993, Goodwin et al. (2004) focus on corn and soybeans in the Corn Belt and also wheat and barley in the Northern Great Plains. Their results, for the 1985-1993 time frame, confirm the hypothesis that premium subsidies will modestly increase crop insurance participation. Working with 2011 county-level contract choice data, Du et al. (2014) find that higher coverage levels are chosen where production conditions are better and yields are less risky. O'Donoghue (2014) tests the effect of premium subsidies on demand for crop insurance across major crops, including corn, soybeans and wheat. Based on county-level data from 1989 to 2012, he shows that an increase in subsidies can induce higher enrollment at higher coverage levels, but the effect is not strong.

With reference to 2009 data, Du et al. (2017) point out that intensive margin participation has been far from complete where FCIP is intended to assess pre-subsidy premiums as actuarially fair in the aggregate. These observations are noteworthy given the high subsidy rates and Mossin's (1968) argument that risk averse individuals should purchase full coverage when faced with an actuarially fair insurance policy. Employing a large insurance unit-level dataset for corn and soybeans and a mixed logit framework, Du et al. also show that the probability of choosing an insurance product would decline with an increase in out-of-pocket premium expenditures. This suggests that participation may be dampened by behavioral concerns, including placing a heavier weighting on more definite expenditures than on less certain indemnity receipts. Ramirez and Shonkwiler (2017) and Price et al. (2019) suggest an alternative motivation for reluctance to participate, namely that premiums may be fair on the whole but still very bad deals for a significant fraction of potential users.

While extensive margin participation has increased over time, temporal variations in participation exist. As can be seen from variations along trend lines in figures 1.1a and 1.1b, which refer to the previously defined 12 State Region. As seen in Figure 1.1a, the increase in the fraction of total crop acres that are insured is uneven over time and is especially large after a higher indemnity ratio year. Figure 1.1b provides temporal data on indemnity ratios for the 12 State Region. The indemnity ratio depends largely on weather events, and in particular on extreme rainfall and/or temperature outcomes during the course of the growing season. It can be seen from boxed segments in the figure that the large indemnity ratio increases between 2007 and 2008 (when a price decline caused revenue insurance payouts) and also between 2011 and 2012 (a drought year) were followed immediately by acreage participation increases. The temporal pattern for the Midwestern and Great Plains region is also reflected at the state level even though different states have different insured acre fractions. For the 2001-2017 interval, Figure 1.2a shows that corn acreage participation increased from 88% to 96% in South Dakota, from 62% to 85% in Illinois, and from 57% to 77% in Michigan. Furthermore, many locations saw strong acreage participation increases in years when others did not. State indemnity ratio data in Figure 1.3 can be seen to correspond with Figure 1.2 state area participation data, but at a lag.

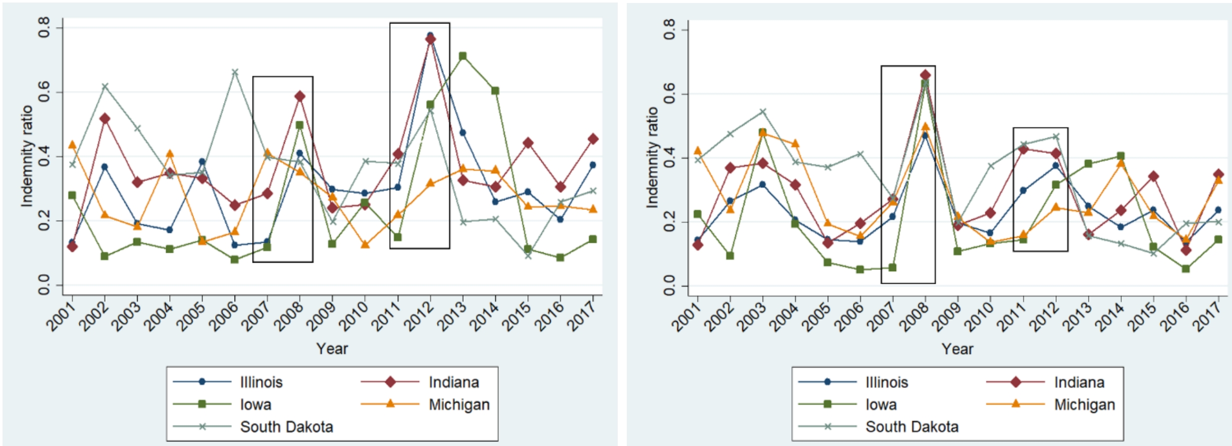


(a) Corn



(b) Soybeans

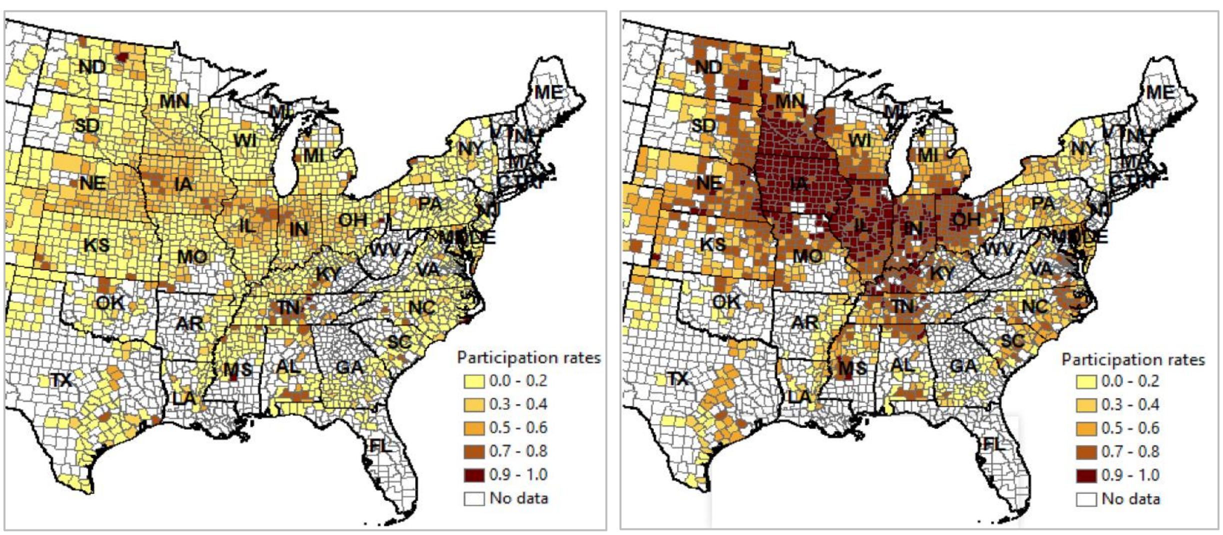
Figure 1.2 Extensive margin participation, as measured by fraction of total crop acres that are insured for corn and soybeans by selected states over the period 2001-2017



(a) Corn (b) Soybeans

Figure 1.3 Average indemnity ratio for corn and soybeans in selected states over the period 2001-2017

At the intensive margin, average coverage levels demonstrate somewhat similar patterns. Figure 1.4 provides two maps, one for 2001 and the other for 2017, declaring the fraction of corn acres in a county that took out 75% coverage or higher in yield and/or revenue insurance. In a given year it is clear that Western Corn Belt coverage levels are higher than those in Great Plains, Wisconsin, Michigan, Eastern Ohio and other fringe Corn Belt areas. Comparing the two years, in most areas the 2017 participation rate at this coverage level far exceeded the 2001 rate.

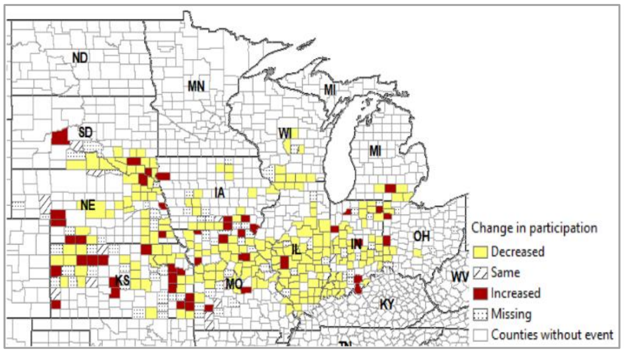


(a) 2001 (b) 2017

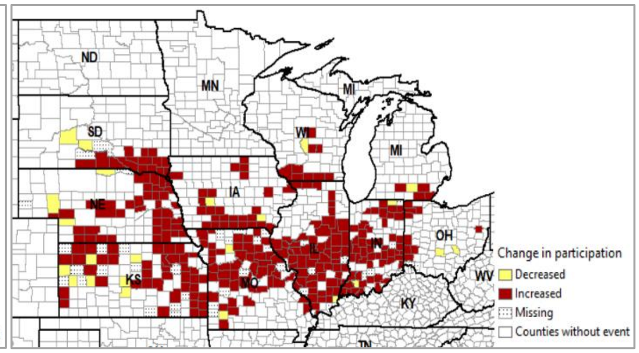
Figure 1.4 Change in intensive margin participation in the east of the Rockies between 2001 and 2017, as measured by fraction of total corn acres that are insured at coverage levels of at least 75%

Data suggest that intensive margin participation has grown after an indemnity ratio increase. Figure 1.5 considers counties with indemnity ratio greater than 70% in the 2012 drought year to be event counties. These maps indicate changes in area participation among those event counties in 2013 when compared with 2012 for three categories: CAT, buy-up policies, and coverage levels of at least 75%. It is evident that participation in most event counties increased in 2013 for buy-up and at higher coverage levels, but decreased for CAT policies. One way to measure this shift toward higher coverage levels is with cumulative area participation curves (CAPC), which sum total insured acres in a crop that have no more than coverage level x, as given on the curve's x axis. Figure 1.6 provides CAPCs in 2012 and 2013 for both corn and soybeans. The figure shows that for each crop the 2013 CAPC is below that in 2012. Growers increased insurance program participation at the intensive margin after the drought year while area participation decreased for CAT policies. The change in participation may be caused by the prior large indemnities or by severe weather shocks, where recency effects arise.

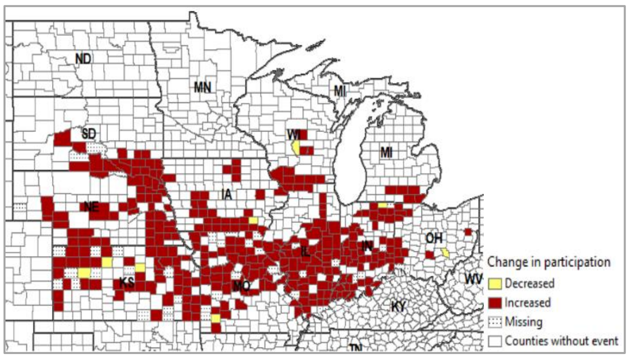
To further investigate variation in participation as measured by both the insured acres and coverage levels, we will incorporate recency effects into the standard expected utility theoretical model of demand for crop insurance. The model is to be viewed as illustrative rather than assertive. Its purpose is to provide guidance on the incentives that shape intensive and extensive margin responses.



(a) CAT



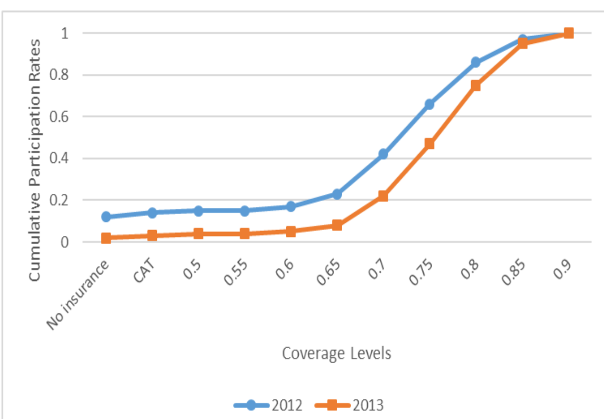
(b) Buy-up



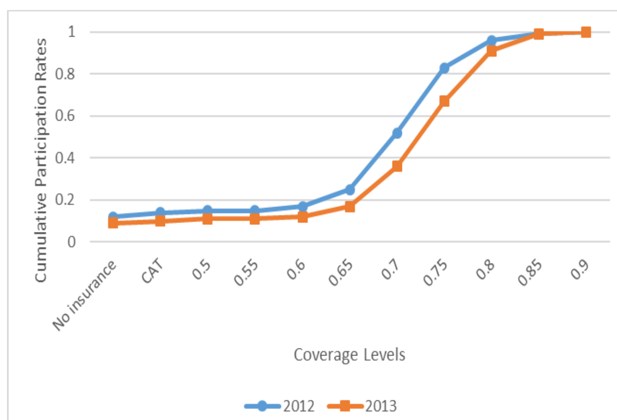
(c) At coverage levels of at least 75%

Figure 1.5 Changes in intensive margin participation in the Upper Midwest, as measured by fraction of total corn acres that are insured in event counties in 2013 when compared with the drought year 2012 for CAT, buy-up policies and at coverage levels of at least 75%

Note: Here the event counties are defined as those whose indemnity ratio was greater than 0.7 in 2012



(a) Corn



(b) Soybeans

Figure 1.6 Cumulative participation in the 12 State Region, as measured by fraction of total crop acres that are insured for corn and soybeans in drought year 2012 and the following year 2013

Theoretical Framework

For a given farm, write crop revenue in year t as R_t. It is held to be random with year-invariant cumulative distribution function $F(R_t)$, support $[0, \infty)$ and mean value $\bar{R}$. Farmer can choose revenue insurance at coverage level ψ_t. When $R_t < \psi_t\bar{R}$ then the insurance contract will pay the farmer $\psi_t\bar{R} - R_t$, and when $R_t \geq \psi_t\bar{R}$ then the contract will pay 0. The actuarially fair premium of coverage level ψ_t is

(1.1) $$a(\psi_t) = \int_0^{\psi_t\bar{R}} (\psi_t\bar{R} - R_t)dF(R_t).$$

The premium subsidy rate is $s(\psi_\mathrm{t}) > 0$, which is a declining function of coverage level according to the current government policy. The farmer will pay $(1 - s(\psi_t))a(\psi_t)$ when purchasing coverage level ψ_t. Farm production costs are given as *C*. At coverage level ψ_t, the farmer's profit is

(1.2) $$\pi(\psi_t) = \max\{R_t, \psi_t\bar{R}\} - C - n(\psi_t),$$

where $n(\psi_t) = (1 - s(\psi_t))a(\psi_t)$ is the net (after subsidy) premium. Whenever the farmer does not participate in crop insurance, i.e., whenever $\psi_t = 0$, then profit is $\pi(0) = R_t - C$.

For a farmer with an increasing and concave utility of profit function $U(.)$, the utility of choosing coverage level ψ_t is $U[\pi(\psi_t)]$ and the farmer's expected utility will be

(1.3) $$E[U(\pi(\psi_t))] = \int_0^{\infty} U(\max\{R_t, \psi_t\bar{R}\} - C - n(\psi_t))dF(R_t).$$

It is held to be concave in coverage level, i.e., to display decreasing marginal value of coverage. The farmer faces the two-step maximization problem

(1.4) $$\max\left\{\max_{\psi_t} E[U(\pi(\psi_t))], E[U(R_t - C)]\right\},$$

where the second argument in the outer max{.,.} statement represents the extensive margin non-participation choice. A risk-averse individual should purchase full coverage when faced with an actuarially fair insurance policy (Mossin 1968). Thus the expected utility maximizing grower faced with actuarially fair and subsidized insurance contracts will both participate and take out the highest coverage level available. In this standard model of insurance decisions, past events do not enter equation (1.4) directly as the utility in period *t* depends solely on the net return in period *t*.

As mentioned in the introduction, be it for crop insurance or other asset insurance, this theoretical result is not fully supported by empirical data. Anomalies have been observed between data and standard model. Over-insurance and under-insurance are both found in some insurance markets such as automobile insurance, home insurance and health insurance (Kunreuther et al. 2013). For FCIP there exist high variations in the growth of participation (Makki and Somwaru 2001), and under-insurance has been observed (Du et al. 2017), where potential reasons include nonlinear probability weighting or loss aversion. Other events may also affect demand, including events that affect the availability of alternative risk management tools, moral hazard, and adverse election (Just et al. 1999; Sherrick et al. 2004). Here we focus on recency effects as a possible explanation for non-optimal choices. We examine how crop insurance participation decisions are affected by past experience with a simple updating model that seeks to account for recency effects. Our model is somewhat similar to the temporal difference reinforcement learning model introduced by Sutton and Barto (2018) and applied by Cai et al. (2016). However, in our model decision makers update their belief regarding the insurance product's value, which is impacted by both the indemnity experience and prior weather events.

As shown in Figure 1.7, extensive and intensive margin participation decisions are made in early Spring, labeled as time t. Any prior year indemnity occurred in the prior fall at time $t - 0.5$, and weather events causing these indemnities occurred during the prior Summer, labeled $t -$

0.75. One channel through which adverse weather events can have an effect is directly on participation, which is route A. The other is indirect as mediated through indemnities, i.e., first B and then C.

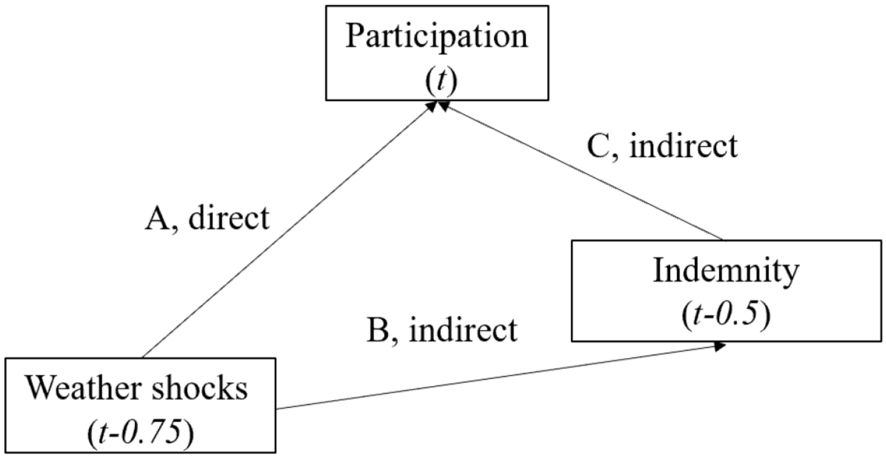


Figure 1.7 The effects of recent experience on participation

To account for potential recency effects, we expand the traditional expected utility of profit function as follows:

(1.5) $E[V(\psi_t, W_{t-1})] = E[U(\pi(\psi_t), B[J(W_{t-1}), W_{t-1}])|W_{t-1}]$,

where larger values of W_{t-1} represent worse weather. Function $V(.)$ is the farmer's expanded utility and it incorporates recency effects into the standard utility function, $U(.)$. Note several major differences between equations (1.3) and (1.5) but they all stem from allowing lagged weather event variables, W_{t-1}, to appear in equation (1.5). By conditioning expected utility on recent events we allow for adjustments in a farmer's assessments of yield or revenue outcome probabilities, requiring a Bayesian update of expected utility as suggested by Chong and Ifft (2016).

In addition, recency effects are allowed for by letting preferences depend on past weather events by way of the function $B[J(W_{t-1}), W_{t-1}]$, to be explained shortly. The utility function can change with the value of this recency effects function. For example, bad recent weather can make the grower more risk averse in the manner of Pratt (1964), so that demand for higher coverage levels increases. Or losses arising from incomplete insurance may tighten credit constraints on a grower such that she or her bank manager see the need for higher coverage levels. Thus we allow preferences to shift with context. The stability of risk preferences has long been a matter of some controversy, if only because measurement of preferences is imprecise (Schildberg-Hörisch 2018). For example, the 2011 Japanese earthquake was found to reduce risk aversion among men but not women (Hanaoka et al. 2018). In our case the matter of stability is somewhat moot because model (1.3) is static and accounting for recent events requires a somewhat more dynamic model. Adverse recent events may reflect a decline in wealth so that when the utility function adhered to the decreasing absolute risk aversion (DARA) property then a larger value of W_{t-1} should lead to greater risk aversion, which would likely induce higher demand for insurance. Thus risk preference may be stable over time and yet might not appear to be so absent an accounting for changing circumstances.

The recency effects component is itself a function of two arguments: the previous year's indemnity experience as represented by indemnity payout $J(W_{t-1})$, and also direct weather shocks in the previous time period with $B_2 > 0$, B_2 being the partial derivative of $B[.,.]$ with respect to the second term W_{t-1}. The past indemnity payout is of course a function of weather variables where $J(W_{t-1})$ is a continuously differentiable and increasing function, $J_{W_{t-1}} > 0$. Whether recent weather when acting through indemnities should have qualitatively the same recency effect as when acting directly is debatable, i.e., the recency function derivative with respect to indemnities, B_1, might be positive or negative. Indemnities are, in themselves, likely to increase wealth and so at least partially offset the direct effect of adverse weather. On the other hand, indemnities may in their own right signal the merits of insurance and so render growers averse to the risk associated with not having insurance. The total impact of an adverse weather shock on the recency effect is given as $B_{W_{t-1}} = B_1 J_{W_{t-1}} + B_2$. We will hold that this is positive in sign because even if one takes the perspective that indemnities act only on replenishing wealth, having no other effect on preferences, then incomplete coverage will leave the grower less wealthy, and so more risk averse under DARA.

Extending the above notation to the entire participation problem, equation (1.4) becomes:

$$(1.6) \quad \max\left\{\max_{\psi_t} E[V(\psi_t, W_{t-1})], E[U(R_t - C, B[J(W_{t-1}), W_{t-1}])|W_{t-1}]\right\},$$

where $J(W_{t-1})$ remains in the non-participation alternative because it is the consequence of a previously made decision. We will consider the inner, intensive margin coverage level optimization problem first and then turn to the extensive margin discrete choice problem. The optimal coverage level is given by setting the derivative of equation (1.5) with respect to ψ_t equal to zero, i.e.,

$$(1.7) \quad \frac{\partial \mathrm{E}[V(\psi_t, W_{t-1})]}{\partial \psi_t} = \frac{\partial \mathrm{E}[U(\pi(\psi_t), B[J(W_{t-1}), W_{t-1}])|W_{t-1}]}{\partial \psi_t} = 0.$$

Expression (1.7) may be rewritten as:

$$(1.8) \quad \bar{R} \int_0^{\psi_t \bar{R}} U'[\pi(\psi_t), B[.,.]|W_{t-1}] dF(R_t) = \frac{\partial n(\psi_t)}{\partial \psi_t} \int_0^{\infty} U'[\pi(\psi_t), B[.,.]|W_{t-1}] dF(R_t).$$

It can be readily shown that an increase in risk aversion is likely to increase the optimal coverage level because it will make marginal utility over interval $[0, \psi_t \bar{R}]$ larger in comparison with marginal utility when averaged over the entire support $[0, \infty)$. Thus, to the extent that an increase in the recency effects aggregator $B[.,.]$ increases risk aversion it should lead to an increase in coverage level.

The effect of a past weather event on the marginal value of coverage is given as a further derivation of (1.7):

$$(1.9)\quad \frac{\partial^2 \mathrm{E}[V(\psi_t, W_{t-1})]}{\partial\psi_t \partial W_{t-1}} = \frac{\partial^2 \mathrm{E}[U(\pi(\psi_t), B[.,.])|W_{t-1}]}{\partial\psi_t \partial W_{t-1}} + \frac{\partial \mathrm{E}[U(\pi(\psi_t), B[.,.])|W_{t-1}]}{\partial\psi_t \partial B} \times \left(B_1 J_{W_{t-1}} + B_2\right).$$

If adverse past weather events increase the expected marginal value of coverage, i.e., if expression (1.9) has positive value, then the grower will increase coverage. One way in which this could occur is through revised expectations, i.e., shifting the conditioner W_{t-1}, as reflected by the first right-hand expression in (1.9). This is a direct effect. If production is held to be more risky than had previously been believed then demand for insurance might increase. Another way in which the expected marginal value of coverage could increase is through changing the history-conditioned utility function, as reflected by right-hand product expression in (1.9). One part of the product term, that involving B_2, is a direct effect. The other part, involving $B_1 J_{W_{t-1}}$, is indirect in that it is mediated through indemnity payouts. We have already argued that each of these product terms in (1.9) is likely to be positive, and so the entire expression is likely to be positive. Thus we argue that recency is likely to increase intensive margin participation.

We turn now to the extensive margin choice in (1.6). When including recency effects then the grower's value of expected utility of profit absent insurance is likely to decline more severely after an adverse weather shock than does the grower's value of expected utility given at least some coverage. After all, the purpose of participation is to provide buffering. This should be true regardless of the way in which recency affects the utility function, be it through leading to a revision of probability assessments or through changing preferences. Thus extensive margin participation is also likely to increase as a result of adverse recent weather shocks.

Growers will come to different participation choices depending on their own preferences and technologies. Specify $\mathbb{S}(W_{t-1}) > 0$ as the history-dependent share of growers who participate in a region, in our case a county, and $\mathbb{M}(W_{t-1}) > 0$ as the region's mean coverage level conditional on participation. Then unconditional mean coverage level is equal to $\mathbb{U}(W_{t-1}) = \mathbb{S}(W_{t-1})\mathbb{M}(W_{t-1})$ where residual share $1 - \mathbb{S}(W_{t-1})$ all have coverage level 0. Upon logging this expression and then considering the response to recent weather, the total recency effect can be characterized as

$$(1.10)\quad \frac{d\ln[\mathbb{U}(W_{t-1})]}{dW_{t-1}} = \frac{d\ln[\mathbb{S}(W_{t-1})]}{dW_{t-1}} + \frac{d\ln[\mathbb{M}(W_{t-1})]}{dW_{t-1}},$$

where the first right-hand derivative is the extensive margin response when aggregated over all of a region's growers and the second right-hand is the intensive margin response. We have argued that both terms should be positive, and so the total recency effect should be positive. The remains of this paper will bring data to both right-hand terms in equation (1.10).

Data Description and Variable Construction

In our empirical analysis, we will examine how past years' weather conditions W_{t-1}, and past indemnity experience $J(W_{t-1})$ affect decisions on coverage levels ψ_t. In the current FCIP, ψ_t could be zero, i.e., no participation, or any of {0.5, 0.55, 0.6, 0.65, 0.75, 0.8, 0.85, 0.9} where 0.5 can be CAT or buy-up. We examine the extensive margin by studying insured acreage share, where $\psi_t > 0$, and the intensive margin share by studying the weighted average coverage level conditional on $\psi_t > 0$.

We employ crop insurance participation data from Summary of Business (SOB) and Cause of Loss (COL) historical data files, which are maintained by the U.S. Department of Agriculture's (USDA) Risk Management Agency (RMA). The SOB dataset contains county-level crop insurance participation information, including net reported acreage, the number of policies earning premium, as well as the number of indemnified policies under different coverage categories and coverage levels for major crops across the United States.[5] The COL dataset includes determined acreage data at different stages.[6] County-level planted acreage data for corn and soybeans are obtained from a USDA National Agricultural Statistics Service (NASS) survey.[7] We focus on insured acres and coverage levels participation choices each year during 2001-2017 for two primary crops (corn and soybeans) in the counties of the 12 State Region, as previously defined. These states account for the vast majority of the country's corn and soybean crops.

Let $P_{i,t}^{l}$ represent participation, where we use the notation to refer to both extensive margin and intensive margin participation. In what follows we explain in some detail our calculation of the extensive margin participation variable. The fraction of total crop acres that are insured is calculated by dividing net reported acres by the sum of planted acres and prevented planting acres for each county-crop-year observation. Prevented planting acres indicate the number of acres that cannot be planted because of flood, drought, or some other natural disaster. These acres are included in net reported acres but not in planted acres. We compute prevented planting acres by summing determined acres (i.e., the number of acres lost due to damage) across loss stage codes labels P2, PF and PT, which are the prevented planting codes in COL Data Files. Let $NR_{i,t}^{l}$ denote the net acres reported as insured, $PA_{i,t}^{l}$ indicate the planted acres, and $PP_{i,t}^{l}$ be the prevented planting acres for crop $l \in \{\text{corn, soybeans}\}$ in county i in year t. Then the participation at the extensive margin can be specified as

(1.11) $P_{i,t}^{l} = NR_{i,t}^{l}/(PA_{i,t}^{l} + PP_{i,t}^{l})$.

In addition, participation at the intensive margin is measured by areage weighted average

[5] Detailed dataset variable lists are available at https://www.rma.usda.gov/data/sob/sccc/sobsccc_1989forward.pdf.
[6] Detailed dataset variable lists are available at https://www.rma.usda.gov/SummaryOfBusiness/CauseOfLoss.
[7] Detailed data are available at https://quickstats.nass.usda.gov/.

coverage level (WACL), which is computed by using net reported acres at different coverage levels.

To consider the effect of prior year indemnities on participation choices, we define the indemnity ratio to be the ratio of the number of policies indemnified to policies earning premium. Let $H_{i,t}^{l}$ represent indemnity ratio, $I_{i,t}^{l}$ denote the number of yield and revenue insurance policies indemnified, and $E_{i,t}^{l}$ be the number of policies earning a premium. Then the indemnity ratio is

(1.12) $H_{i,t}^{l} = I_{i,t}^{l}/E_{i,t}^{l}$.

Weather outcomes are fundamental inputs into crop growth, so we use growing degree days (*G*) to measure beneficial heat, stress degree days (*S*) to measure heat stress, and the Palmer Z index to measure moisture stress. We study these variables separately because no commonly accepted summary corn favorability weather variable is available and also because a separated analysis will allow us to assess whether any recency effects vary by source of shock. Variable *G* is defined as the sum over growing season days of degrees in Celsius between lower (T^{l}) and upper (T^{h}) thresholds, a temperature interval for which the plant is well-adapted to convert this heat into growth. Variable *S* provides a way of measuring temperature stress for a specific crop within its growing season. This variable is defined as the sum over growing season days of degrees in Celsius in excess of threshold T^{k}, a number exceeding T^{h} and above which the plant is poorly-adapted to even survive in the long run. May-August is the assumed growing season for corn and soybeans. The formulas for variable *G* and *S* are

(1.13) $G_{i,t} = \sum_{d\in\Omega_t}[0.5(\min(\max(T_{i,d}^{max}, T^{l}), T^{h}) + \min(\max(T_{i,d}^{min}, T^{l}), T^{h})) - T^{l}]$,

(1.14) $S_{i,t} = \sum_{d\in\Omega_t}[0.5(\max(T_{i,d}^{max}, T^{k}) + \max(T_{i,d}^{min}, T^{k})) - T^{k}]$,

where *i* is county, *t* is year, *d* is day, and Ω_t is the year *t* set of growing season days for both corn and soybeans. The thresholds are $T^l = 10°\text{C}$, $T^h = 30°\text{C}$, $T^k = 32.2°\text{C}$ (Xu et al. 2013).[8]

We use daily temperature to calculate annual variables G and S at the county level. Station-level daily maximum and minimum temperatures are obtained from the Global Historical Climatology Network (GHCN-D) dataset by National Oceanic and Atmospheric Administration (NOAA) (Menne et al. 2021). In order to calculate $G_{i,t}$ and $S_{i,t}$ we transform station-level daily maximum and minimum temperatures into county-level daily data. We do so by taking the average daily maximum and average daily minimum temperatures for all stations in each county. We insert these county-level daily maximum and minimum temperatures during the growing season into equations (1.13) and (1.14). Then we construct deviations of variables G and S from their ten-years' average over 1991-2000, the decade just before our 2001-2017 research period, letting $\overline{G} = 0.1 \sum_{j=1991}^{2000} G_{i,j}$, and $\overline{S} = 0.1 \sum_{j=1991}^{2000} S_{i,j}$. The fractional deviations are

(1.15) $GD_{i,t} = (G_{i,t} - \overline{G})/\overline{G},$

(1.16) $SD_{i,t} = (S_{i,t} - \overline{S})/\overline{S}.$

These two constructions represent normalized county-conditioned temperature deviations from historical weather conditions.

Moisture stress is measured by the Palmer Z index (Xu et al. 2013). It reflects the departure of a particular month's weather from that month's average moisture condition, regardless of what has occurred in prior or subsequent months (Heim, 2002). Monthly Palmer Z (PZ) statistics for climate divisions in the conterminous U.S. are obtained directly from the NOAA website.[9] To transform these climate division data into county-level data, we calculate the area intersections between climate divisions and each county, and then weight PZ by county

[8] The conversions are $10°\text{C} = 50°\text{F}, 30°\text{C} = 86°\text{F}, 32.2°\text{C} = 90°\text{F}$.
[9] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/, accessed on 06 September 2018.

intersection areas. We take the average monthly county-level PZ for May-August to represent water stress for the corn and soybean growing seasons. The value $PZ = 0$ is to be expected, while $PZ \leq -2$ represents drought and $PZ \geq 5$ represents flooding (Xu et al. 2013). In order to consider dry and wet weather conditions separately, we calculate

(1.17) $dry_{i,t} = -\min(0, PZ_{i,t})$,

(1.18) $wet_{i,t} = \max(0, PZ_{i,t})$,

where $PZ_{i,t}$ is the average PZ value for county *i* in year *t*. Therefore, the larger the value of 'dry' (respectively, 'wet') the drier (respectively, wetter) the weather. The preferred weather condition for crop growth is neither too dry nor too wet.

We construct the county-year-crop panel from NASS, RMA and NOAA data. The panel is unbalanced since county×year observations can be lost in many ways. For example, NASS combines counties with small planted acreage into one combined county observation for each state in each year, which is labeled as "other (combined) counties." In addition, county-level GD and SD are calculated from station-level data. Some counties do not contain a station observation for some years so that we cannot generate GD and SD variables for these counties in some years. When constructing a balanced panel, we do not include either the combined counties from NASS or the missing counties from NOAA. However, our estimation focuses on the time variability in participation related to recent events, so the imbalance is not expected to be an issue. We have applied our model to both the unbalanced and balanced panels. The estimation results are similar, so we only present the results for unbalanced panel here. Variable definitions can be found in Table 1.1. Table 1.2 shows the variable descriptive statistics.

Table 1.1Definition of variables

	Variable	Description
Participation	*P*	(*Extensive margin*) Fraction of total crop acres that are insured = Net reported acres / (Planted acres + Prevented planting acres) (*Intensive margin*) Acreage weighted average coverage level
Indemnity ratio	*H*	Number of policies indemnified/Number of policies earning premium
Weather variables	*GD*	Deviation from the average GDD over 1991-2000
	SD	Deviation from the average SDD over 1991-2000
	dry	Negative value of the minimum among 0 and the Palmer Z value
	wet	The maximum among 0 and the Palmer Z value

Note: For participation we have two measures—extensive margin (fraction of total crop acres that are insured) and intensive measure (acreage weighted average coverage level)—where "net reported acres" and "coverage level" are from SOB and "prevented planting acres" is from COL. "Planted acres" is from NASS. For indemnity ratio, both the number of policies indemnified and the number of policies earning premium are from SOB.

Table 1.2 Variable descriptive statistics

	Variables		Obs	Mean	Std.Dev.	Min	Max
Corn	Fraction of total crop acres that are insured (*P*)	Full samples	14,961	0.799	0.152	0.035	1.000
		Buy-up	14,961	0.744	0.194	0.000	1.000
		CAT	14,195	0.058	0.085	0.000	0.716
	WACL (*P*)	Full samples	14,961	0.684	0.080	0.000	0.897
	Indemnity Ratio (*H*)	Full samples	14,961	0.318	0.245	0.000	1.000
		Buy-up	14,960	0.338	0.254	0.000	1.000
		CAT	13,515	0.084	0.182	0.000	1.000
Soybeans	Fraction of total crop acres that are insured (*P*)	Full samples	14,191	0.796	0.151	0.000	1.000
		Buy-up	14,191	0.747	0.188	0.000	1.000
		CAT	13,220	0.053	0.074	0.000	0.759
	WACL (*P*)	Full samples	14,191	0.692	0.076	0.000	0.893
	Indemnity Ratio (*H*)	Full samples	14,189	0.290	0.220	0.000	1.000
		Buy-up	14,188	0.308	0.232	0.000	1.000
		CAT	12,452	0.064	0.155	0.000	1.000
Weather variables	*GD*		13,296	0.011	0.120	-1.000	0.807
	SD		13,296	0.404	1.767	-1.000	27.455
	dry		14,961	0.382	0.769	0.000	5.135
	wet		14,961	0.866	0.962	0.000	4.838

Note: WACL represents area weighted average coverage level. Coverage level for the CAT contract is set equal to 0.5.

Model specification

Two-Step Parametric Estimation

We estimate a two-step parametric model to examine the direct effect of prior year indemnities, and also the indirect and direct effects of prior adverse weather on crop insurance participation choices at both extensive and intensive margins. This allows us to decompose the effect of adverse weather on participation choices into the effect of adverse weather on indemnities in the first step, and also the effect of prior indemnities and prior adverse weather on insurance participation in the second step. Then we develop estimations for corn and soybeans based on different policies (buy-up vs CAT).

In the first step, we estimate the effect of adverse weather on indemnity in order to further test for the indirect effect on participation through the response to indemnity experience. The indemnity ratio $H_{i,t}^{l}$ for crop *l* in county *i* and year *t* is specified as the dependent variable. The weather variables are denoted as the vector $W_{i,t} = (GD_{i,t}, SD_{i,t}, dry_{i,t}, wet_{i,t})'$ for county *i* in year *t*. The time-fixed regression equation is

(1.19) $H_{i,t}^{l} = \alpha_0^l + \alpha_1^l W_{i,t} + \delta_t^l + \varepsilon_{i,t}^l,$

where δ_t^l denotes the year fixed effect, and $\varepsilon_{i,t}^l$ denotes the error item.

In the second step, to test for the direct effects of prior indemnities and adverse weather shocks on participation choices, let $P_{i,t}^{l}$ denote participation choices with our two measures: extensive margin and intensive margin. We specify the dependent variable as the logit transformation of participation $P_{i,t}^{l}$, which is $\ln[P_{i,t}^{l}/(1 - P_{i,t}^{l})]$. The main explanatory variables are indemnity ratio $H_{i,t}^{l}$ and weather variables $W_{i,t}$. The time-fixed regression equation is

(1.20) $\ln[P_{i,t}^{l}/(1 - P_{i,t}^{l})] = \beta_0^l + \beta_1^l H_{i,t-1}^{l} + \beta_2^l W_{i,t-1} + \theta_t^l + u_{i,t}^l,$

where θ_t^l denotes the year fixed effect, and $u_{i,t}^l$ denotes the error item. When we apply the logit transformation on participation $P_{i,t}^{l}$ within its domain [0, 1] for the percent of insured acres and [0,1) for weighted average coverage level, zero-valued participation is replaced with 0.0001 before transformation, while one-valued participation is replaced with 0.9999 before transformation, since the domain of the logit transformation function is (0,1). The logit transformation is applied because $P_{i,t}^{l}$ is bounded between 0 and 1, so the effect of any particular independent variable cannot be constant throughout the range. After applying the logit transformation, the logit of $P_{i,t}^{l}$ can take on any real value, so it is natural to model the regression as a linear function (Papke and Wooldridge 1996).

Nonparametric Estimation

We employ a nonparametric flexible event study model (Gallagher 2014) to estimate the longer-run impact of large indemnities on subsequent participation choices, in which we include state-by-year effects and crop reporting district (CRD) fixed effects. The fixed effects nonparametrically control for state-specific yearly factors and unobserved or unchanging CRD characteristics. State-by-year fixed effects account for state-specific yearly trends that may affect participation, such as commodity prices, state-level responses to weather shocks, state economic conditions, and policy changes in FCIP. CRD fixed effects preclude inclusion of the underlying location-specific factors, such as soil conditions. The causal interpretation of estimation comes from the assumption that whether a county experiences a large loss in a particular year is random conditional on state-by-year and CRD fixed effect. Our main estimation equation is:

(1.21) $\ln[P_{i,t}^{l}/(1-P_{i,t}^{l})] = \sum_{\tau=-T}^{T} \phi_{\tau}^{l} D_{i,t,\tau}^{l} + \eta_{s,t}^{l} + \sigma_{c}^{l} + \xi_{i,t}^{l}.$

The independent variables are the event time indicator variables, $D_{i,t,\tau}^{l}$, which track the year of a large indemnity ratio as well as the years before and after a large loss. Here we assert that a large loss event occurs in one county when the county's indemnity ratio is greater than a specific cutoff point where we consider 0.1, 0.3, 0.5, 0.7 and 0.9. The value of a cutoff point can denote the magnitude of a large loss. For calendar year t and crop l, the indicator variable $D_{i,t,0}^{l}$ equals to 1 whenever a large loss appears in county i for year t; the indicator variable $D_{i,t,\tau}^{l}$ equals 1 whenever a large loss appears in county i in year $t-\tau$. As counties may have more than one large loss during the event study, each loss is coded with its own indicator variable. For example, were county i to have a large loss in years 2006 and 2012, then for the calendar year 2010 the indicator $D_{i,2010,4}^{l}$ would equal 1 since it is 4 years after the loss year 2006 while the indicator $D_{i,2010,-2}^{l}$ would also equal 1 since it is 2 years before the loss year 2012. We take $\tau \in \{-5, \ldots, 0 \ldots, 5\}$ in equation (1.21), since we are interested in the participation response in the years around a large loss. Regarding the other terms in (1.21), parameter $\eta_{s,t}^{l}$ represents the state-by-year fixed effects term, parameter σ_{c}^{l} denotes the CRD fixed effects term, and $\xi_{i,t}^{l}$ is an error term.

Estimation Results

We estimate equations (1.20) and (1.21) for both types of participation measures, extensive margin and intensive margin.

The Effects of Indemnities and Weather Shocks on Participation

Table 1.3 shows the estimated results for equation (1.19) in the first step when applied to corn. As expected, for all of full samples, buy-up and CAT policies adverse weather conditions are shown to be important determinants of the proportion of policies that are indemnified. The strong significance of these results and the availability of the data used also underpin our earlier claim that crop insurance is a near-ideal real-world setting in which to study recency effects.

Table 1.3 The first-step indemnity regression with FE for corn, equation (1.19)

Dependent variable	Indemnity ratio		
Categories	Full samples	Buy-up	CAT
GD	-0.054**	-0.064***	-0.031*
	(0.021)	(0.022)	(0.018)
SD	0.023***	0.025***	0.011***
	(0.002)	(0.002)	(0.001)
dry	0.927***	0.958***	0.612***
	(0.031)	(0.032)	(0.025)
wet	0.249***	0.258***	0.200***
	(0.021)	(0.022)	(0.017)
Year FE	Yes	Yes	Yes
Constant	0.221***	0.262***	0.047***
	(0.007)	(0.008)	(0.006)
Observations	11,976	11,975	10,935
R-squared	0.290	0.283	0.134
Number of counties	892	892	877

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

The second step regression results for equation (1.20) are presented in Table 1.4, in which we apply our two measures of participation. At the extensive margin we can observe that past year indemnity ratio plays a positive and significant role in participation for full samples and buy-up. For buy-up policies, the coefficient for *L.IndemnityRatio* is 0.393, where *L.* represent the one-year lag operator on the relevant variable, in this case *IndemnityRatio*. On the contrary, the *L.IndemnityRatio* coefficient for CAT is -0.548, indicating that prior indemnity ratio can discourage CAT policy participation. Although we do not know for sure, because we do not have grower-level contract choice data, this is likely an intensive margin effect whereby growers switch from CAT to buy-up policies in response to a large loss event.

When it comes to the direct effect of prior weather shocks, at the extensive margin only the $L.wet$ coefficients are significantly negative and only for full samples and buy-up policies. Furthermore, the data suggest that excess moisture can decrease subsequent area participation in crop insurance. For CAT policies, the $L.dry$ coefficient is significant at the 1% level. Drought can decrease acreage participation in CAT policies. At the intensive margin, the results show that severe heat stress and excess moisture may decrease coverage levels chosen. Therefore, the direct effects of prior indemnity ratio on participation at both extensive and intensive margins are positive, while the direct effects on participation are not consistent across different weather events and they are partially insignificant.

Table 1.4 The second-step participation regression with FE for corn, equation (1.20)

Dependent Variables	Extensive margin Logit of fraction of total crop acres that are insured			Intensive margin Logit of WACL
Categories	Full samples	Buy-up	CAT	Full samples
L.IndemnityRatio	0.357^{***}	0.393^{***}	-0.548^{***}	0.135^{***}
	(0.041)	(0.034)	(0.059)	(0.005)
L.GD	0.090	0.057	0.033	0.003
	(0.093)	(0.080)	(0.105)	(0.011)
L.SD	0.010	0.006	-0.012	-0.002^{**}
	(0.007)	(0.006)	(0.008)	(0.001)
L.dry	-0.059	0.154	-0.588^{***}	0.023
	(0.139)	(0.120)	(0.150)	(0.016)
L.wet	-0.326^{***}	-0.243^{***}	0.011	-0.027^{***}
	(0.091)	(0.078)	(0.100)	(0.010)
Year FE	Yes	Yes	Yes	Yes
Constant	1.170^{***}	0.524^{***}	-2.378^{***}	0.716^{***}
	(0.033)	(0.028)	(0.033)	(0.004)
Observations	11,976	11,975	10,935	11,976
R-squared	0.153	0.302	0.503	0.695
Number of counties	892	892	877	892

Note: WACL represents weighted average coverage level. Coverage level for the CAT contract is set equal to 0.5. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Combining the Table 1.3 and Table 1.4 results, adverse weather shocks are shown to have indirect effects on participation at both margins. First, the weather variables' vector allows for the identification of recency effects in regard to risks posed. Then, past indemnities provide a positive channel through which recent adverse weather shocks have indirect effects on both the insured acres and coverage level chosen. But the direct effects of weather shocks are not consistent across different weather events. Tables 1.5 and 1.6 report the soybeans regression results in the first and second step, respectively. The results are similar to those for corn.

Table 1.5 The first-step indemnity regression with FE for soybeans, equation (1.19)

Dependent Variable	Indemnity ratio		
Categories	Full samples	Buy-up	CAT
GD	-0.101***	-0.114***	-0.000
	(0.019)	(0.020)	(0.017)
SD	0.012***	0.012***	0.003**
	(0.001)	(0.001)	(0.001)
dry	0.739***	0.764***	0.375***
	(0.031)	(0.032)	(0.027)
wet	0.182***	0.187***	0.168***
	(0.019)	(0.020)	(0.017)
Year FE	Yes	Yes	Yes
Constant	0.240***	0.287***	0.046***
	(0.006)	(0.007)	(0.005)
Observations	11,392	11,391	10,116
R-squared	0.346	0.359	0.055
Number of counties	841	841	813

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 1.6 The second-step participation regression with FE for soybeans, equation (1.20)

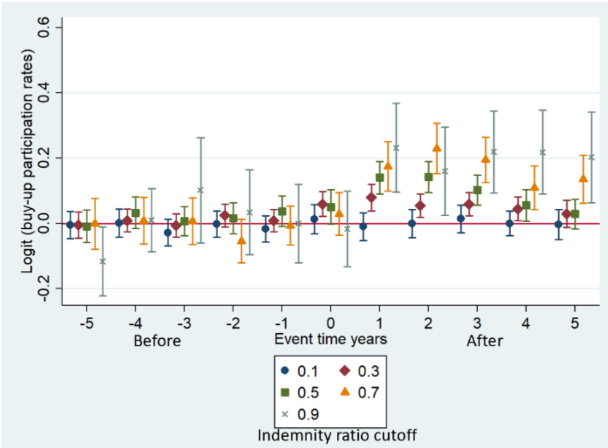
	Extensive margin			Intensive margin
Dependent Variables	Logit of fraction of total crop acres that are insured			Logit of WACL
Categories	Full samples	Buy-up	CAT	Full samples
L.IndemnityRatio	0.188***	0.229***	-0.271***	0.125***
	(0.052)	(0.044)	(0.070)	(0.006)
L.GD	0.060	0.066	0.009	0.009
	(0.101)	(0.089)	(0.111)	(0.011)
L.SD	0.014*	0.013**	-0.005	0.001
	(0.007)	(0.007)	(0.008)	(0.001)
L.dry	-0.215	0.011	-0.884***	0.111***
	(0.168)	(0.149)	(0.183)	(0.018)
L.wet	-0.324***	-0.285***	-0.232**	0.009
	(0.103)	(0.091)	(0.114)	(0.011)
Year FE	Yes	Yes	Yes	Yes
Constant	1.472***	0.799***	-2.418***	0.737***
	(0.036)	(0.033)	(0.036)	(0.004)
Observations	11,392	11,391	10,116	11,392
R-squared	0.128	0.249	0.492	0.659
Number of counties	841	841	813	841

Note: WACL represents weighted average coverage level. Coverage level for the CAT contract is set equal to 0.5. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

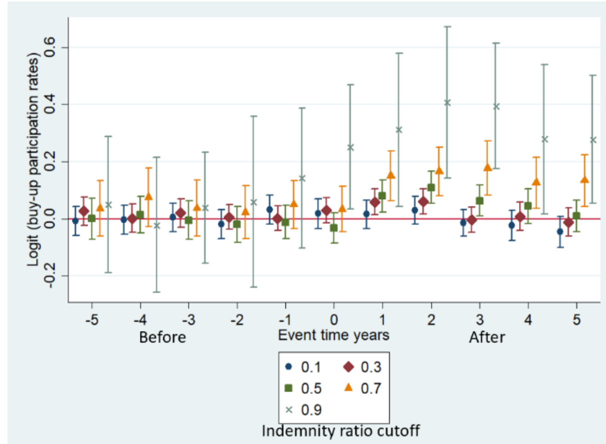
The Lasting Effects of Large Indemnities on Participation

The short- and long-run effects of large indemnities on extensive margin participation for buy-up and CAT policies as well as intensive margin participation can be found in figures 1.8-1.10. These figures plot the coefficients of event time indicator, ϕ_{τ}^{l}, which are estimated when implementing equation (1.21) on the 2001-2017 county-year panel. Event times are plotted on the x-axis. Year 0 is a large loss year while years -1 through -5 are the years before that large loss, and years 1 through 5 are the years after the loss, respectively. The bands represent the 95 percent confidence intervals.

Panels a and b in Figure 1.8 plot point estimates with the buy-up data for corn and soybeans, respectively, and the corresponding estimation results on participation for corn are given in Table 1.7. Taking corn as an example in Figure 1.8a, as is to be expected there is no noticeable trend in area participation in the years up to and including a large loss. For the first year after a large loss year, there is a greater significant increase in the insurance's participation relative to the loss year. The increased effect on participation then remains positive and statistically significant for the next four or five years, but it tapers off year by year. This trend is consistent when our definition of a large loss is given as indemnity ratio greater than 0.3, 0.5, 0.7 or 0.9, but it is not significant when the criterion is that the indemnity ratio be greater than 0.1. As the cutoff point values increase, the severity of loss increases. The figure also shows that participation has a greater increase after the event year when facing a severe loss, which is defined with a larger cutoff point. The lasting effects on participation are longer when higher indemnity ratio cutoffs are invoked.



(a) Corn

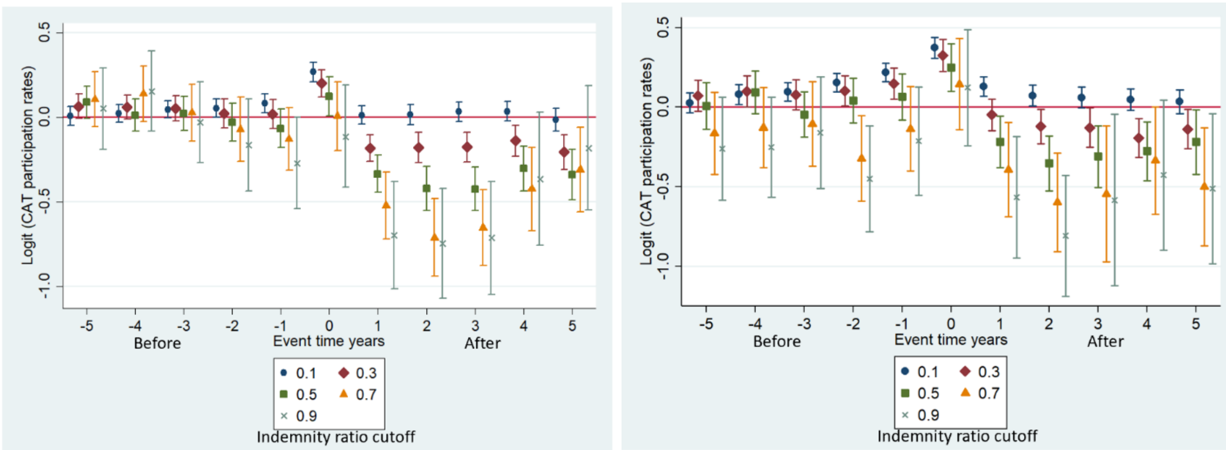


(b) Soybeans

Figure 1.8 How the logit transformation of buy-up contract participation, as measured by fraction of total crop acres that are insured for corn and soybeans in buy-up contracts, responds to a large disaster event

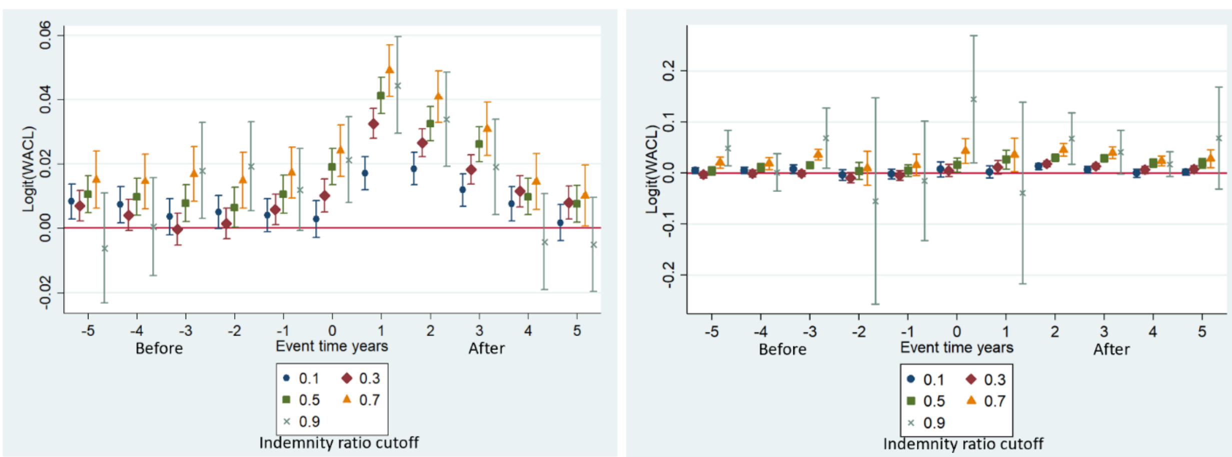
Note: Data are for 12 State Region and 2001-2017 period. The corresponding event coefficient estimates for corn can be found in Table 1.7

Figures 1.9 plots the event time indicators' coefficients for CAT policies. CAT policy enrollment responses are the reverse of the buy-up responses given in Figure 1.8. This would appear to be an intensive margin response. Rather than exit the program, growers respond to the adverse weather shock by replacing CAT policies with buy-up policies. Figure 1.10 presents the event time indicator coefficients for participation as measured by the weighted average coverage level at the intensive margin. The average coverage level chosen increases after a large loss and the gain taper off over time. Moreover, the regression results (available in supplemental materials) for full samples and higher coverage levels at the extensive margin and for buy-up samples at the intensive margins are similar to the buy-up policies at the extensive margin, as presented in Table 1.7.



(a) Corn (b) Soybeans

Figure 1.9 How the logit transformation of CAT participation, as measured by fraction of total crop acres that are insured for corn and soybeans in CAT, responds to a large disaster event
Note: Data are for 12 State Region and 2001-2017 period



(a) Corn (b) Soybeans

Figure 1.10 How the logit transformation of intensive margin participation, as measured by acreage weighted average coverage level (WACL), responds to a large disaster event
Note: Data are for 12 State Region and 2001-2017 period. Coverage level for the CAT contract is set equal to 0.5. Please note vertical scale differences for panel (a) and (b). Soybeans' confidence intervals are wider, leading to scaling compatibility problems. Mean effects for soybeans are larger than those for corn.

Table 1.7 How the logit transformation of buy-up contract participation, as measured by fraction of total crop acres that are insured in buy-up contracts, responds to a large disaster event for corn, equation (1.21)

	The indemnity ratio cut-off points				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: logit of buy-up contract participation				
5 years before event	-0.005	-0.005	-0.009	-0.001	-0.116**
	(0.021)	(0.020)	(0.025)	(0.040)	(0.054)
4 years before event	0.001	0.009	0.033	0.008	0.010
	(0.022)	(0.018)	(0.025)	(0.036)	(0.049)
3 years before event	-0.028	-0.006	0.008	0.007	0.101
	(0.021)	(0.018)	(0.023)	(0.036)	(0.082)
2 years before event	-0.002	0.025	0.015	-0.054	0.035
	(0.021)	(0.018)	(0.024)	(0.034)	(0.066)
1 year before event	-0.016	0.008	0.037	-0.006	-0.001
	(0.020)	(0.018)	(0.024)	(0.030)	(0.061)
Event year	0.013	0.059***	0.051*	0.029	-0.016
	(0.023)	(0.019)	(0.027)	(0.033)	(0.059)
1 year after event	-0.010	0.079***	0.140***	0.174***	0.232***
	(0.021)	(0.021)	(0.026)	(0.038)	(0.069)
2 years after event	-0.000	0.055***	0.142***	0.230***	0.160**
	(0.022)	(0.018)	(0.024)	(0.039)	(0.069)
3 years after event	0.014	0.059***	0.102***	0.195***	0.219***
	(0.022)	(0.018)	(0.023)	(0.035)	(0.064)
4 years after event	0.000	0.045**	0.055**	0.110***	0.218***
	(0.019)	(0.019)	(0.025)	(0.034)	(0.065)
5 years after event	-0.003	0.029	0.029	0.135***	0.203***
	(0.023)	(0.021)	(0.023)	(0.037)	(0.071)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.463***	0.391***	0.397***	0.439***	0.434***
	(0.073)	(0.038)	(0.033)	(0.027)	(0.021)
Observations	14,961	14,961	14,961	14,961	14,961
R-squared	0.402	0.405	0.409	0.412	0.406
Number of counties	973	973	973	973	973

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

Conclusion

It is important to understand how recent experience affects individuals' decision-making when they face uncertain risks. FCIP has become a cornerstone of agriculture programs in the United States while similar programs in other countries are either well-established or in development. This paper seeks to better understand how recency effects influence farmers' crop insurance participation decisions at extensive and intensive margins. We not only document the existence of recency effects in farmers' decision-making processes but also examine the impacts of recent events through different channels. A better understanding of recency effects may provide more useful information for the improvement of crop insurance programs.

Our paper extends the standard theoretical model of insurance demand by incorporating recency effects caused by weather shocks or large indemnities. We construct two channels through which recent experience can affect insurance product's valuation. One is the direct effect; the other is the indirect effect as mediated through indemnities. We apply two estimation approaches to examine these recency effects. In one a two-step parametric model is applied, and we decompose the effects of adverse weather events on participation into the effect on indemnities in the first step and also the effects of prior indemnities and prior adverse weather shocks on insurance participation in the second step. In the other approach, we use a nonparametric flexible event study model to test for the long-run impacts of large indemnities on subsequent participation. Moreover, we apply the above estimations at both extensive and intensive margins.

Our estimation results contribute to the literature by highlighting the importance of considering recency effects in insurance participation. First, for both extensive and intensive margins we provide additional evidence that prior large indemnities promote higher crop insurance participation in the following year. Our work adds to those of Cai et al. (2016) for rice production insurance in China, and to Stein (2016) and Bjerge and Trifkovic (2018) for weather index insurance in India, where our data are much more extensive, regard multiple shock sources and apply to actual market choices. Second, we explore how weather shocks affect insurance participation. Our results show that the direct effects of weather are not consistent across different weather events and are insignificant for some events. This finding, when combined with the clear-cut effects of indemnity, suggests that adverse weather events affect insurance participation largely indirectly through the indemnity channel. We also show that the total effect of a large loss on participation peaks just after the event, and then begins to steadily decline. In doing so we provide support for the generality of findings in Gallagher (2014) regarding flood insurance.

From a policy perspective, promoting crop insurance participation at low cost outlay has been an ongoing challenge for the U.S. Federal Government. A better understanding of recency effects may help in this regard although our current understanding of these effects is insufficient to make policy proposals. One matter is whether there exist opportunities to take advantage of human psychological inertia, i.e., the tendency to make a decision such as enrolling in crop insurance or choosing a higher coverage level and then being unmotivated to change it unless shocked into doing so. A development on our inquiries is to decompose the temporal response to a weather shock into permanent and transient components. If the response is largely temporary then there may be little to gain from a policy strategy to take account of these demand effects.

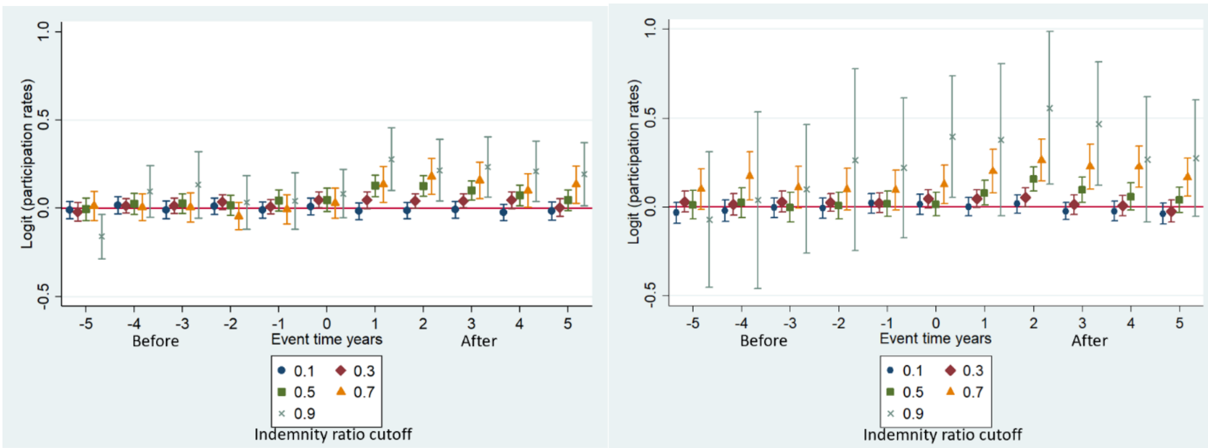
A further matter is whether responses are stronger for some shocks than for others. We found strong responses to four sorts of weather shocks. However, revenue insurance also covers adverse price shocks. Currently our analysis cannot address price shocks because they are likely to be captured by our time fixed effects, but an alternative specification might be able to allow for the measurement of responses to price shocks. Doing so could provide interesting additional insights. For many crops, substitute risk management instruments are available and are widely used, including forward and futures contracts and also put options. Given these alternatives, the insurance contract response to a price shock may be different. The response may be muted while shifting between revenue and yield contracts may also occur. Responses may differ between crops for which price derivative markets are deep, as in corn or wheat, and those for which they are not, as in sorghum.

Our empirical analysis has not sought to clarify whether recency effects are rational. This would be a challenging endeavor, but certain strategies for doing so may be feasible. Perhaps the easiest way to do so is to consider how yield probabilities are revised in light of a weather event. Following Royal and Walls (2019) who estimate associations between risk perceptions, insurance take-up and flood experience, we suggest eliciting yield probabilities through a grower survey and correlating these with weather histories. To be most informative, such a data set would have to be in panel form so that an assessment could be made of updating after a weather shock. Historical farm-level yield data and Bayesian methods might be used to develop plausible bounds on objective revisions, to be compared with grower revisions.

A fourth matter that merits further scrutiny is whether the group response to a shock differs from private responses. Weather risk is generally, but not always, systemic in nature. Thus it is difficult to ascertain whether the aggregate response equals the sum of private responses or is also in part determined by how others in the area respond to the same shock. This is a version of Manski's (1993) reflection problem. But some weather shocks can be quite localized, as with hail and with minor flooding events. This distinction may allow for insights into the social dimension of responses when compared with the private dimension. However, grower-level data might be necessary to pursue that line of thought.

APPENDIX

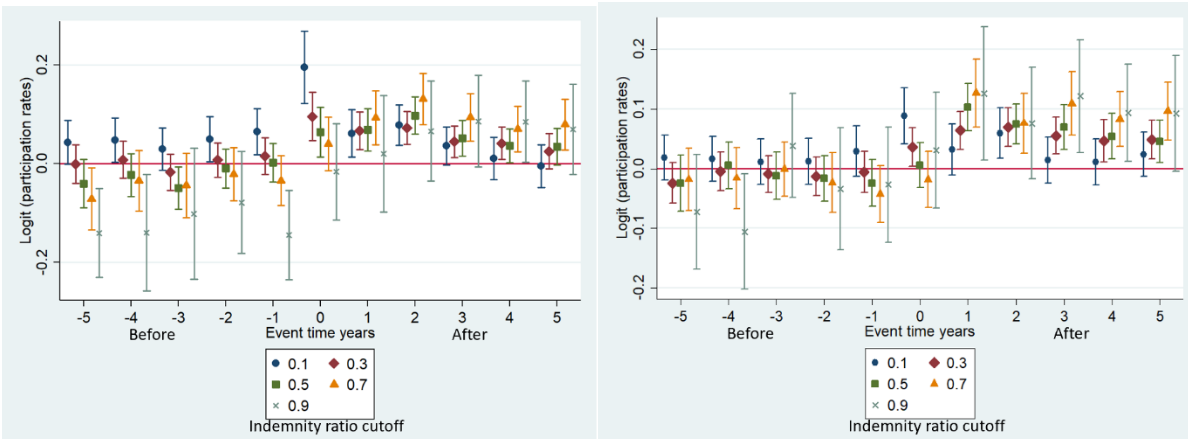
APPENDIX A: Supplemental Figures and Tables



(a) Corn (b) Soybeans

Figure 1A.1 How the logit transformation of extensive margin participation, as measured by fraction of total crop acres that are insured for corn and soybeans, responds to a large disaster event

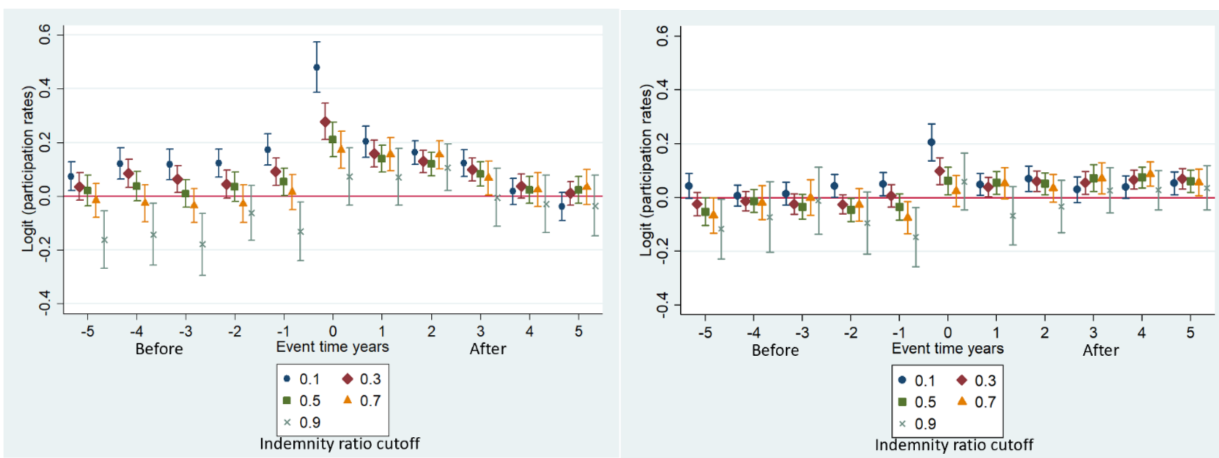
Note: Data are available for 12 State Region and 2001-2017 period. The states are Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Ohio, South Dakota and Wisconsin. Figure 1A.1 shows the logit transformation of extensive margin participation estimates from the nonparametric estimation. The figures plot event study coefficients from the estimation of Equation (1.21) using the 2001-2017 panel’s full samples including both buy-up and CAT contracts for corn and soybeans respectively. Here we assert that a large loss event occurs in one county when the county’s indemnity ratio is greater than a specific cutoff point such as 0.1, 0.3, 0.5, 0.7, 0.9. The value of a cutoff point can denote the magnitude of a large loss. The different cutoff points are denoted by different symbols. Event times are plotted on the x-axis. Year 0 is a large loss year while years -1,…, -5 are the years before that large loss, and years 1,…, 5 are the years after the loss. The bands represent the 95 percent confidence intervals. The corresponding event coefficient estimates can be found in Table 1.1 and Table 1.5.



(a) Corn (b) Soybeans

Figure 1A.2 How the logit transformation of acreage participation at coverage levels of at least 65%, as measured by fraction of total crop acres that are insured for corn and soybeans at coverage levels of 65% or greater than 65%, responds to a large disaster event

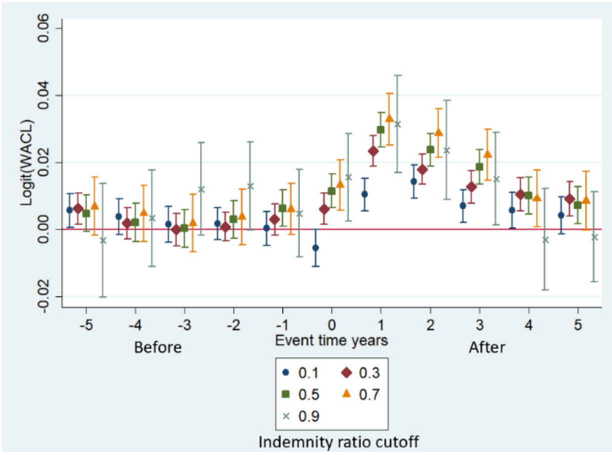
Note: Data are for 12 State Region and 2001-2017 period. The corresponding event coefficient estimates can be found in Table 1.3 and Table 1.7

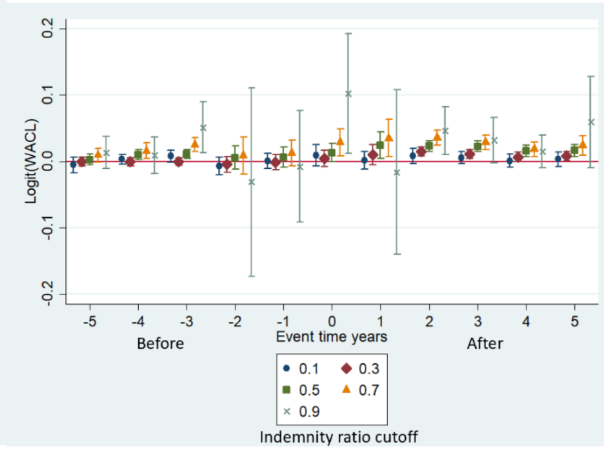


(a) Corn (b) Soybeans

Figure 1A.3 How the logit transformation of acreage participation at coverage levels of at least 75%, as measured by fraction of total crop acres that are insured for corn and soybeans at coverage levels of 75% or greater than 75%, responds to a large disaster event

Note: Data are for 12 State Region and 2001-2017 period. The corresponding event coefficient estimates can be found in Table 1.4 and Table 1.8





(a) Corn (b) Soybeans

Figure 1A.4 How the logit transformation of intensive margin participation for buy-up contracts, as measured by acreage weighted average coverage level (WACL) in buy-up contracts, responds to a large disaster event

Note: Data are for 12 State Region and 2001-2017 period. The corresponding event coefficient estimates can be found in Table 1.11 and Table 1.13. Please note vertical scale differences for panel (a) and (b). Soybeans' confidence intervals are wider, leading to scaling compatibility problems. Mean effects for soybeans are larger than those for corn.

Table 1A.1 How the logit transformation of extensive margin participation, as measured by fraction of total corn acres that are insured with all samples including buy-up and CAT contracts, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total corn acres that are insured				
5 years before event	-0.009	-0.020	-0.005	0.014	-0.160**
	(0.025)	(0.027)	(0.032)	(0.042)	(0.064)
4 years before event	0.017	0.015	0.025	0.007	0.096
	(0.025)	(0.020)	(0.031)	(0.038)	(0.075)
3 years before event	-0.008	0.015	0.027	0.005	0.134
	(0.026)	(0.022)	(0.028)	(0.042)	(0.096)
2 years before event	0.012	0.036*	0.017	-0.044	0.034
	(0.023)	(0.022)	(0.029)	(0.039)	(0.078)
1 year before event	-0.009	0.009	0.044	-0.006	0.043
	(0.023)	(0.021)	(0.030)	(0.042)	(0.082)
Event year	0.011	0.049**	0.049	0.030	0.083
	(0.024)	(0.023)	(0.034)	(0.044)	(0.070)
1 year after event	-0.016	0.046*	0.128***	0.136***	0.279***
	(0.024)	(0.024)	(0.031)	(0.052)	(0.091)
2 years after event	-0.013	0.042**	0.127***	0.181***	0.216**
	(0.024)	(0.021)	(0.030)	(0.052)	(0.089)
3 years after event	-0.008	0.043**	0.101***	0.159***	0.235***
	(0.024)	(0.020)	(0.028)	(0.052)	(0.087)
4 years after event	-0.023	0.046*	0.073**	0.101**	0.210**
	(0.024)	(0.024)	(0.030)	(0.048)	(0.087)
5 years after event	-0.015	0.005	0.046	0.135**	0.193**
	(0.027)	(0.026)	(0.030)	(0.054)	(0.091)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	1.120***	1.088***	1.098***	1.135***	1.130***
	(0.080)	(0.039)	(0.033)	(0.029)	(0.026)
Observations	14,961	14,961	14,961	14,961	14,961
R-squared	0.218	0.219	0.222	0.223	0.222
Number of counties	973	973	973	973	973

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the 2001-2017 panel's full samples for corn. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.2 How the logit transformation of CAT contract participation, as measured by fraction of total corn acres that are insured in CAT contracts, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total corn acres that are insured				
5 years before event	0.007	0.066*	0.089*	0.106	0.052
	(0.029)	(0.038)	(0.048)	(0.083)	(0.123)
4 years before event	0.022	0.059	0.013	0.139*	0.155
	(0.027)	(0.036)	(0.049)	(0.084)	(0.120)
3 years before event	0.047*	0.053	0.022	0.028	-0.030
	(0.026)	(0.038)	(0.052)	(0.085)	(0.122)
2 years before event	0.054*	0.023	-0.031	-0.071	-0.162
	(0.028)	(0.043)	(0.057)	(0.097)	(0.139)
1 year before event	0.081***	0.019	-0.066	-0.129	-0.270**
	(0.028)	(0.043)	(0.058)	(0.094)	(0.137)
Event year	0.268***	0.200***	0.122**	0.007	-0.113
	(0.030)	(0.042)	(0.059)	(0.103)	(0.154)
1 year after event	0.012	-0.182***	-0.335***	-0.521***	-0.698***
	(0.028)	(0.041)	(0.056)	(0.100)	(0.161)
2 years after event	0.016	-0.180***	-0.420***	-0.712***	-0.746***
	(0.030)	(0.045)	(0.066)	(0.117)	(0.166)
3 years after event	0.033	-0.176***	-0.424***	-0.652***	-0.713***
	(0.029)	(0.045)	(0.065)	(0.115)	(0.171)
4 years after event	0.036	-0.139***	-0.303***	-0.424***	-0.363*
	(0.029)	(0.046)	(0.067)	(0.125)	(0.200)
5 years after event	-0.013	-0.206***	-0.339***	-0.309**	-0.181
	(0.034)	(0.052)	(0.076)	(0.128)	(0.187)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	-2.491***	-2.396***	-2.363***	-2.357***	-2.356***
	(0.040)	(0.033)	(0.031)	(0.030)	(0.030)
Observations	14,195	14,195	14,195	14,195	14,195
R-squared	0.553	0.554	0.558	0.557	0.554
Number of counties	963	963	963	963	963

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the CAT contract samples of the 2001-2017 panel for corn. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.3 How the logit transformation of participation at coverage levels of at least 65%, as measured by fraction of total corn acres that are insured at the coverage levels of 65% or greater than 65%, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total corn acres that are insured				
5 years before event	0.043*	-0.001	-0.041	-0.072**	-0.140***
	(0.023)	(0.020)	(0.025)	(0.032)	(0.046)
4 years before event	0.048**	0.008	-0.023	-0.035	-0.140**
	(0.023)	(0.019)	(0.022)	(0.031)	(0.060)
3 years before event	0.029	-0.017	-0.049**	-0.044	-0.101
	(0.022)	(0.019)	(0.022)	(0.033)	(0.067)
2 years before event	0.050**	0.008	-0.010	-0.021	-0.078
	(0.023)	(0.018)	(0.020)	(0.027)	(0.053)
1 year before event	0.065***	0.016	0.002	-0.035	-0.145***
	(0.024)	(0.019)	(0.020)	(0.026)	(0.046)
Event year	0.195***	0.096***	0.064**	0.040	-0.016
	(0.038)	(0.025)	(0.026)	(0.028)	(0.050)
1 year after event	0.061**	0.067***	0.069***	0.093***	0.020
	(0.025)	(0.020)	(0.022)	(0.028)	(0.060)
2 years after event	0.078***	0.072***	0.098***	0.131***	0.066
	(0.021)	(0.017)	(0.019)	(0.026)	(0.052)
3 years after event	0.036*	0.045***	0.052***	0.094***	0.086*
	(0.019)	(0.016)	(0.018)	(0.025)	(0.047)
4 years after event	0.011	0.041**	0.037**	0.070***	0.085**
	(0.022)	(0.017)	(0.018)	(0.023)	(0.042)
5 years after event	-0.005	0.025	0.034*	0.079***	0.070
	(0.022)	(0.018)	(0.019)	(0.026)	(0.047)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	-1.190***	-0.892***	-0.816***	-0.804***	-0.797***
	(0.107)	(0.058)	(0.042)	(0.035)	(0.028)
Observations	14,903	14,903	14,903	14,903	14,903
R-squared	0.658	0.656	0.656	0.657	0.656
Number of counties	973	973	973	973	973

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the samples at coverage levels of at least 65% from the 2001-2017 panel for corn. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.4 How the logit transformation of participation at coverage levels of at least 75%, as measured by fraction of total corn acres that are insured at the coverage levels of 75% or greater than 75%, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total corn acres that are insured				
5 years before event	0.073***	0.036	0.021	-0.016	-0.161***
	(0.027)	(0.026)	(0.029)	(0.032)	(0.054)
4 years before event	0.122***	0.085***	0.038	-0.026	-0.142**
	(0.030)	(0.027)	(0.028)	(0.035)	(0.059)
3 years before event	0.118***	0.063**	0.010	-0.035	-0.179***
	(0.029)	(0.025)	(0.026)	(0.032)	(0.058)
2 years before event	0.123***	0.044*	0.035	-0.028	-0.061
	(0.027)	(0.027)	(0.027)	(0.036)	(0.052)
1 year before event	0.174***	0.092***	0.054**	0.015	-0.130**
	(0.029)	(0.026)	(0.026)	(0.033)	(0.056)
Event year	0.480***	0.278***	0.210***	0.173***	0.074
	(0.048)	(0.034)	(0.033)	(0.035)	(0.054)
1 year after event	0.203***	0.160***	0.141***	0.155***	0.073
	(0.029)	(0.025)	(0.025)	(0.031)	(0.054)
2 years after event	0.163***	0.129***	0.120***	0.154***	0.107**
	(0.023)	(0.021)	(0.022)	(0.027)	(0.044)
3 years after event	0.123***	0.099***	0.082***	0.068**	-0.004
	(0.026)	(0.022)	(0.023)	(0.032)	(0.055)
4 years after event	0.018	0.039*	0.024	0.024	-0.029
	(0.025)	(0.023)	(0.025)	(0.032)	(0.054)
5 years after event	-0.039	0.010	0.024	0.034	-0.035
	(0.026)	(0.023)	(0.026)	(0.033)	(0.058)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	-2.931***	-2.381***	-2.172***	-2.054***	-1.992***
	(0.129)	(0.084)	(0.060)	(0.047)	(0.040)
Observations	14,771	14,771	14,771	14,771	14,771
R-squared	0.684	0.672	0.667	0.666	0.664
Number of counties	972	972	972	972	972

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the samples at coverage levels of at least 75% from the 2001-2017 panel for corn. Standard errors are at the significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1A.5 How the logit transformation of extensive margin participation, as measured by fraction of total soybean acres that are insured with all samples including buy-up and CAT contracts, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total soybean acres that are insured				
5 years before event	-0.033	0.030	0.012	0.100^{*}	-0.070
	(0.030)	(0.030)	(0.041)	(0.058)	(0.194)
4 years before event	-0.022	0.015	0.023	0.174^{**}	0.039
	(0.031)	(0.030)	(0.043)	(0.069)	(0.253)
3 years before event	-0.004	0.029	-0.003	0.110^{*}	0.100
	(0.028)	(0.030)	(0.042)	(0.061)	(0.184)
2 years before event	-0.006	0.025	0.007	0.099^{*}	0.264
	(0.029)	(0.025)	(0.038)	(0.060)	(0.260)
1 year before event	0.020	0.022	0.017	0.095^{*}	0.220
	(0.029)	(0.028)	(0.036)	(0.058)	(0.200)
Event year	0.014	0.046^{*}	0.015	0.126^{**}	0.395^{**}
	(0.029)	(0.026)	(0.033)	(0.055)	(0.174)
1 year after event	0.001	0.046^{*}	0.079^{**}	0.200^{***}	0.378^{*}
	(0.027)	(0.025)	(0.035)	(0.062)	(0.218)
2 years after event	0.017	0.053^{**}	0.156^{***}	0.263^{***}	0.556^{**}
	(0.026)	(0.027)	(0.035)	(0.060)	(0.219)
3 years after event	-0.024	0.013	0.097^{***}	0.225^{***}	0.466^{***}
	(0.024)	(0.028)	(0.036)	(0.064)	(0.177)
4 years after event	-0.024	0.007	0.059	0.225^{***}	0.268
	(0.028)	(0.029)	(0.039)	(0.059)	(0.179)
5 years after event	-0.038	-0.025	0.039	0.167^{***}	0.275^{*}
	(0.030)	(0.032)	(0.037)	(0.055)	(0.167)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	1.315^{***}	1.225^{***}	1.286^{***}	1.262^{***}	1.287^{***}
	(0.103)	(0.055)	(0.040)	(0.031)	(0.029)
Observations	14,191	14,191	14,191	14,191	14,191
R-squared	0.186	0.187	0.189	0.192	0.190
Number of counties	931	931	931	931	931

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the 2001-2017 panel's full samples for soybeans. Standard errors are at the significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1A.6 How the logit transformation of buy-up contract participation, as measured by fraction of total soybean acres that are insured in buy-up contracts, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total soybean acres that are insured				
5 years before event	-0.008	0.027	0.001	0.036	0.050
	(0.026)	(0.025)	(0.037)	(0.049)	(0.121)
4 years before event	-0.002	0.002	0.014	0.075	-0.021
	(0.026)	(0.025)	(0.033)	(0.052)	(0.120)
3 years before event	0.005	0.021	-0.005	0.038	0.039
	(0.026)	(0.025)	(0.035)	(0.050)	(0.099)
2 years before event	-0.018	0.006	-0.019	0.023	0.060
	(0.026)	(0.022)	(0.032)	(0.047)	(0.152)
1 year before event	0.032	0.003	-0.011	0.050	0.142
	(0.026)	(0.022)	(0.030)	(0.043)	(0.125)
Event year	0.018	0.030	-0.031	0.035	0.251**
	(0.027)	(0.022)	(0.027)	(0.040)	(0.111)
1 year after event	0.016	0.060***	0.080***	0.151***	0.312**
	(0.025)	(0.023)	(0.029)	(0.044)	(0.137)
2 years after event	0.030	0.060***	0.110***	0.166***	0.408***
	(0.024)	(0.022)	(0.029)	(0.043)	(0.135)
3 years after event	-0.014	-0.003	0.064**	0.178***	0.395***
	(0.023)	(0.023)	(0.028)	(0.048)	(0.112)
4 years after event	-0.023	0.008	0.045	0.127***	0.279**
	(0.027)	(0.025)	(0.031)	(0.046)	(0.133)
5 years after event	-0.046*	-0.011	0.011	0.134***	0.278**
	(0.027)	(0.025)	(0.028)	(0.046)	(0.114)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.595***	0.577***	0.636***	0.599***	0.611***
	(0.087)	(0.049)	(0.037)	(0.027)	(0.025)
Observations	14,191	14,191	14,191	14,191	14,191
R-squared	0.343	0.343	0.345	0.346	0.346
Number of counties	931	931	931	931	931

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the buy-up contract samples of the 2001-2017 panel for soybeans. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.7 How the logit transformation of CAT contract participation, as measured by fraction of total soybean acres that are insured in CAT contracts, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total soybean acres that are insured				
5 years before event	0.026	0.072	0.006	-0.165	-0.261
	(0.032)	(0.050)	(0.075)	(0.132)	(0.165)
4 years before event	0.080**	0.099**	0.093	-0.129	-0.252
	(0.032)	(0.050)	(0.068)	(0.128)	(0.161)
3 years before event	0.097***	0.078	-0.046	-0.106	-0.159
	(0.030)	(0.048)	(0.073)	(0.135)	(0.179)
2 years before event	0.153***	0.103**	0.041	-0.322**	-0.451***
	(0.030)	(0.048)	(0.072)	(0.137)	(0.169)
1 year before event	0.219***	0.147***	0.065	-0.137	-0.212
	(0.030)	(0.049)	(0.074)	(0.135)	(0.173)
Event year	0.373***	0.325***	0.249***	0.145	0.122
	(0.033)	(0.051)	(0.076)	(0.146)	(0.186)
1 year after event	0.130***	-0.048	-0.219***	-0.392***	-0.567***
	(0.031)	(0.051)	(0.082)	(0.151)	(0.195)
2 years after event	0.073**	-0.121**	-0.354***	-0.598***	-0.808***
	(0.033)	(0.055)	(0.088)	(0.158)	(0.194)
3 years after event	0.061*	-0.129**	-0.311***	-0.545**	-0.584**
	(0.034)	(0.063)	(0.099)	(0.218)	(0.274)
4 years after event	0.048	-0.193***	-0.277***	-0.335*	-0.427*
	(0.034)	(0.062)	(0.094)	(0.172)	(0.240)
5 years after event	0.034	-0.138**	-0.219**	-0.500***	-0.512**
	(0.039)	(0.062)	(0.104)	(0.189)	(0.241)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	-2.586***	-2.429***	-2.386***	-2.368***	-2.368***
	(0.038)	(0.031)	(0.031)	(0.031)	(0.031)
Observations	13,220	13,220	13,220	13,220	13,220
R-squared	0.532	0.528	0.527	0.526	0.526
Number of counties	910	910	910	910	910

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the CAT contract samples of the 2001-2017 panel for soybeans. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.8 How the logit transformation of participation at coverage levels of at least 65%, as measured by fraction of total soybean acres that are insured at the coverage levels of 65% or greater than 65%, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total soybean acres that are insured				
5 years before event	0.018	-0.024	-0.024	-0.018	-0.072
	(0.019)	(0.017)	(0.024)	(0.027)	(0.049)
4 years before event	0.016	-0.005	0.005	-0.016	-0.105**
	(0.019)	(0.016)	(0.020)	(0.026)	(0.049)
3 years before event	0.011	-0.009	-0.012	-0.001	0.038
	(0.019)	(0.016)	(0.020)	(0.023)	(0.044)
2 years before event	0.012	-0.013	-0.016	-0.024	-0.033
	(0.020)	(0.016)	(0.019)	(0.026)	(0.052)
1 year before event	0.029	-0.006	-0.024	-0.043*	-0.027
	(0.022)	(0.018)	(0.020)	(0.024)	(0.049)
Event year	0.088***	0.036**	0.006	-0.019	0.031
	(0.024)	(0.016)	(0.019)	(0.024)	(0.049)
1 year after event	0.032	0.064***	0.103***	0.126***	0.126**
	(0.022)	(0.016)	(0.020)	(0.029)	(0.057)
2 years after event	0.059***	0.070***	0.075***	0.076***	0.076
	(0.022)	(0.016)	(0.017)	(0.026)	(0.048)
3 years after event	0.014	0.055***	0.069***	0.109***	0.121**
	(0.020)	(0.016)	(0.019)	(0.027)	(0.048)
4 years after event	0.011	0.046**	0.054***	0.083***	0.094**
	(0.020)	(0.018)	(0.019)	(0.023)	(0.041)
5 years after event	0.024	0.049***	0.045**	0.096***	0.092*
	(0.019)	(0.016)	(0.018)	(0.025)	(0.050)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	-0.696***	-0.537***	-0.523***	-0.529***	-0.546***
	(0.085)	(0.045)	(0.032)	(0.026)	(0.023)
Observations	14,177	14,177	14,177	14,177	14,177
R-squared	0.673	0.675	0.675	0.676	0.673
Number of counties	931	931	931	931	931

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the samples at coverage levels of at least 65% from the 2001-2017 panel for soybeans. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.9 How the logit transformation of participation at coverage levels of at least 75%, as measured by fraction of total soybean acres that are insured at the coverage levels of 75% or greater than 75%, responds to a large disaster event, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of fraction of total soybean acres that are insured				
5 years before event	0.043*	-0.024	-0.053**	-0.067**	-0.117**
	(0.023)	(0.022)	(0.026)	(0.034)	(0.057)
4 years before event	0.007	-0.013	-0.013	-0.019	-0.072
	(0.020)	(0.018)	(0.022)	(0.032)	(0.066)
3 years before event	0.014	-0.024	-0.034	-0.001	-0.011
	(0.022)	(0.020)	(0.024)	(0.034)	(0.063)
2 years before event	0.043**	-0.026	-0.046**	-0.027	-0.095
	(0.022)	(0.018)	(0.022)	(0.031)	(0.059)
1 year before event	0.050**	0.006	-0.035	-0.076**	-0.147***
	(0.022)	(0.021)	(0.025)	(0.030)	(0.056)
Event year	0.206***	0.098***	0.062**	0.024	0.059
	(0.035)	(0.025)	(0.026)	(0.029)	(0.054)
1 year after event	0.049**	0.039**	0.055**	0.054*	-0.068
	(0.020)	(0.018)	(0.022)	(0.030)	(0.055)
2 years after event	0.070***	0.060***	0.051**	0.035	-0.034
	(0.024)	(0.020)	(0.021)	(0.026)	(0.049)
3 years after event	0.029	0.055**	0.072***	0.071**	0.027
	(0.024)	(0.021)	(0.025)	(0.029)	(0.043)
4 years after event	0.040*	0.067***	0.075***	0.087***	0.028
	(0.021)	(0.018)	(0.020)	(0.023)	(0.037)
5 years after event	0.053**	0.070***	0.060***	0.057**	0.036
	(0.021)	(0.019)	(0.021)	(0.025)	(0.042)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	-1.893***	-1.587***	-1.530***	-1.551***	-1.556***
	(0.096)	(0.057)	(0.044)	(0.035)	(0.032)
Observations	14,129	14,129	14,129	14,129	14,129
R-squared	0.700	0.698	0.698	0.697	0.697
Number of counties	928	928	928	928	928

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the samples at coverage levels of at least 75% from the 2001-2017 panel for soybeans. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.10 How the logit transformation of intensive margin participation, as measured by acreage weighted average coverage level (WACL), responds to a large disaster event for corn, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of WACL				
5 years before event	0.008^{***}	0.007^{***}	0.011^{***}	0.015^{***}	-0.006
	(0.003)	(0.002)	(0.003)	(0.005)	(0.009)
4 years before event	0.007^{**}	0.004^{*}	0.010^{***}	0.015^{***}	0.000
	(0.003)	(0.002)	(0.003)	(0.004)	(0.008)
3 years before event	0.004	-0.000	0.008^{***}	0.017^{***}	0.018^{**}
	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
2 years before event	0.005^{*}	0.002	0.007^{**}	0.015^{***}	0.019^{***}
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
1 year before event	0.004	0.006^{**}	0.011^{***}	0.017^{***}	0.012^{*}
	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Event year	0.003	0.010^{***}	0.019^{***}	0.024^{***}	0.021^{***}
	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
1 year after event	0.017^{***}	0.033^{***}	0.041^{***}	0.049^{***}	0.045^{***}
	(0.003)	(0.002)	(0.003)	(0.004)	(0.008)
2 years after event	0.019^{***}	0.027^{***}	0.033^{***}	0.041^{***}	0.034^{***}
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
3 years after event	0.012^{***}	0.018^{***}	0.026^{***}	0.031^{***}	0.019^{**}
	(0.003)	(0.002)	(0.003)	(0.004)	(0.008)
4 years after event	0.008^{***}	0.012^{***}	0.010^{***}	0.015^{***}	-0.004
	(0.003)	(0.002)	(0.003)	(0.004)	(0.008)
5 years after event	0.002	0.008^{***}	0.008^{***}	0.010^{**}	-0.005
	(0.003)	(0.003)	(0.003)	(0.005)	(0.007)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.663^{***}	0.675^{***}	0.674^{***}	0.678^{***}	0.685^{***}
	(0.011)	(0.006)	(0.005)	(0.004)	(0.004)
Observations	14,961	14,961	14,961	14,961	14,961
R-squared	0.794	0.799	0.800	0.798	0.793
Number of counties	973	973	973	973	973

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the 2001-2017 panel for corn. The coverage level equals to 0.5 at CAT coverage when calculating the weighted average coverage level. Standard errors are at the significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1A.11 How the logit transformation of intensive margin participation for buy-up contracts, as measured by acreage weighted average coverage level (WACL) in buy-up contracts, responds to a large disaster event for corn, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of WACL				
5 years before event	0.006**	0.006***	0.005*	0.007	-0.003
	(0.003)	(0.002)	(0.003)	(0.004)	(0.009)
4 years before event	0.004	0.002	0.002	0.005	0.003
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
3 years before event	0.001	-0.000	0.000	0.002	0.012*
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
2 years before event	0.002	0.001	0.003	0.004	0.013*
	(0.002)	(0.002)	(0.003)	(0.004)	(0.007)
1 year before event	0.000	0.003	0.006**	0.006	0.005
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
Event year	-0.006**	0.006***	0.011***	0.013***	0.016**
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
1 year after event	0.010***	0.023***	0.030***	0.033***	0.031***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
2 years after event	0.014***	0.018***	0.024***	0.029***	0.024***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.008)
3 years after event	0.007***	0.013***	0.019***	0.022***	0.015**
	(0.003)	(0.002)	(0.003)	(0.004)	(0.007)
4 years after event	0.006**	0.010***	0.010***	0.009**	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
5 years after event	0.004	0.009***	0.007***	0.008*	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.832***	0.829***	0.829***	0.833***	0.835***
	(0.010)	(0.006)	(0.005)	(0.004)	(0.003)
Observations	14,960	14,960	14,960	14,960	14,960
R-squared	0.723	0.727	0.729	0.726	0.723
Number of counties	973	973	973	973	973

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using samples of buy-up contract from the 2001-2017 panel for corn. Standard errors are at the significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 1A.12 How the logit transformation of intensive margin participation, as measured by acreage weighted average coverage level (WACL), responds to a large disaster event for soybeans, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of WACL				
5 years before event	0.005*	-0.003	0.004	0.021***	0.049***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.018)
4 years before event	0.005	-0.001	0.011***	0.018***	0.001
	(0.003)	(0.003)	(0.004)	(0.006)	(0.019)
3 years before event	0.008*	-0.001	0.015***	0.036***	0.069**
	(0.004)	(0.003)	(0.003)	(0.005)	(0.030)
2 years before event	-0.004	-0.009*	0.004	0.010	-0.055
	(0.005)	(0.005)	(0.009)	(0.017)	(0.103)
1 year before event	-0.002	-0.005	0.005	0.016	-0.016
	(0.005)	(0.005)	(0.006)	(0.011)	(0.060)
Event year	0.007	0.005	0.016**	0.043***	0.145**
	(0.008)	(0.006)	(0.007)	(0.012)	(0.064)
1 year after event	0.002	0.012*	0.027***	0.036**	-0.039
	(0.006)	(0.007)	(0.009)	(0.017)	(0.091)
2 years after event	0.013***	0.018***	0.030***	0.046***	0.067***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.026)
3 years after event	0.007**	0.013***	0.029***	0.040***	0.041*
	(0.003)	(0.003)	(0.004)	(0.006)	(0.022)
4 years after event	-0.000	0.006*	0.019***	0.024***	0.017
	(0.004)	(0.004)	(0.004)	(0.005)	(0.012)
5 years after event	0.002	0.007**	0.019***	0.028***	0.069
	(0.003)	(0.003)	(0.005)	(0.009)	(0.051)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.697***	0.720***	0.702***	0.704***	0.710***
	(0.014)	(0.009)	(0.009)	(0.007)	(0.007)
Observations	14,191	14,191	14,191	14,191	14,191
R-squared	0.616	0.618	0.620	0.620	0.621
Number of counties	931	931	931	931	931

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using the 2001-2017 panel for soybeans. The coverage level equals to 0.5 at CAT coverage when calculating the weighted average coverage level. Standard errors are at the significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1A.13 How the logit transformation of intensive margin participation for buy-up contracts, as measured by acreage weighted average coverage level (WACL) in buy-up contracts, responds to a large disaster event for soybeans, equation (1.21)

	The cutoff points of indemnity ratio				
	0.1	0.3	0.5	0.7	0.9
VARIABLES	Dependent variable: Logit of WACL				
5 years before event	-0.005	0.000	0.003	0.009*	0.014
	(0.006)	(0.003)	(0.004)	(0.005)	(0.013)
4 years before event	0.003	-0.001	0.010**	0.016***	0.009
	(0.003)	(0.003)	(0.004)	(0.006)	(0.014)
3 years before event	0.008*	-0.001	0.011***	0.025***	0.051***
	(0.005)	(0.003)	(0.003)	(0.005)	(0.020)
2 years before event	-0.007	-0.004	0.006	0.009	-0.031
	(0.007)	(0.006)	(0.009)	(0.014)	(0.072)
1 year before event	0.001	-0.001	0.006	0.013	-0.007
	(0.006)	(0.006)	(0.008)	(0.010)	(0.043)
Event year	0.009	0.005	0.013*	0.029***	0.102**
	(0.008)	(0.006)	(0.007)	(0.010)	(0.046)
1 year after event	0.002	0.010	0.025**	0.035**	-0.016
	(0.007)	(0.008)	(0.010)	(0.014)	(0.063)
2 years after event	0.008	0.015***	0.023***	0.036***	0.046**
	(0.006)	(0.003)	(0.004)	(0.006)	(0.018)
3 years after event	0.006	0.011***	0.023***	0.029***	0.032*
	(0.005)	(0.003)	(0.004)	(0.006)	(0.018)
4 years after event	0.001	0.007*	0.016***	0.018***	0.015
	(0.005)	(0.004)	(0.004)	(0.005)	(0.013)
5 years after event	0.003	0.008**	0.017***	0.024***	0.059*
	(0.006)	(0.004)	(0.005)	(0.007)	(0.035)
State-by-year FE	Yes	Yes	Yes	Yes	Yes
CRD FE	Yes	Yes	Yes	Yes	Yes
Constant	0.868***	0.877***	0.864***	0.868***	0.875***
	(0.015)	(0.012)	(0.010)	(0.007)	(0.006)
Observations	14,191	14,191	14,191	14,191	14,191
R-squared	0.390	0.391	0.393	0.394	0.394
Number of counties	931	931	931	931	931

Note: Each column contains event coefficient estimates from a distinct regression of Equation (1.21) with different indemnity ratio cutoff points such as 0.1, 0.3, 0.5, 0.7, 0.9. Each estimation includes state-by-year and crop reporting district (CRD) fixed effects using samples of buy-up contract from the 2001-2017 panel for soybeans. Standard errors are at the significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

REFERENCES

REFERENCES

Bakkensen, L.A., X. Ding, and L. Ma. 2019. Flood Risk and Salience: New Evidence from The Sunshine State. *Southern Economic Journal* 85(4): 1132-1158.

Bjerge, B., and N. Trifkovic. 2018. Extreme Weather and Demand for Index Insurance in Rural India. *European Review of Agricultural Economics* 45(3): 397-431.

Cai, J., and C. Song. 2017. Do Disaster Experience and Knowledge Affect Insurance Take-Up Decisions? *Journal of Development Economics* 124: 83-94.

Cai, J., A. De Janvry, and E. Sadoulet. 2015. Social Networks and the Decision to Insure. *American Economic Journal: Applied Economics* 7(2): 81-108.

Cai, J., A. De Janvry, and E. Sadoulet. 2016. Subsidy Policies and Insurance Demand (No. W22702). National Bureau of Economic Research.

Camerer, C.F., and G. Loewenstein. 2011. "Behavioral Economics: Past, Present, Future." in Advances in Behavioral Economics, Edited By Camerer, C.F., Loewenstein, G. and Rabin, M., 3-51. Princeton University Press.

Chong, H., and J. Ifft. 2016. (Over)Reacting to Bad Luck: Low Yields Increase Crop Insurance Participation. Presentation at SCC-76 2016 Annual Meeting, "Economics and Management of Risks in Agriculture and Natural Resources." March 17-19, 2016, Pensacola Beach, FL.

Du, X., H. Feng, and D.A. Hennessy. 2017. Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics* 99(3): 732-756.

Du, X., D.A. Hennessy, and H. Feng. 2014. A Natural Resource Theory of US Crop Insurance Contract Choice. *American Journal of Agricultural Economics* 96(1): 232-252.

Fredrickson, B.L., and D. Kahneman. 1993. Duration Neglect in Retrospective Evaluations of Affective Episodes. *Journal of Personality and Social Psychology* 65(1): 45-55.

Gallagher, J. 2014. Learning About an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States. *American Economic Journal: Applied Economics* 6(3): 206-233.

Geruso, M., T.J. Layton, G. Mccormack, and M. Shepard. 2019. The Two Margin Problem in Insurance. Unpublished Working Paper. Available at Https://Papers.Ssrn.Com/Sol3/Papers.Cfm?Abstract_Id=3385492.

Glauber, J.W. 2004. Crop Insurance Reconsidered. *American Journal of Agricultural Economics* 86(5): 1179-1195.

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

Hanaoka, C., H. Shigeoka, and Y. Watanabe. 2018. Do Risk Preferences Change? Evidence from the Great East Japan Earthquake. *American Economic Journal: Applied Economics* 10(2): 298-330.

Heim Jr, R.R. 2002. A Review of Twentieth-Century Drought Indices Used in the United States. *Bulletin of The American Meteorological Society* 83(8): 1149-1166.

Just, R.E., L. Calvin, and J. Quiggin. 1999. Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives. *American Journal of Agricultural Economics* 81(4): 834-849.

Kousky, C. 2017. Disasters as Learning Experiences or Disasters as Policy Opportunities? Examining Flood Insurance Purchases after Hurricanes. *Risk Analysis* 37(3): 517-530.

Kramer, R.A. 1983. Federal Crop Insurance, 1938-1982. *Agricultural History* 57(2): 181-200.

Kunreuther, H.C., M.V. Pauly, and S. Mcmorrow. 2013. Insurance and Behavioral Economics: Improving Decisions in the Most Misunderstood Industry. Cambridge University Press.

Makki, S.S., and A. Somwaru. 2001. Farmers' Participation in Crop Insurance Markets: Creating the Right Incentives. *American Journal of Agricultural Economics* 83(3): 662-667.

Manski, C.F. 1995. Identification of Endogenous Social Effects. *Review of Economic Studies* 60(3): 531-542.

Menne, M. J., I. Durre, B. Korzeniewski, S. Mcneal, K. Thomas, X. Yin, S. Anthony, R. Ray, R. S. Vose, B. E.Gleason, and T. G. Houston. 2012. *Global Historical Climatology Network - Daily (GHCN-Daily), Version 3*. NOAA National Climatic Data Center. Http://Doi.Org/10.7289/V5D21VHZ. Accessed 06 October 2018."

Mossin, J. 1968. Aspects of Rational Insurance Purchasing. *Journal of Political Economy* 76(4): 553-568.

O'Donoghue, E. 2014. *The Effects of Premium Subsidies On Demand for Crop Insurance* (No. 178405). United States Department of Agriculture, Economic Research Service.

Papke, L.E., and J.M. Wooldridge. 1996. Econometric Methods for Fractional Response Variables with an Application to 401(K) Plan Participation Rates. *Journal of Applied Econometrics* 11(6): 619-632.

Pétraud, J., S. Boucher, and M. Carter. 2015. *Competing Theories of Risk Preferences and the Demand for Crop Insurance: Experimental Evidence from Peru.* Paper Presented at the 2015 Conference, August 9-14, 2015, Milan, Italy 211383, International Association of Agricultural Economists.

Pratt, J.W. 1964. Risk Aversion in the Small and in the Large. *Econometrica* 32(1-2): 122-136.

Price, M., C. Yu, D.A. Hennessy, and X. Du. 2019. Are Actuarial Crop Insurance Rates Fair? An Analysis Using a Penalized Bivariate B-Spline Method. *Journal of The Royal Statistical Society Series C (Applied Statistics)* 68(5): 1207-1232.

Ramirez, O.A., and J.S. Shonkwiler. 2017. A Probabilistic Model of the Crop Insurance Purchase Decision. *Journal of Agricultural and Resource Economics* 42(1): 10-26.

Royal, A., and M. Walls. 2019. Flood Risk Perception and Insurance Choice: Do Decisions in the Floodplain Reflect Overoptimism? *Risk Analysis* 39(5): 1088-1104.

Santeramo, F.G. 2019. I Learn, You Learn, We Gain Experience in Crop Insurance Markets. *Applied Economic Perspectives and Policy* 41(2): 284-304.

Schildberg-Hörisch, H. 2018. Are Risk Preferences Stable? *Journal of Economic Perspectives* 32(2):135-154.

Schreiber, C.A., and D. Kahneman. 2000. Determinants of the Remembered Utility of Aversive Sounds. *Journal of Experimental Psychology: General* 129(1): 27-42.

Sherrick, B.J., P.J. Barry, P, P.N. Ellinger, and G.D. Schnitkey. 2004. Factors Influencing Farmers' Crop Insurance Decisions. *American Journal of Agricultural Economics* 86(1): 103-114.

Shields, D.A. 2015. Federal Crop Insurance: Background. Congressional Research Service, 7-5700.

Stein, D. 2016. Dynamics of Demand for Rainfall Index Insurance: Evidence from A Commercial Product in India. *The World Bank Economic Review* 32(3): 692-708.

Sutton, R. S., and A.G. Barto. 2018. Reinforcement Learning: An Introduction, 2nd Edn. Cambridge: MIT Press.

Xu, Z., D.A. Hennessy, K. Sardana, and G. Moschini. 2013. The Realized Yield Effect of Genetically Engineered Crops: US Maize and Soybean. *Crop Science* 53(3): 735-745.

CHAPTER 2 Assessing Peer Effects and Subsidy Impacts in Technology Adoption: Application to Grazing Management Choices with Farm Survey Data

Abstract

Rotational grazing provides environmental benefits and is believed by many to be profitable for most graziers. However, the average adoption rate among ranchers is just over 30 percent in the United States. Peer effects are increasingly recognized as an important driver of technology adoption. We develop a model to identify how peer networking affects grazing practice adoption decisions, and also the impacts of subsidies on equilibrium decisions in the aggregate. With farm-level survey data, we apply a simultaneous-equations model to take account of endogeneity issues with peer effects that are measured as the number of adopters a rancher knows or the extent of adoption in a rancher's neighborhood. Empirical analysis provides evidence that there are significant peer effects in the adoption of rotational grazing. This implies that incentive policies will have multiplier effects in the long run on adoption through the peer networking route.

Introduction

Rangelands and pastures cover a large proportion of the earth's land, provide important biodiversity reservoirs, and are major sources of income in some rural areas (Crawford et al. 2019). However, grazing especially at high densities can have adverse environmental impacts, including rangeland degradation, forage quality and quantity reductions, and desertification (Steinfeld et al. 2006; Alkemade et al. 2013). Rotational grazing can address many of these concerns and provide multiple potential private benefits (Teague et al. 2009; Jakoby et al. 2015; Searchinger et al. 2018; Park, Ale and Teague 2017). Many government and nongovernmental agencies promote rotational grazing, the adoption of which could require costly investments in additional fencing, water supply infrastructure, and labor inputs. Despite potential benefits and various efforts, the adoption rate of rotational grazing is still low. Therefore, understanding the factors that influence rotational grazing adoption decisions is of major importance to policymakers.

Social interactions have been shown to be important for technology adoption in a variety of contexts, including high-yield seed varieties (Foster and Rosenzweig 1995), a new crop of sunflower (Bandiera and Rasul 2006), new technologies for pineapple production (Conley and Udry 2010), solar photovoltaic panels (Bollinger and Gillingham 2012), and groundwater extraction for agricultural irrigation (Sampson and Perry 2019). Social learning plays different roles among different technologies and many potentially constructive policies that can be used to facilitate peer effects have been proposed. Kolady et al. (2020) find that spatial peer effects are important in the adoption of conservation tillage and diverse crop rotation, but the magnitude of peer effects is not large. With respect to rotational grazing, some studies on dairy farming find that peer effects serve as drivers of system transformation from traditional management to rotational grazing (Nelson et al. 2014; Manson et al. 2016). Others reveal that there is only weak statistical evidence of a social effect on rotational grazing adoption (Baerenklau 2005). However, rigorous theoretical and empirical analysis of the relationship between peer effects and individual decisions to adopt rotational grazing is very limited in the literature.

Separate from peer effects, some studies have also examined subsidies' impacts on the adoption of new technologies or products through the channel of social learning. For example, Dupas (2014) use data from a two-stage randomized pricing experiment of a new antimalarial bed net in Kenya to estimate the effects of one-off subsidies on demand. Evidence is provided that the subsidies have large, increasing effects on the short-run level of adoption, and also that these short-run subsidies have an economically large and statistically significant effect on the long-run adoption through learning effects where information about the product diffuses through spatial networks. Carter, Laajaj, and Yang (2019) study randomized controlled trials of a government-implemented input subsidy program (ISP) in Africa. They find that a once-off input subsidy coupled to chemical fertilizer and improved seeds purchase for Mozambican maize farmers promotes Green Revolution technology adoption, and the subsidy effects persist after subsidies have been removed. These effects are attributed to direct and social learning effects, where spillovers from subsidized farmers to their social networks are observed such that agricultural contacts of subsidized farmers also see increases in technology adoption. Cai, de Janvry, and Sadoulet (2020) apply data from a two-year pricing experiment on the impact of a subsidy on weather insurance take-up. They provide evidence that the social effect of observing payouts in farmers' networks promotes insurance participation among those who are uninsured.

In this paper, we investigate whether and to what extent peer effects may affect the adoption of rotational grazing on the U.S. Great Plains and how subsidies affect adoption when there are peer effects. Peer effects arise when the returns for an individual rancher to adopting rotational grazing are influenced by his or her peers' adoption decisions. There are multiple mechanisms through which peer effects may affect the returns to adopting rotational grazing. One possibility is learning; for example, ranchers likely differ in their knowledge about rotational grazing technology and also in the private costs and benefits of adoption. As more knowledgeable ranchers adopt rotational grazing, other ranchers in their peer networks will learn about detailed operation skills that reduce the potential technology-related costs, or about cost and benefit information that will reduce the uncertainty surrounding a novel technology.

To identify peer effects, we first develop a theoretical framework that depicts how graziers decide on a grazing practice, and also whether and how they develop a social network to learn about a new technology, rotational grazing in this paper. In our model, we assume that ranchers can pursue networking to learn information about rotational grazing from adopters which will produce networking costs and reduce potential technology-related costs. We investigate how each rancher's adoption decision is affected by other ranchers' choices through learning information in their peer network. Then we use a survey sample of 874 beef producers on the Great Plains to examine peer effects. Methodologically, we apply a simultaneous equations model (SEM) due to Maddala (1983) to estimate the interaction effects between ranchers' adoption decisions and peer networking. We apply two kinds of peer networking indicators. One, the number of adopters that each rancher personally knows, measures personal contacts. The other, the estimated percentage of adopters among ranchers in the neighborhood who are within a 20-mile radius of a rancher's property, measures geographic proximity.

Overall, we find strong evidence that peer effects influence ranchers' decisions to adopt rotational grazing, while potential adopters are more willing to network with other adopters and know more information about rotational grazing. Subsidies will promote rotational grazing adoption through peer networking. To be specific, the probability of rotational grazing adoption increases by 0.09 after knowing one additional peer adopter; while the probability of adoption increases by 0.023 when perceiving a 1% increase in the neighborhood adoption. If the one-time subsidy increases by one dollar per acre, then the probability of adopting low-intensity rotational grazing will increase by 0.008; similarly, the probability of adopting management intensive grazing will increase by 0.003. In addition, we also find evidence that perceived additional labor inputs is an important barrier to adoption, which suggests that cost-sharing programs will be more effective if they are also used to alleviate concerns about labor requirements than to offset initial setup costs.

Our paper contributes to the literature in the following ways. First, our theoretical model considers that individuals make technology adoption decisions and actively pursue networking simultaneously. We apply a simultaneous equations model to address these two endogenous decisions of technology adoption and adopter network choices. Most previous work has studied only one of the two decisions (i.e., adoption decision), and applied linear-in-mean methods to identify peer effects that may induce the so-called "reflection problem" (Manski 1993).[10] Second, our finding that social learning can encourage rotational grazing adoption contributes to the literature on social learning and technology adoption (Foster and Rosenzweig 1995; Bandiera and Rasul 2006; Conley and Udry 2010; Bollinger and Gillingham 2012; Sampson and Perry 2019). Third, we contribute to the literature on the short-run and long-run effects of subsidies and social learning (Dupas 2014; Carter, Laajaj and Yang 2019; Cai, de Janvry and Sadoulet 2020) by showing that subsidies have a multiplier effect on rotational grazing adoption through

[10] "Reflection problem" refers to that the average behavior in a group affects the behavior of the individuals within the group and vice versa (Manski 1993).

peer networking. Finally, our work provides significant insights for policy makers who may be able to leverage peer effects when seeking to promote the adoption of new technologies (Graziano and Gillingham 2015; Sampson and Perry 2019). Understanding how peer effects contribute to conservation practice adoption can help promote the efficient design of policies aimed at obtaining the greatest environmental benefits when managing scarce resources.

In the next section, we provide background on rotational grazing practices and review the factors known to influence adoption decisions. Following that, we provide a comprehensive review of the existing literature on peer effects in technology adoption in the general agricultural sector and as applied in the adoption of grazing practices. We then set up a conceptual framework and identify hypotheses related to rotational grazing adoption decisions. After that, we describe the survey and other data that we analyze and the variables that we construct. In our estimation section, we apply a simultaneous equations model to examine peer effects and subsidy impacts on rotational grazing adoption. After reporting and analyzing the estimation results, we conclude with a brief summary as well as some comments on policy implications and peer effects research.

Background on Rotational Grazing Practice

Different grazing strategies have evolved or been developed (e.g., continuous, rest rotation, and short duration), each with different grass productivity potential and ecological consequences (Roche et al. 2015; Hawkins 2017; Crawford et al. 2019; Windh et al. 2019; Derner et al. 2021). At one extreme is continuous grazing, where a herd is put on one grassland tract for the entire grazing season. Alternatively, under rotational grazing the land is partitioned into a number of paddocks and the herd is rotated over these paddocks during the season. To be specific, under low-intensity rotational grazing (RG), the number of paddocks is relatively small and the herd remains on a paddock for weeks or months before moving to the next. When a large number of paddocks are involved, usually 20 or more, and cattle are moved more frequently, usually every 1 to 7 days, the strategy is referred to as management intensive grazing (MIG) (Undersander et al. 2002).

The potential private and social benefits derived from rotational grazing are multi-faceted. Rotational grazing presents the animals with more uniform, succulent grass and forces them to be less picky whereas animals grazing extensively congregate near shade and water. Damaged, erosion-prone patches where invasive weed and insect species can enter are prevented with more intensively grazed strategies. Under MIG grass can extend its root system deeper during the resting phase, ensuring greater drought resilience while parasite cycles are interrupted when animals are absent during critical stages. In Brazilian beef cattle grazing, production per unit land has been shown to increase with an increase in grazing intensity so that nutrient inputs and greenhouse gas (GHG) emissions per unit production decline (Searchinger et al. 2018). Some research also concludes that rotational grazing strategies can potentially provide both higher profit from ranching (Teague et al. 2009; Jakoby et al. 2015) and mitigate concerns about erosion, runoff, GHG emissions, and grassland ecosystem habits loss (Park et al. 2017).

United States Federal government agencies promote rotational grazing. For example, in 2015, the U.S. Department of Agriculture (USDA) adapted components of the Conservation Reserve Program to support working grasslands, including more intensive grazing, through rental payments and cost-sharing subsidies for fencing and watering infrastructure. Despite the potential benefits and despite various efforts aimed at promoting adoption, the most recent U.S. Census of Agriculture data reveals that the adoption rate of rotational grazing was low (about

33.8%) in 2017 (USDA, 2017). Investigating the reasons behind this phenomenon and developing a better understanding of the mechanisms underlying ranchers' grazing strategy adoption decisions are important in light of the environmental concerns listed above and the need for viable grassland agriculture infrastructure to support ranching activity in the area.

Many researchers have studied the factors that affect ranchers' grazing adoption decisions. Additional potential costs of implementing a rotational grazing system are an important constraint, including infrastructural costs and labor costs (Gillespie et al. 2008; Windh et al. 2019; Wang et al. 2020). Compared to continuous grazing, implementing a rotational grazing strategy requires additional expenses in terms of one-time installation expenses and reoccurring maintenance costs. Windh et al. (2019) identify three major cost components, namely fencing infrastructure, water infrastructure, and labor costs, for five grazing management scenarios: i) continuous grazing on one large pasture; rotational grazing with either ii) permanent cross-fencing or iii) temporary electric fencing; iv) continuous grazing with non-contiguous pastures; or v) rotational grazing with non-contiguous pastures. Their study ecosystem is shortgrass steppe, the primary site being the USDA-Agricultural Research Service's Central Plains Experimental Range (CPER) located near Nunn, Colorado. They find that fencing infrastructure costs are the largest component for all five scenarios, accounting for between 69% and 83% of total adoption costs. Gillespie et al. (2008) also identify the main disadvantages of rotational grazing, which include initial capital expenditures and greater investment risks. When assessing the two grazing strategies at comparable stocking rates in Louisiana, they find that fixed expenses per acre including depreciation and interest on machinery and equipment are $23.41 greater for rotational grazing with eight paddocks than for continuous grazing.

There is no consensus, however, concerning labor cost differences between continuous and rotational grazing. For example, Gillespie et al. (2008) analyze a data set using a time and motion study method to determine labor requirements for different grazing strategies in the U.S. Gulf Coast region. They find that rotational grazing systems are more time-intensive than continuous grazing systems due to the additional time required to move livestock among pastures and to maintain the additional infrastructure. By contrast, Windh et al. (2019) calculate the labor costs for both rotational grazing and continuous grazing scenarios. They find that rotational grazing scenarios require approximately 10 hours of additional labor over the grazing season from mid-May to early October to move cattle among pastures with the same total acreage of 3,200 acres, but total labor for rotational grazing remains less than for continuous grazing, due to the shorter checking times associated with smaller pasture area.

A Literature Review on the Peer Effects in Technology Adoption in Agriculture and Rotational Grazing Choices

Theories of social learning indicate that the sign of the relationship between peer effects and technology adoption is ambiguous. Peer effects may hinder the adoption of a technology. The rationale for this 'holding back' motive is that it is more beneficial to defer the adoption until many associates have already adopted because they can provide valuable information on the technology's merits in general and also for a specific operation. On the other hand, the motivation for adopting early may be to gain large profits early if the technology works out. In addition, if the technology works and many people adopt then output prices may fall and late adopters may not achieve as much additional profit as do early adopters.

There are different ways to measure and model peer effects in agricultural technology adoption. One approach to measuring peer effects is based on an individual's set of close contacts. For example, Granovetter (1985) finds that social ties between farmers and their family and friends are considered strong in the sense that they are long-term, embody mutual trust and reciprocity, and are not easily undone. Foster and Rosenzweig (1995) provide evidence that close contacts are most important for providing information on high-yield seed variety adoption in rural India. Bandiera and Rasul (2006) present evidence on how farmers' decisions to adopt a new crop, sunflower, relate to adoption choices among their network of family and friends in Zambezia Province, Northern Mozambique. They use the number of adopters among the farmer's self-reported network of family and friends as a proxy for social networks. They then apply an estimation strategy that allows for a nonlinear relationship between the probability of adoption and the number of adopters in the network. The inverse-U shaped relationship they find suggests that peer effects are positive when there are few adopters in the network, and negative when there are many.

The empirical literature on social learning has also defined networks based on geographical or cultural proximity (Bertrand, Luttmer and Mullainathan 2000; Munshi and Myaux 2002). In the agricultural context, Munshi (2004) finds that wheat growers place relatively more weight on their neighbors' past acreage allocations and yield realizations than on their own past decisions. Conley and Udry (2010) investigate the role of social learning in the diffusion of new agricultural technology for pineapple production in Ghana's Akwapim South District. The detailed information they collect on who individuals know and talk to about farming is used to define each individual's information neighborhood. In finding evidence that farmers adjust their inputs to align with those of their information neighbors who were surprisingly successful in the previous periods, their work provides further support for social learning in agricultural technology adoption. Strong evidence has also been provided that peer effects influence farmers' decisions to adopt groundwater irrigation. Using a rich dataset on groundwater rights for the period 1943-2014 and a nearest neighbor peer group definition, Sampson and Perry (2019) conclude that one additional neighbor adopting groundwater for irrigation increases the groundwater extraction probability by an average of 0.25 percentage points.

Few studies have addressed peer effects in the adoption of grazing strategies, and most of these are related to dairy farming. Peer effects in some of these studies are measured based on geographical proximity. For example, Baerenklau (2005) considers three mutually exclusive groups of networks among that study's sample farmers, namely in the northern, south-west, and east parts of Wisconsin. The research applies farm-level panel data covering 1996-2000 from 34 Wisconsin dairy farmers to examine the importance of behavioral drivers in rotational grazing adoption. They discern only weak statistical evidence of a peer group effect and the economic significance of this effect also appears to be small. These results suggest that targeting incentives at early adopters in certain areas may not be a very effective approach.

Other papers regarding grazing strategies focus on both measurements of social networking, i.e., close contacts, and geographical or cultural groups. Nelson et al. (2014) conduct 53 interviews with confined herd, low-intensity, and rotational grazing dairy producers as well as 35 interviews with associated network actors in Wisconsin, Pennsylvania, and New York. They find that information exchanges among neighbors and local grazing groups have some influence on how the initial decision on rotational grazing is arrived at. They also conclude that information exchanges or cost-sharing supports from agricultural or natural resource agencies play an important role as drivers of system transformation from traditional management to rotational grazing within the region's dairy production sector. The results indicate that more diverse networks between graziers and government agencies or other institutions will be needed to promote rotational grazing.

Manson et al. (2016) develop a stylized model of peer effects in dairy farming using 53 farms in the same three states as Nelson et al. (2014). While they find that peer effects are important for rotational grazing adoption, the effects differ depending on how farmers are connected with other people. For example, being in a formal organization or being well known to one another through personal relationships promotes adoption. They also find that rotational grazing adoption depends on different aspects of the social landscape, including the number of dairy households, the probability that neighboring farmers share strong network relationships, and how networks are formed geospatially. These findings suggest that initiatives aimed at strengthening various kinds of social networks among ranchers are important for promoting rotational grazing. For example, farmers are more likely to convert to rotational grazing if they get active encouragement from a trusted person, an extension agent or a familiar state actor with a long-term relationship who provides support for those making the transition, or extension agencies and university researchers who can support the formation of peer-learning networks.

Our paper contributes to the literature on peer effects by applying two kinds of indicators for peer networking: one is the number of rotational grazing adopters that each rancher personally knows, which belongs to the above-mentioned class of close contact metrics; the other is ranchers' perceived adoption rate in the neighborhood, which belongs to the class of geographical or cultural proximity metrics. These two measurements provide an integrated perspective for evaluating peer effects on rotational grazing adoption.

Conceptual Framework and Hypotheses

This section describes a theoretical framework that will be subsequently used to guide the empirical estimations. The framework focuses on how ranchers make decisions related to grazing practices and social networking. We begin by assuming that profit under extensive grazing (i.e., continuous grazing) is simplified as

(2.1) $\pi_i^{\text{ext}} = pq - l_i^{\text{ext}} - c,$

where p equals beef price, q equals beef quantity output, l_i^{ext} equals i^{th} farm tract-specific labor requirements under extensive grazing, and c equals other costs, including for water and fencing.

On the other hand, profit under intensive grazing (i.e., rotational grazing) is

(2.2) $\pi_i^{\text{int}} = pq(1+\delta) - l_i^{\text{ext}} - \hat{l}_i - c + s - \min_{e_i}\{Fh(e_i) + C(e_i, m, \theta_i)\},$

where $\delta > 0$ represents productivity gain under intensive grazing, since the decision is trivial whenever rotational grazing does not improve productivity ($\delta \leq 0$) but requires additional costs compared to extensive grazing. The term $\hat{l}_i$ represents the i^{th} farm additional labor requirements under intensive grazing, a detail that admits heterogeneity in relation to labor intensity and farm conditions. The term s is a subsidy associated with adopting intensive grazing; the case without government subsidy is represented by $s = 0$. The expression $Fh(e_i) > 0$ equals costs associated with the rotational grazing technology where $h(0) = 1$. Here $e_i \geq 0$ refers to adopter network size, so that $h(e_i) \in (0,1]$ is a decreasing function of adopter network size, i.e., $h'(e_i) \leq 0$. The quantity $F = Fh(0) > 0$ denotes the scale of fixed costs needed to adopt intensive grazing for the socially isolated grazier. Thus, $Fh(e_i)$ implies that the costs associated with rotational grazing decrease as a farmer's network size increases. The networking cost is represented by the continuous and appropriately differentiable function $C(e_i; m, \theta_i)$ which is held to be increasing and convex in adopter network size. Further, $m \in [0,1]$, the share of ranchers adopting the technology in the rancher's local region is assumed to reduce networking costs because opportunities to network with adopters are more readily available. Parameter θ_i represents rancher and ranch characteristics. These characteristics can be ordered so that higher values of θ_i reduce the cost of networking, $\partial C(\cdot) / \partial \theta_i \leq 0$. We will also assume that they reduce the marginal cost of networking, $\partial^2 C(\cdot) / \partial e_i \partial \theta_i \leq 0$.

Social networking can have different effects and the effects may differ at different stages of novel technology adoption and diffusion. According to Xiong et al. (2016), the main conduit for social network effects at the early stage is through information acquisition whereas experience effects and externality effects are most important at intermediate stages and maturity stages, respectively. Information effects refer to an individual is informed about the new technology and obtain basic information including the suitability of the technology from their peers, be they adopters or non-adopters. Experience effects refer to when an individual obtains knowledge and resources from peers who are current users, and so will help to reduce technological costs of adoption and to mitigate uncertainty. Externality effects occur when an individual is forced to decide whether to adopt the technology by peer pressure that is not directly related to the new technology's profitability (Xiong et al. 2016). While it is likely that networking will, to some extent, impose all three types of effects at all stages of adoption and innovation. Identifying the predominant effects of different stages facilitates analysis.[11]

[11] A separate but closely issue is that of production network costs, typically due to agglomeration economies that may not have to do with learning. See Cowan and Gunby (1996), Roe, Irwin and Sharp (2002), Holmes and Lee (2012), and Arora et al. (2021).

In our case, rotational grazing adoption and diffusion seem to be most appropriately characterized as being at the intermediate stage, with an average adoption rate of just over 30% in the United States. Thus, we focus on the experience effects, assuming that the motive for peer networking in our case is to learn more information about rotational grazing practice and reduce the adoption cost.[12] Thus the adopter chooses $\min_{e_i} Fh(e_i)+C(e_i,m,\theta_i)$, with the first-order condition $Fh'(e_i)+C_{e_i}(e_i,m,\theta_i)=0$, to obtain optimal adopter network size $e_i^*(\cdot)$ where $h'(e_i^*)\leq 0$ and $C_{e_i}(e_i^*,m,\theta_i)\geq 0$. A corner solution exists, i.e., $e_i^*(\cdot)=0$ whenever $-Fh'(\cdot)<C_{e_i}(\cdot)$ for $e_i=0$. It is readily shown that $de_i^*(\cdot)/dm\geq 0$ whenever $d^2C(\cdot)/de_i dm\leq 0$ and $de_i^*(\cdot)/d\theta_i\geq 0$ whenever $d^2C(\cdot)/de_i d\theta_i\leq 0$. Writing $J(F,m,\theta_i)\equiv\min_{e_i} Fh(e_i)+C(e_i,m,\theta_i)$, the envelope theorem implies that $J(F,m,\theta_i)$ is increasing in the first argument and decreasing in the other two. The adopter's profit function can be re-written as

$$\text{(2.3)}\qquad \pi_i^{\text{int}} = pq(1+\delta)-l_i^{\text{ext}}-\hat{l}_i-c-J(F,m,\theta_i)+s.$$

Here the positive decreasing function $J(F,m,\theta_i)$ characterizes network economies obtained from being able to learn about the intensive grazing technology from other adopters in the local region. This network spillover could alternatively have been included as a benefit in increasing revenue but the effect would be essentially the same.

We turn now to understanding how ranchers' adoption choices and network decisions respond to a change in the (privately) exogenous characteristics such as θ_i and m. With a

[12] We could posit that the experience effects occur after a rancher has learned from early networking whether rotational grazing is likely to be suitable for the ranch. Other ranchers have decided that rotational grazing is not suitable for their farm and so will not make further networking efforts. Thus, the network size in our analytical framework is additional to such early network size. This is consistent with our empirical data where network size exceeds zero for some non-adopters.

higher value of θ_i, the optimal adopter network size $e_i^*(F,m,\theta_i)$ will increase. Also the sum of technological costs and networking costs $J(F,m,\theta_i)$ will decrease, which will increase the probability of adopting rotational grazing. Thus, the optimal adopter network size and the rotational grazing adoption probability change in the same direction as the change in θ_i. Similar effects occur when there is an increase in the share of adopters in the local region, *m*. Therefore, we come to the following hypothesis:

Hypothesis 1: *The probability of adopting intensive grazing and the choice of adopter network size are positively associated with each other.*

However, it is hard to justify any causality between the two endogenous decisions: intensive grazing adoption and network size. That is, we simply cannot claim that intensive grazing adoption causes larger optimal network size or the other way around as both of these are endogenous decisions. In our empirical section, we apply a simultaneous-equations model to account for this endogeneity issue.

Rancher utility from extensive grazing is given as the sum of an idiosyncratic term, η_i^{ext}, and profit, π_i^{ext}. Similarly, producer utility from intensive grazing is given as the sum of an idiosyncratic term, η_i^{int}, and profit, π_i^{int}. These terms are held to follow extreme value distributions and the producer is assumed to make the choice that maximizes expected utility:

$$\text{(2.4)} \quad \max[\eta_i^{\text{ext}} + pq - l_i^{\text{ext}} - c, \eta_i^{\text{int}} + pq(1+\delta) - l_i^{\text{ext}} - \hat{l}_i - c - J(F,m,\theta_i) + s].$$

Following standard arguments (McFadden 1974) the probability that tract i is intensively grazed is then

$$\text{(2.5)} \quad \Pr(\text{int}) = \frac{e^{\lambda\times[pq(1+\delta)-l_i^{\text{ext}}-\hat{l}_i-c-J(F,m,\theta_i)+s]}}{e^{\lambda\times[pq(1+\delta)-l_i^{\text{ext}}-\hat{l}_i-c-J(F,m,\theta_i)+s]}+e^{\lambda\times[pq-l_i^{\text{ext}}-c]}} = \frac{e^{\lambda\times[pq\delta-\hat{l}_i-J(F,m,\theta_i)+s]}}{e^{\lambda\times[pq\delta-\hat{l}_i-J(F,m,\theta_i)+s]}+1};$$

where λ is a positive constant which reflects the smoothing that arises from integrating over random variables in (2.4). In equilibrium, it will be the case that $\Pr(\text{int}) = m$ and so

$$(2.6)\qquad m = \frac{e^{\lambda\times[pq\delta-\hat{l}_i-J(F,m,\theta_i)+s]}}{e^{\lambda\times[pq\delta-\hat{l}_i-J(F,m,\theta_i)+s]}+1}.$$

Figure 2.1 illustrates two possible shapes of equation (2.6) where more than one solution is shown. Differentiation and then use of relation (2.6) above provides

$$(2.7)\qquad \frac{dm}{ds} = \frac{\lambda m(1-m)}{1+\lambda J_m(F,m,\theta_i)m(1-m)}.$$

The effect of a change in labor requirement differential, $d\hat{l}_i$, on equilibrium share will of course be of the same magnitude but opposite in direction.

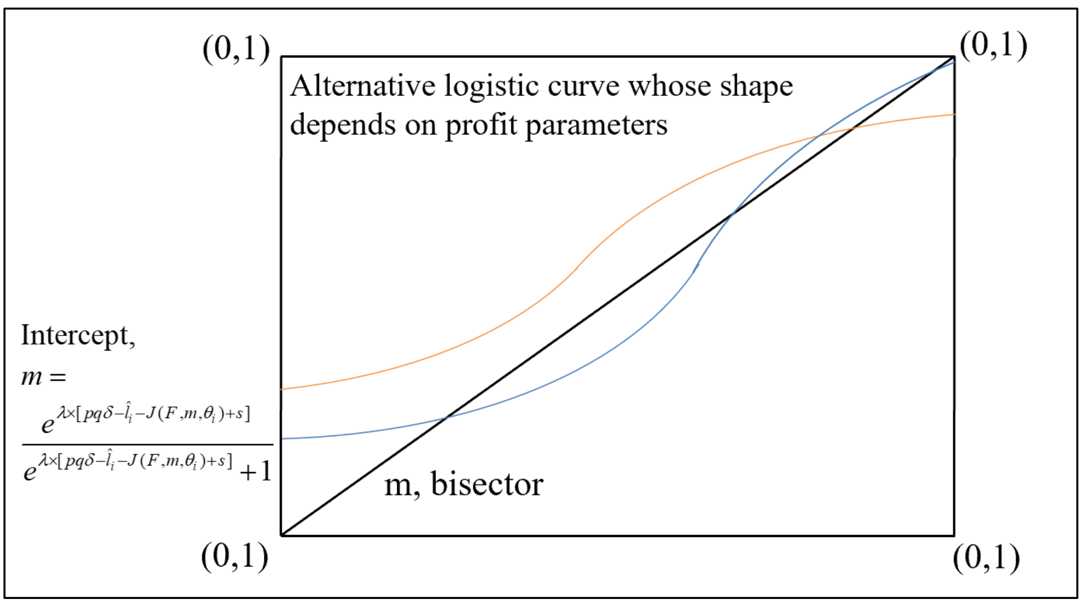


Figure 2.1 The probability of adopting intensive grazing system as a function of neighborhood adoption rates

Three further comments are warranted regarding (2.7). One is that the derivative is small in value whenever the share is either very small or very large, $m \approx 0$ or $m \approx 1$. To be specific, after dividing both numerator and denominator by $m(1-m)$, the equation (2.7) becomes

$\frac{dm}{ds} = \frac{\lambda}{\frac{1}{m(1-m)} + \lambda J_m(F, m, \theta_i)}$, which is closer to zero whenever $1/[m(1-m)]$ goes to infinity with $m \approx 0$ or $m \approx 1$. This is because then the profit differential is so large, in one direction or the other, that the subsidy is unlikely to sway any producers. Either intensive grazing is so uncompetitive that the subsidy has little impact on adoption or intensive grazing is so competitive that all are adopting and here too the subsidy has no impacts on adoption.

The second comment is that the extent of these positive network effects depends on the marginality of the adoption decision, through $m(1-m)$, on smoothing induced by idiosyncratic factors as represented by λ, and also on the sensitivity of profits to adoption as represented by $J_m(F, m, \theta_i)$. Expression $m(1-m)$ is largest when $m = 0.5$ and the median grazier encounters equal profits, $\pi_i^{\text{ext}} = \pi_i^{\text{int}}$. Notice here too that $m(1-m)$ provides the inverse U shape discussed in Bandiera and Rasul (2006). That is, leaving $J_m(\cdot)$ aside, $\text{sign}\{dm/ds\}$ inherits the inverse U shape.

The final comment is that, assuming $\lambda J_m(F, m, \theta_i) m(1-m) > -1$, the responsiveness to subsidy exceeds $\lambda m(1-m)$ which would be responsiveness were there no network effect on adoption cost. Turning to adopter network size, we may write

$$(2.8) \qquad \frac{de_i^*(F, m(s), \theta_i)}{ds} = \frac{de_i^*(F, m(s), \theta_i)}{dm}\frac{dm}{ds} = \frac{de_i^*(F, m(s), \theta_i)}{dm}\frac{\lambda m(1-m)}{1 + \lambda J_m(F, m, \theta_i) m(1-m)} \geq 0,$$

and so we have

Hypothesis 2: *With a subsidy for intensive grazing, a rancher will choose a larger adopter network size and is more likely to adopt intensive grazing.*

Expression (2.7) may be written as

(2.9) $$\frac{dm}{ds} = \lambda m(1-m)\left\{1+z+z^2+ \quad ... \quad\right\}; \qquad z = -\lambda J_m(F, m, \theta_i)m(1-m) > 0.$$

The polynomial terms $z+z^2+ \quad ...$ represent network feedback effects whereby subsidy-induced adoption in the region induces further adoption by increasing practice profitability. Given the above, it is noteworthy that the presence of positive network spillovers provides a rationale for a subsidy. The theory of supermodular games establishes that all Nash equilibria in choice settings such as ours will be below the value that maximizes each grower's payoff, see Theorem 7 in Milgrom and Roberts (1990). Thus, and assuming that there are no other external effects such as similar complementarities for choosing extensive grazing, the sum of grower payoffs will increase with a subsidy. This inference is separate from the ecological impacts unaccounted for in grower objective functions that would arise from increased adoption.

Based on these remarks, we have the following hypothesis:

Hypothesis 3: *Subsidies have a multiplier effect on intensive grazing adoption through peer networking.*

As previously mentioned, we will apply a simultaneous-equations model to examine the above hypotheses. Before that, however, we will describe the data and data context that will be used.

Survey Data Description

Survey Basic Information

To better understand rotational grazing strategies and ranchers' adoption decision mechanism, we sent out a survey to beef operators in 49 counties in North Dakota and 58 counties in South Dakota as well as 81 counties in Central and North Texas in early 2018. The screening criterion for rancher selection was that each respondent operated at least 100 non-feedlot cattle.[13] We purchased contact information for 4,500 randomly selected ranchers in three states from Survey Sampling International.[14] The survey was implemented by following the Dillman mail survey administration method (Dillman, Smyth and Christian 2014). During the period from late January 2018 to early April 2018, we sent out an advance letter of notification, two survey questionnaire mailings, and two postcard reminders. In late June 2018, a final survey packet was re-sent to secure a higher response rate. A total of 874 recipients completed and returned the survey questionnaires. The overall response rate was 20.6%, with state-level response rates of 16.5% in North Dakota, 22.4% in South Dakota, and 22.9% in Texas. Among all the respondents, the average sum of native rangeland and improved pasture acreage was about 2,800, and the average number of cattle per respondent was 364. The percentage of respondents' total household income from ranching operation was typically between 20% and 40%. The mail survey also requested detailed information on ranch operation, ranch management practices and land use, as well as information on adoption status, peer networking, perceptions about the infrastructure costs and labor inputs, and rancher characteristics. Below we describe parts of the survey and the variables to be used in our empirical analysis.

Adoption Status and Decisions

The survey provides ranchers' adoption information at both extensive (whether to adopt) and intensive (the number of pastures per group of animals to choose) margins. At the extensive margin, the questionnaire asked survey participants about grazing practices on their owned and

[13] To account for the differences in the number of qualified ranches in each county, we used proportional sampling to select 1,500 ranches in each state. The sample size for each county is obtained from multiplying 1,500 by a ratio, the ratio being the number of qualified farms for each county over the total number of qualified farms across each state's selected counties (Wang et al., 2020).
[14] As of July 2021, the company is now part of Dynata. https://www.dynata.com/press/announcing-new-name-and-brand-research-now-ssi-is-now-dynata/.

rented lands. We define a rancher as an adopter if the rancher was currently practicing rotational grazing; otherwise, the rancher was a non-adopter. A discrete choice variable is set to represent each rancher's adoption status. It equals one whenever the rancher was an adopter and zero otherwise. Among 874 ranchers in the sample, 59% were currently practicing rotational grazing, and 41% never adopted or had discontinued its practice. The distribution of surveyed adopters can be found in Figure 2.2. The adoption rate in the sample exceeded the 2017 average adoption rate (33%) among the three states of North Dakota, South Dakota and Texas (USDA NASS, 2017). To test for basic differences among adopters (n=520) and non-adopters (n=354), we compared rangeland and pasture acreage and beef cattle numbers among these two groups. On average, native rangeland and improved pasture acreage were 3,082 and 2,396 for adopters and non-adopters, respectively, which is statistically different (t=-1.897, p=0.058). The average number of cattle were 381 and 240 for adopters and non-adopters, respectively (t=-1.090, p=0.276).

At the intensive margin, adopters were queried about their current and desired number of pastures per group of animals on the ranch, and were given five-choice options (1='no more than 5', 2='6-11', 3='12-18', 4='19-30' and 5='more than 30'). The last four categories are combined. Among adopters 45.8% reported having no more than 5 pastures per group of animals on the ranch. Similarly, we also aggregated into two categories the desired number of pastures reported by adopters. On average the desired number of pastures exceeded the current number, indicating that adopters are more likely to choose higher intensity levels in the future.

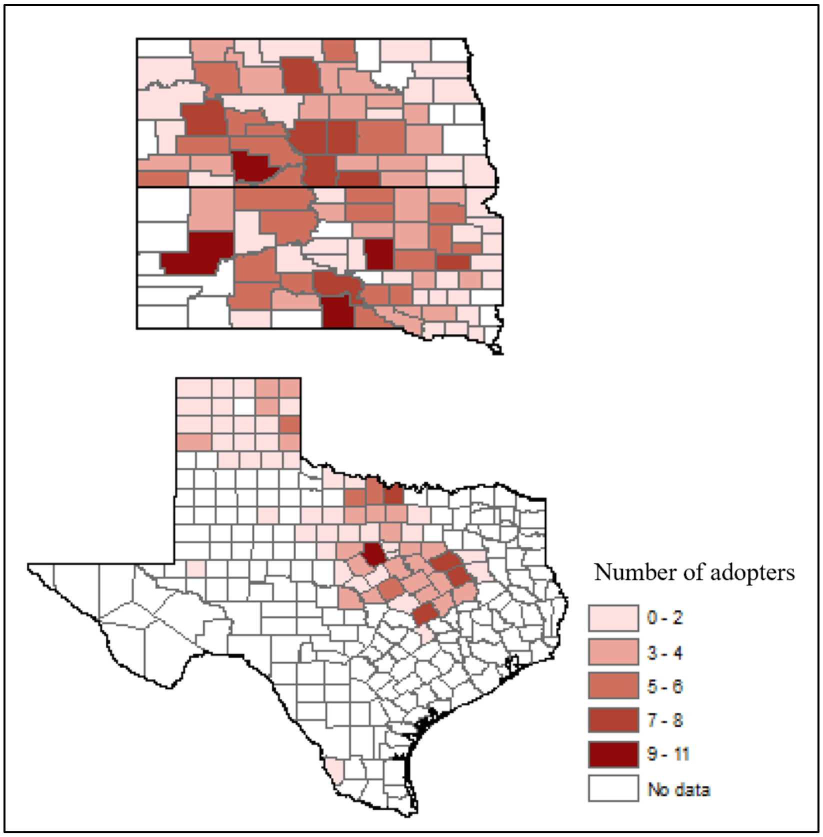


Figure 2.2 The distribution of adopters in the survey

For non-adopters, we further analyze their willingness to adopt rotational grazing at both extensive (whether they are likely to adopt) and intensive (the ideal number of pastures per group of animals in the future) margins. At the extensive margin, non-adopters were asked about the likelihood of adopting RG or MIG in the next five years. They were also asked whether they would adopt RG or MIG if a one-time subsidy were provided, the subsidy level alternatives being \$10/acre, \$30/acre, \$50\$/acre and \$70/acre. At the intensive margin, non-adopters were asked to provide the number of pastures per group of animals that they thought as ideal for future adoption and were, as with adopters, given five options. Compared with adopters, the distribution of non-adopters' intensity level choices tended to be lower.

Peer Networking

We have two indicators for adopter network size, one being 'number of adopters known', and the other is 'perceived neighborhood adoption'. The survey provided two corresponding sets of questions. One was "how many ranchers do you personally know who have already adopted RG or MIG?" with four options (1= 'none (0)', 2='some (1-5)', 3='quite a few (6-12)' and 4='many (>12)'); the other was "in your best estimation, what percentage of all ranchers within a 20-mile radius of your property use RG or MIG?", with five options (1='nobody (0%)', 2='some (1-20%)', 3='quite a few (20-40%)', 4='many (>40%)', and 5='have no clue').[15]

Our survey also listed five information sources that might affect their rotational grazing decision-making, these being government agencies (such as NRCS), associations (such as Grassland Coalition, Society for Range Management), university extension, independent consultants, and other ranchers. Respondents were asked to assess the importance of the above information sources by indicating five levels (1='not important', 2='slightly important', 3='somewhat important', 4='quite important', 5='very important'). From National Agricultural Statistics Service (USDA NASS, 2017), we also collected county-level data on rotational grazing share in cattle, goat, and sheep operations.

Infrastructure Costs and Labor Costs

Compared to continuous grazing, implementing a rotational grazing strategy requires additional expenses for infrastructure and labor. 'Initial cost' refers to the estimated initial investment costs in $/acre for both fencing and water systems, and five categories were provided for responses, namely 1='less than $10', 2='$10-$25', 3='$26-$40', 4='$41-$70' and 5='more

[15] Respondents who choose ='have no clue' are dropped when we analyze peer networking. We use the mean value in each category to generate a continuous variable for each of two adopter network size indicators.

than $70'.[16] 'Labor' refers to the effects of rotational grazing adoption on labor and management time needed to operate the ranch. Five response alternatives were provided: 1='significantly decreased', 2='slightly decreased', 3='no influence', 4='slightly increased' and 5='significantly increased.'

Rancher and Ranch Characteristics

In order to understand the factors influencing adoption decisions, variables that describe rancher and ranch characteristics will be included in our estimations. 'Operating years' and 'education' depict rancher characteristics, where 'operating years' refers to the number of years a rancher has been the primary operator on any part of her or his current farm or ranch. 'Education' refers to the highest level of completed education, which is categorized using five discrete values with 1='less than high school', 2='high school', 3='some college/technical school', 4='4-year college degree', 5='advanced degree.'

Variables that describe ranch characteristics include 'internal fences' (a dummy indicator for whether the ranch has some internal or cross fencing), 'ranch size' (the total number of cows and replacement heifers), 'distance' (the estimated distance in miles from a rancher's home to her or his largest tract of grazing land), and 'ranching income.' 'Ranching income' refers to the approximate percentage of total household income that comes from ranching operations, and is categorized using 1='less than 20%', 2= '20% up to 40%', 3='40 up to 60%', 4= '60% up to 80%' and 5='80% or more.' In addition, we purchased each respondent's exact farm address from SSI, which allowed us to collate survey information with public domain data (e.g., land

[16] For initial costs, only non-adopters were required to choose among the five options. Adopters were asked to report the exact values of initial costs. To be consist, we converted the continuous variables of adopters into five discrete categories.

quality in the vicinity).

Table 2.1 Variable definitions and data sources

Category	Variable	Description	Source
Adoption decisions	Adoption	Adoption status indicator, 1='adopter', 0='non-adopter'	Survey
	Willingness to adopt (for non-adopters)	Willingness to adopt RG or MIG given a one-time subsidy	Survey
	Current intensity (for adopters)	Number of pastures per group of animals that adopters currently have on the ranch, 0='no more than 5', 1='greater than 5'	Survey
	Desired intensity (for adopters)	Number of pastures per group of animals that adopters desire to have on the ranch, 0='no more than 5', 1='greater than 5'	Survey
	Future intensity (for non-adopters)	Number of pastures per group of animals that non-adopters desired to have, 0='no more than 5', 1='greater than 5'	Survey
Network indicators	Number of adopters known	Number of rotational grazing adopters that the rancher personally knows	Survey
	Perceived neighborhood	Perceived percentage of rotational grazing adopters within a 20-mile radius of home	Survey
	Rotational grazing share in county	Share of rotational grazing in cattle, goat and sheep operations at county-level	NASS, 2017
Costs and labor	Initial cost	Estimated initial investment costs	Survey
	Labor	Perceived effects of rotational grazing on needed labor and management time	Survey
Rancher Characteristics	Operating years	Number of years as primary operator	Survey
	Education	Highest level of education	Survey
	Ranching income	Percentage of total household income from ranching operation	Survey
Ranch characteristics	Internal fences	Whether the ranchers have some internal or cross fencing	Survey
	Ranch Size	The number of cows and replacement heifers (by 1,000)	Survey
	Distance	Distance in miles from home to largest land	Survey
	LCC I & II	Share of land with LCC equal to I and II	SSURGO[17]
	Slope less than 3%	Share of land with slope no greater than 3%	SSURGO

We collected land capability classification (LCC) and slope variables from the United States Department of Agriculture Natural Resource Conservation Service SSURGO database.

[17] SSURGO database is from the United States Department of Agriculture Natural Resource Conservation Service.

LCC ascription is based on the severity of limitations for crop production, which is used to proxy soil quality. Classes I and II soils have few limitations and are typically cropped intensively while Class III soils have moderate limitations for crop production. Class IV soils are very marginal for crop production while Class V–VIII soils are seldom cropped. The 'LCC I&II' variable denotes the share of all land that has LCC equal to I or II (and so productive under crop production) within 1-mile of the ranch's location. A 1-mile radius is chosen because we would like to appropriately indicate the extent of productive land in the ranch's vicinity. Similarly, the variable 'Slope less than 3%' refers to the share of the area within a 1-mile radius that has a slope no greater than 3%. This variable is also used as a proxy for better quality land in that such land is easier to manage and is less prone to erosion under intensive use. The description and definitions of the above-mentioned variables can be found in Table 2.1.

Empirical Methods

Identifying Peer Effects

One key issue about peer effects identification by the existing literature is that clustering behavior among individuals in the same group can stem from one or both among impacts due to peers' characteristics (exogenous or contextual effects) or impacts due to peers' outcomes (endogenous effects) (Manski 1993). Exogenous or contextual effects refer to similar behavior among individuals in the same group due to the exogenous characteristics of the group. Examples in our grazing practice adoption context include similarities in soil characteristics and climate. Endogenous effects refer to the interactions through which an individual's behavior is causally affected by the behavior of others in the same group. These effects may arise through learning information from peers. For example, a rancher may obtain information from another ranching friend that reveals something about the costs and benefits of rotational grazing. In this paper, we are interested in endogenous effects, and especially through the learning information channel.

Distinguishing between endogenous effects and contextual effects may be difficult because of simultaneity in behavior among interacting individuals, which is also referred to as the “reflection problem” (Manski 1993). To be specific, the average behavior in a group affects the behavior of the individuals within the group and vice versa. In our case, this problem is of little significance in several respects. First, our conceptual framework describes a rancher who decides to choose a grazing practice and actively pursues networking simultaneously. To address this simultaneity, we apply SEM that is captured in equations (2.10) – (2.12) to be discussed in detail. We take the average adoption rate in a large geographic unit as exogenous, and our estimations test interactive effects between adoption and the network, which is different from the reflection problem in which individuals behave interactively within the same group.[18]

Second, the influence of an individual’s decision to adopt rotational grazing is likely to only be felt through a lag due to the time needed to complete fencing and water infrastructure. We follow the recent literature and assume that an individual's networking information may depend on the “installed base” of adoption decision within the group (Bollinger and Gillingham 2012; Sampson and Perry 2019). The installed base is the cumulative adoption up to the previous calendar year and is taken as being exogenous.

Third, many recent studies reveal that the identification of peer effects depends on the network’s structure, and endogenous peer effects can be identified under intransitivity, when

[18] The network effects modeled in our analysis are similar to the “indirect network effect” as defined by Rysman (2019). The key feature of the indirect network effect is that the utility from adopting depends on the existence of intermediate goods or the amount of intermediate goods in the network, but does not depend directly on the group mean adoption rate or other distributional measures of group adoption. The number of adopters a rancher knows, and the extent of adoption in a rancher’s neighborhood measure indirect network effects as they are not group mean but are affected by group mean.

peers' peers are not peers (Bramoullé, Djebbari and Fortin 2009; Bramoullé, Djebbari and Fortin 2020). We do not assume that individuals interact in groups as in the linear-in-means model by Manski. Our surveyed ranchers are not partitioned into some closed groups in which individuals are affected by all others in their group and by none outside of it.

Finally, our data on peer information indicators are self-reported, which is related to "motivated beliefs" (Bénabou 2015) that investigate how and why "people believe what they want to believe" (Epley and Gilovich 2016) in the extensive economics and psychology literature. Our SEM approach can capture the possibility that an adopter is more likely to network with other adopters, and also that a rancher's self-reported extent of adoption in personal contacts or neighborhood can be affected by the rancher's views and choices.

Simultaneous Equations Model

Following our conceptual framework, the main objectives pursued in empirical modeling are to examine how ranchers make decisions about choosing grazing practices and also adopter network size as well as how subsidies affect decision processes. To be specific, we examine four questions: (1) how ranchers' adoption decisions respond to peer networking and vice versa when no subsidies are provided; (2) with a hypothetical subsidy, how non-adopters' willingness to adopt rotational grazing responds to peer networking and vice versa, and also the effects of subsidy; (3) at the intensive margin, whether ranchers' choices are affected by peer networking, i.e., whether peer networking affects the choice between RG and MIG; (4) how other factors (including initial costs and labor requirement) affect ranchers' above-described decisions.

Our conceptual framework implies that adoption decisions would more properly be viewed as jointly or simultaneously determined with adopter network size choices, rather than being treated as exogenous. If we apply a single logit or probit equation to examine the factors that influence adoption with the network indicators as independent variables, then a non-zero covariance between the disturbance term and the independent variables exists. To correct for this simultaneity bias, a simultaneous equations model (SEM) (Maddala 1983) is used here to examine the factors affecting rotational grazing adoption. The two endogenous variables are adoption decision and the networking effort choice, where the first of these endogenous variables is binary. The SEM is applied as below:[19]

(2.10) $A_i^* = \beta_0 + \beta_1 e_i + \beta_2 X_i + \beta_3 s_i + \varepsilon_1$,

(2.11) $e_i = \gamma_0 + \gamma_1 A_i^* + \gamma_2 m_i + \varepsilon_2$,

(2.12) $A_i = \begin{cases} 1 \text{ whenever } A_i^* > 0 \\ 0 \text{ otherwise} \end{cases}$,

where A_i is a dichotomous variable indicating a rancher's adoption decision (i.e., whether a rancher has adopted rotational grazing, or whether a non-adopter will be likely to adopt it in the future with a subsidy, or whether a rancher chooses a high intensity level), and A_i^* is the associated latent variable. The peer network indicator is given as e_i , and s_i is a one-time subsidy. The share of rotational grazing operations in the total number of cattle, goat, and sheep operations within each respondent's county is given as m_i, and all the other influencing factors are denoted as X_i. For easy references, all variables have been described in Table 2.1. The parameters β_0, β_1, β_2, β_3, γ_0, γ_1, and γ_2 are to be estimated, while ε_1 and ε_2 are the error terms.

[19] This corresponds to Maddala's (1983, pp. 244-245) model 3.

Inserting (2.11) into (2.10), we obtain:

$$(2.13)\quad A_i^* = \frac{\beta_0 + \beta_1\gamma_0}{1-\beta_1\gamma_1} + \frac{\beta_1\gamma_2}{1-\beta_1\gamma_1} m_i + \frac{\beta_2}{1-\beta_1\gamma_1} X_i + \frac{\beta_3}{1-\beta_1\gamma_1} s_i + \frac{1}{1-\beta_1\gamma_1}(\varepsilon_1 + \beta_1\varepsilon_2),$$

which reveals that peer effects may involve a multiplier on subsidy under some conditions. Response to subsidy changes from β_3 to $\beta_3/(1-\beta_1\gamma_1)$. Therefore, the subsidy will have a greater impact given feedback mediated through peer networking whenever $\beta_1\gamma_1 \in (0,1)$.

In the equilibrium outcome, it will be the case the weighted sum of adoption decision A_i among all the ranchers in the county should equal to average adoption rate m_i. The subsidy impacts on the adoption rate in the equilibrium can be derived from equations (2.10)-(2.11), which is connected to our theoretical framework. However, data inavailability places limits on the empirical analysis; for example, we do not know the peer networking structure among our surveyed ranchers and whether ranchers' peers are included in our sample. It is also difficult to obtain all the ranchers' responses in each county. Although our empirical approach does not quantify the subsidy's impacts on the equilibrium, it provides insights on how the subsidy affects ranchers' adoption and adopter network size choices in the decision process.

The SEM is a two-stage estimation procedure in which the first step is to eliminate that part of the endogenous variable that is correlated with the disturbance terms. This stage involves regressing the adoption and network variables on exogenous variables to arrive at predicted values. In the second stage, these predictions are then used to compute the maximum likelihood estimates of the explanatory variables.

To estimate the system (2.10)-(2.12), the reduced form equations are

$$(2.14)\quad A_i^* = \pi_1' Z_i + \upsilon_1,$$

(2.15) $e_i = \pi_2' Z_i + \upsilon_2$,

where π_1' and π_2' are parameter vectors to be estimated, while υ_1 and υ_2 are error terms. The term Z_i is a matrix of all the exogenous variables in (2.10) and (2.11), which includes county-level adoption rate m_i and all variables in X_i (i.e., initial infrastructure costs, labor costs, operating years, education level, percentage of total household income from ranching operation, the existence of internal fences, ranch size, distance from home to ranch, and land quality). The choice of these variables as exogeneous is mainly based on Feder et al. (1985) who extensively review factors affecting agricultural technology adoption. They identify the following variables as major determinants of adoption: labor availability, capital, farm size, off-farm income sources, tenure, supply constraints and prices of agricultural outputs and inputs. Because A_i^* is not observed, we can only estimate π_1' / σ_1, where $\sigma_1^2 = \mathrm{Var}(\upsilon_1)$. Hence, we have

(2.16) $A_i^{**} = \dfrac{A_i^*}{\sigma_1} = \dfrac{\pi_1'}{\sigma_1} Z_i + \dfrac{\upsilon_1}{\sigma_1} = \pi_1^{*\prime} Z_i + \upsilon_1^*$.

In the first stage, we estimate equation (2.15) by OLS to obtain $\hat{\pi}_2'$ and $\hat{e}_i$, and also estimate equation (2.16) using maximum likelihood estimation by probit method to obtain $\hat{\pi}_1^{*\prime}$ and $\hat{A}_i^{**}$. In the second stage, we estimate equation (2.17) below by using maximum likelihood estimation on a probit specification, and we estimate equation (2.18) by OLS:

(2.17) $A_i^{**} = \dfrac{\beta_1}{\sigma_1} \hat{e}_i + \dfrac{\beta_2}{\sigma_1} X_i + \dfrac{\beta_3}{\sigma_1} s_i + \dfrac{\varepsilon_1}{\sigma_1}$,

(2.18) $e_i = \gamma_1 \sigma_1 \hat{A}_i^{**} + \gamma_2 m_i + \varepsilon_2$.

The above two-stage estimation procedure follows the broad approach given in Maddala (1983) and Keshk (2003).

Results and Discussions

Summary Information about Adopters and Non-adopters

Table 2.2 provides adoption variable and explanatory variable descriptive statistics for both adopters and non-adopters. At the extensive margin, the adoption rate in our sample is 59% with 520 adopters and 354 non-adopters. Among non-adopters, 36% (13%, respectively) reported being likely to adopt RG (MIG, respectively) in the next five years. At the intensive margin, the average desirable intensity level (the number of desired pastures per group of animals on the ranch) exceeds the current level among adopters, which may be caused by limiting ranch conditions. For non-adopters, the ideal intensity level (55% at > five pastures) in the future approximately equals the adopters' average current level (54% at > five pastures).

Lack of information is one potential barrier to adoption for many ranchers. Among our surveyed respondents 37.7% of non-adopters and 22.9% of adopters reported 'lack of information' to be 'some challenge, 'quite a challenge, or a 'great challenge.' Several potential information sources can provide information about rotational grazing, including government agencies, associations, university extension, and independent consultants. Mean response values in Table 2.3 show that adopters ranked all sources as more important than non-adopters, which suggests that adopters were willing to expand their social network to obtain information. Moreover, the two most important sources are government agencies and other ranchers. To be specific, 40.7% of adopters and 30% of non-adopters reported government agencies as 'quite important' or 'very important'; while 36.1% of adopters and 28.7 of non-adopters considered other ranchers to be 'quite important' or 'very important.'

Table 2.2 Descriptive statistics

	All samples			Adopters					Non-adopters				
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Adoption	874	0.59	0.49	520	1	0	1	1	354	0	0	0	0
Willingness to adopt (RG) (for non-adopters)									286	0.36	0.48	0	1
Willingness to adopt (MIG) (for non-adopters)									259	0.13	0.34	0	1
Current intensity (for adopters)				480	0.54	0.50	0	1					
Desire intensity (for adopters)				419	0.70	0.46	0	1					
Future intensity (for non-adopters)									249	0.55	0.50	0	1
Number of adopters known (RG)	857	7.54	3.66	513	8.76	2.40	0	12	344	5.72	4.40	0	12
Number of adopters known (MIG)	802	3.18	4.37	475	3.85	4.56	0	12	327	2.21	3.89	0	12
Perceived neighborhood adoption (RG)	825	14.92	12.02	497	19.05	12.38	0	40	328	8.66	8.14	0	40
Perceived neighborhood adoption (MIG)	753	3.92	6.25	447	4.44	6.23	0	40	306	3.16	6.22	0	40
Rotational grazing share in county	873	0.39	0.13	520	0.41	0.12	0.19	0.65	353	0.37	0.13	0.19	0.68
Initial cost	522	3.37	1.39	286	3.31	1.55	1	5	236	3.44	1.17	1	5
Labor (RG)	748	1.83	0.68	459	1.67	0.61	1	3	289	2.09	0.70	1	3
Labor (MIG)	381	2.08	0.88	136	1.5	0.73	1	3	245	2.41	0.78	1	3
Operating years	857	36.23	12.71	515	35.26	11.94	2	68	342	37.69	13.68	0	75
Education	850	3.24	0.97	514	3.27	0.91	1	5	336	3.19	1.04	1	5
Ranching income	845	3.62	1.38	508	3.72	1.36	1	5	337	3.47	1.40	1	5
Internal fences	783	0.68	0.47	479	0.69	0.46	0	1	304	0.67	0.47	0	1
Ranch Size	846	0.24	0.33	506	0.26	0.23	0	2.33	340	0.22	0.44	0	7.15
Distance	847	11.23	24.25	511	11.06	23.28	0	200	336	11.48	25.69	0	300
LCC I & II	867	43.83	40.77	516	44.56	39.75	0	100	351	42.76	42.25	0	100
Slope less than 3%	867	43.13	38.26	516	39.99	37.62	0	100	351	47.75	38.78	0	100

Table 2.3 Mean values and T-tests for the importance of information sources between non-adopters and adopters

Sources	All samples		Adopters		Non-adopters		T-test	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	t value	Pr (|T| > |t|)
Government agencies (such as NRCS)	2.921	1.307	3.074	1.277	2.679	1.320	-4.305	0.000
Associations (such as Grassland Coalition, Society for Range Management)	2.270	1.223	2.403	1.263	2.057	1.126	-3.988	0.000
University extension	2.682	1.195	2.809	1.180	2.480	1.194	-3.891	0.000
Independent consultants	2.114	1.144	2.148	1.152	2.060	1.131	-1.078	0.282
Other ranchers	2.886	1.199	3.012	1.140	2.685	1.264	-3.859	0.000

Note: t-test of equivalence of means of adopters versus non-adopters.

Although rotational grazing usually requires additional infrastructure costs including fencing and water as well as labor requirement, adopters and non-adopters have different opinions about initial costs and labor inputs. The average initial investment costs reported by adopters were about '\$26-\$40' per acre, while non-adopters perceived slightly higher initial costs compared to adopters. Adopters reported that the effect of rotational grazing on labor and management time was between 'significantly decreased' and 'slightly decreased', while non-adopters thought rotational grazing needed more labor than adopters.

Peer Effects and Adoption Decisions

Table 2.4 presents SEM estimation results for adoption decisions and peer networking without subsidies. Columns 1 and 2 present results with the number of adopters that each rancher knows as the peer networking indicator where Column 2 does not control for ranch and rancher characteristics. Columns 3 and 4 present results with perceived neighborhood adoption rate as the peer networking indicator where, as with column 2, column 4 does not control for ranch and rancher characteristics. Looking across specifications, our results demonstrate robust evidence of peer effects in the adoption of rotational grazing with two indicators. Table 2.5 presents the corresponding marginal effects and standard errors. For example, controlling for rancher and ranch characteristics, the effect of knowing one additional adopter increases the probability of adoption by 0.09. Also the effect of perceiving a 1% increase in neighborhood adoption increases the probability of adoption by 0.023.

Results in the lower part of Table 2.4 also show that adopters know more friends and neighbors who adopt and are more willing to network. By learning more information about rotational grazing technology and management techniques, adopters will likely improve grazing performance and reduce adoption costs. The positive coefficients on adoption also indicate that a rancher’s self-reported estimate of practice prevalence in her/his close contact or neighborhood is affected by the rancher’s own choices. Moreover, the coefficients on lagged county-mean adoption rate in the previous year are positive and statistically significant across all four specifications, which indicates that greater adoption rates in the geographic unit will provide more opportunities for ranchers to network with adopters.

Table 2.4 SEM estimates for adoption decision and peer effects

	Adoption			
VARIABLES	(1)	(2)	(3)	(4)
Number of adopters known (RG)	0.228*	0.310***		
	(0.120)	(0.104)		
Perceived neighborhood adoption (RG)			0.059*	0.090***
			(0.031)	(0.033)
Initial cost	0.007	0.041	0.007	0.036
	(0.049)	(0.048)	(0.047)	(0.048)
Labor (RG)	-0.578***	-0.430***	-0.581***	-0.418***
	(0.119)	(0.111)	(0.117)	(0.116)
Operating years	-0.001		-0.005	
	(0.006)		(0.005)	
Education	-0.107		-0.052	
	(0.094)		(0.069)	
Ranching income	0.052		0.054	
	(0.050)		(0.047)	
Internal fences	-0.056		0.020	
	(0.131)		(0.127)	
Ranch size	0.514*		0.482*	
	(0.306)		(0.287)	
Distance	-0.002		0.000	
	(0.003)		(0.002)	
LCC I&II	-0.001		0.001	
	(0.002)		(0.001)	
Slope less than 3%	-0.000		-0.001	
	(0.002)		(0.002)	
	Number of adopters known (RG)		Perceived neighborhood adoption (RG)	
Adoption	1.344***	1.063***	4.599***	4.050***
	(0.276)	(0.351)	(0.923)	(1.137)
Rotational grazing share in county	3.464***	3.262***	10.354**	9.593**
	(1.229)	(1.230)	(4.041)	(3.966)
Observations	475	506	463	492

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 2.5 Marginal effects (ME) and standard errors (SE) for adoption decision and peer effect models

VARIABLES	Adoption							
	(1)		(2)		(3)		(4)	
	ME	SE	ME	SE	ME	SE	ME	SE
Number of adopters known (RG)	0.090*	0.047	0.123***	0.041				
Perceived neighborhood adoption (RG)					0.023*	0.012	0.035***	0.013
Initial cost	0.003	0.019	0.016	0.019	0.003	0.019	0.014	0.019
Labor (RG)	-0.228***	0.047	-0.171***	0.044	-0.229***	0.046	-0.162***	0.046
Operating years	-0.000	0.002			-0.002	0.002		
Education	-0.042	0.037			-0.021	0.027		
Ranching income	0.021	0.020			0.021	0.018		
Internal fences	-0.022	0.052			0.008	0.050		
Ranch size	0.203*	0.121			0.190*	0.113		
Distance	-0.001	0.001			0.000	0.001		
LCC I&II	-0.000	0.001			0.000	0.001		
Slope less than 3%	-0.000	0.001			-0.000	0.001		

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In addition, Table 2.4 also shows that rotational grazing adoption is discouraged by greater labor requirements and also restricted by small ranch size. Rotational grazing may require more time inputs to move livestock among pastures and to maintain additional infrastructure compared to continuous grazing (Gillespie et al. 2008), so ranchers are less likely to adopt it when they perceive these additional labor requirements. With regard to the positive coefficients on ranch size, ranchers grazing a larger number of animals are more likely to adopt rotational grazing probably because fixed costs can be spread over more cattle units. On the other hand, greater ranch sizes are associated with greater initial investment costs when implementing rotational grazing, which is reflected in the positive coefficient on initial costs in column 2, where operator characteristics have not been controlled for.

Peer Effects and Subsidy Impacts on Adoption Decisions among Non-adopters

In order to promote rotational grazing adoption, it is important to directly understand how non-adopters' arrive at their decisions. Tables 2.6 and 2.7 present estimation results and marginal effects for non-adopters' willingness to adopt rotational grazing when given a hypothetical one-time subsidy. Our results provide evidence of peer effects in the willingness to adopt RG among non-adopters, but no evidence to support peer effects in the MIG adoption decision.[20] This indicates that peer networking affects non-adopters' willingness to adopt general rotational grazing, but does not influence the further choice of intensity level (i.e., shifting from RG to MIG). The potential reason might be that ranchers refer to information from other adopters when making initial decisions on whether to adopt rotational grazing, but subsequent technical choices about intensity levels will depend on their own operational experience.

However, a one-time subsidy plays an important role in promoting RG and MIG adoption. If the one-time subsidy increases by one dollar per acre then the probability of adopting RG increases by 0.008; similarly, the probability of adopting MIG increases by 0.003. One advantage of a one-time subsidy is that ranchers have the flexibility to recompense both initial infrastructure costs and labor costs since column 2 in Table 2.6 also shows that these additional costs discourage RG adoption. Therefore, as indicated in Figure 2.1, subsidies will have a multiplier effect on rotational grazing adoption through peer effect feedbacks. To be specific, subsidies can attract some non-adopters to adopt rotational grazing and the resulting peer network will induce further adoption.

[20] Most non-adopters did not know many MIG adopters, for example, about 86% of non-adopters knew no MIG adopters and 84% of them thought nobody adopted MIG in their neighborhood.

Table 2.6 SEM estimates for non-adopters' willingness to adopt when offered a hypothetical one-time subsidy

	Willingness to adopt (Non-adopters)			
VARIABLES	(1) RG	(2) RG	(3) MIG	(4) MIG
Subsidy	0.029***	0.029***	0.030***	0.029***
	(0.003)	(0.003)	(0.010)	(0.005)
Number of adopters known (RG)	0.232*			
	(0.120)			
Perceived neighborhood adoption (RG)		0.111**		
		(0.050)		
Number of adopters known (MIG)			1.422	
			(3.269)	
Perceived neighborhood adoption (MIG)				-0.303
				(0.214)
Initial cost	-0.059	-0.115**	0.059	-0.107
	(0.070)	(0.054)	(0.448)	(0.095)
Labor (RG)	-0.081	-0.192**		
	(0.098)	(0.095)		
Labor (MIG)			0.973	-0.306
			(2.441)	(0.228)
Operating years	0.000	-0.005	0.015	0.019*
	(0.006)	(0.005)	(0.021)	(0.010)
Education	-0.158	0.059	-0.525	-0.028
	(0.124)	(0.063)	(1.177)	(0.108)
Ranching income	0.006	0.045	-0.428	-0.022
	(0.049)	(0.044)	(0.780)	(0.089)
Internal fences	0.013	0.059	0.009	0.126
	(0.140)	(0.131)	(0.774)	(0.241)
Ranch size	0.608**	0.854***	-1.837	-0.873
	(0.250)	(0.271)	(3.004)	(0.582)
Distance	-0.003	0.000	-0.016	0.005
	(0.004)	(0.003)	(0.035)	(0.007)
LCC I&II	-0.005**	-0.005***	-0.010	0.008
	(0.002)	(0.002)	(0.028)	(0.005)
Slope less than 3%	-0.000	-0.003*	-0.001	0.004
	(0.002)	(0.002)	(0.006)	(0.004)
	# adopters known	Neighborhood adoption	# adopters known	Neighborhood adoption
Willingness to adopt (RG)	0.499**	-0.012		
	(0.199)	(0.354)		
Willingness to adopt (MIG)			-0.042	0.124
			(0.189)	(0.277)
Rotational grazing share in county	4.938***	11.410***	0.779	5.471***
	(1.141)	(2.086)	(1.117)	(1.610)
Observations	792	770	657	644

Note: Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 2.7 Marginal effects (ME) and standard errors (SE) for non-adopters' willingness to adopt models

VARIABLES	Willingness to adopt (Non-adopters)							
	RG				MIG			
	(1)		(2)		(3)		(4)	
	ME	SE	ME	SE	ME	SE	ME	SE
Subsidy	0.008***	0.001	0.008***	0.001	0.003**	0.001	0.003***	0.001
Number of adopters known (RG)	0.066*	0.034						
Perceived neighborhood adoption (RG)			0.032**	0.014				
Number of adopters known (MIG)					0.135	0.312		
Perceived neighborhood adoption (MIG)							-0.030	0.021
Initial cost	-0.017	0.020	-0.033**	0.016	0.006	0.042	-0.011	0.010
Labor (RG)	-0.023	0.028	-0.055**	0.027				
Labor (MIG)					0.092	0.233	-0.030	0.023
Operating years	0.000	0.002	-0.002	0.001	0.001	0.002	0.002*	0.001
Education	-0.045	0.036	0.017	0.018	-0.050	0.113	-0.003	0.011
Ranching income	0.002	0.014	0.013	0.012	-0.040	0.075	-0.002	0.009
Internal fences	0.004	0.040	0.017	0.037	0.001	0.073	0.012	0.022
Ranch size	0.174**	0.071	0.245***	0.078	-0.174	0.290	-0.086	0.058
Distance	-0.001	0.001	0.000	0.001	-0.002	0.003	0.000	0.001
LCC I&II	-0.001**	0.001	-0.001***	0.001	-0.001	0.003	0.001	0.000
Slope less than 3%	0.000	0.001	-0.001*	0.000	-0.000	0.001	0.000	0.000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Land quality is also an important factor that affects non-adopters' willingness to adopt RG. If land quality is poor, then a non-adopter is more willing to adopt RG. This willingness to adopt might be motivated by the positive ecological effects of rotational grazing, which allows each divided pasture a longer recovery period and thus protect against land degradation. In addition, evidence among non-adopters shows that ranch size is important for RG adoption, perhaps because of scale effects. Wang et al. (2018) have recently reported that the relative benefits of rotational grazing over continuous grazing may be limited for small farms (Wang et al. 2018).

Adoption Decisions at Intensive Margin

Table 2.8 presents estimation results for intensity choices among ranchers. These choices include whether adopters currently have or desire to have greater than five pastures per group of animals on the ranch and whether non-adopters want to have greater than five pastures per group of animals in the future. There is no evidence of peer effects in the intensity choices, and ranchers' intensity choices do not depend on the number of adopters among their personal contacts or adoption rate in the neighborhood. Neither are other variables found to have much impact.

Table 2.8 SEM estimates for intensity choices

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Current intensity for adopters		Desirable intensity for adopters		Future intensity for non-adopters	
Number of adopters known	1.537		0.367		-2.106	
Perceived neighborhood adoption		0.866		0.142		-2.172
Labor	-0.158	-0.092	-0.114	-0.147*	0.016	0.004
Operating years	0.012*	0.012**	0.003	0.004	-0.008	-0.008
Education	0.015	0.039	0.058	0.071	0.147	-0.042
Ranching income	-0.196	-0.149	-0.113	-0.108	-0.076	-0.178
Ranch size	0.199	0.065	-0.127	-0.157	0.147	-0.583
Distance	0.002	0.004	0.000	0.000	0.005	0.010
LCC I&II	-0.002	-0.002	-0.003	-0.003	0.001	-0.001
Slope less than 3%	0.004	0.004	0.005	0.005*	-0.007	-0.006
	# adopters known	Perceived neighborhood adoption	# adopters known	Perceived neighborhood adoption	# adopters known	Perceived neighborhood adoption
Current number for adopters	0.025	0.142				
Desirable number for adopters			0.081	-0.011		
Future number of non-adopters					-0.031	-0.084
Rotational grazing share in county	0.439*	0.618**	0.554**	0.688**	0.588**	0.628**
Observations	439	429	386	377	226	218

Note: *** p<0.01, ** p<0.05, * p<0.1

Conclusion and Further Discussions

Adopting technologies that can protect public resources, is an important topic in the economics literature with direct policy implications. This is especially the case given that some important conservation technologies, including rotational grazing, seem to have adoption rates that are much lower than is desirable for society. This paper seeks to better understand how peer effects and subsidies affect rotational grazing adoption. We develop a theoretical model of grazing practice adoption by assuming that ranchers actively pursue information through peer networking. In doing so we show how subsidies can have a multiplier effect on rotational grazing adoption through indirect peer effects. With farm-level survey data, we apply a simultaneous-equations model to take account of endogeneity issues with peer effects that are measured by two indicators, based on personal close contact and geographic proximity.

Our findings contribute to technology adoption literature by highlighting the importance of peer effects and subsidy impacts in rotational grazing adoption. First, we provide evidence that peer effects promote rotational grazing adoption. Our work adds to the agricultural technology adoption research of Bandiera and Rasul (2006) for a new crop of sunflower, Conley and Udry (2010) for new technologies for pineapple production, and Sampson and Perry (2019) for groundwater rights in that we use a relatively large survey sample, utilize two kinds of peer networking indicators and consider the interaction relationship between adoption decision and networking. Second, our results show that subsidies will have long-run multiplier effects on adoption mediated through the peer networking route. This result provides support for the generality of the findings in Dupas (2014) regarding a new antimalarial bed net and in Carter, Laajaj, and Yang (2019) regarding Green Revolution technology adoption in Mozambique.

Our peer networking estimates have policy importance beyond just documenting the existence of peer effects and subsidy multiplier effects. A strand of the existing literature argues that many approaches can be taken to promote the adoption of novel technologies through managing peer effects (Baerenklau 2005; Bandiera and Rasul 2006; Bollinger and Gillingham 2012; Singh et al. 2018; Kolady et al. 2020). The findings on peer effects and subsidy impacts are especially relevant for policy makers who apply incentive programs such as cost-sharing to encourage voluntary adoption of agricultural conservation practices. Peer effects can provide insights into increasing the efficiency of incentive policies aimed at improving environmental quality through conservation technologies (Baerenklau 2005). For example, policy makers can apply area-targeted policies to promote rotational grazing, i.e., incentive subsidies can be reduced apropriately in areas with higher adoption rates by using the potential power of peer effects so that supportive resources can be concentrated in areas with lower adoption rates.

In addition to government agencies, our surveyed ranchers reported other ranchers, university extension, and associations as important information resources that affected their rotational grazing adoption decisions. University extension could distribute the existing knowledge about the costs and benefits of rotational grazing through ranchers' peer networks. Conservation associations could take some efforts to compensate ranchers who participate in rotational grazing research and education in a manner similar to information provision at solar photovoltaic panel demonstration sites (Bollinger and Gillingham 2012) and cover crop field days (Singh et al. 2018). Our findings also suggest that efforts to leverage peer effects might be most effectively targeted at ranchers with larger ranch scales and a greater number of beef cattle, but of course this approach may conflict with access, inclusion and other policy goals. Overall, governmental and non-governmental agencies could devise a mix of targeted policies, programs, and outreach efforts to scale up the adoption of rotational grazing by utilizing peer effects.

Concerning how to identify peer effects on technology adoption this paper provides insights into theoretical modeling by including network economies, and into empirical methods by addressing the endogeneity issue. However, more efforts should be taken to conduct a comprehensive study of peer effects. One set of matters is the specific nature of peer effects and how they may change over time. Xiong et al. (2016) decompose peer effects into information transmission, experience sharing, and externality effects.. Our current analysis focuses on the experience effects through which experiential knowledge and resources from earlier adopters matter most. Further analysis could explore the dynamic trajectory of peer networking and also investigate how externality effects will influence ranchers' adoption decisions, which may promote or discourage adoption (Xiong et al. 2016).

A further, and very ambitious, topic is to seek for the mechanisms behind peer effects. Our analysis assumes that peer effects occur when people learn information from other adopters and thus technology-related costs will be reduced. However, we do not know the roles that conformity, complementarities, risk sharing, and other motives may play in giving rise to peer effects. Understanding the mechanism behind peer effects is likely to provide insights into policy designs that will promote technology adoption. Progress has been made progress in this regard through structural estimation of theoretical models (Banerjee et al. 2013) and through well-designed experiments (Beugnot et al. 2019; Breza and Chandrasekhar 2019).

Perhaps most important as future research issues are to establish why graziers express limited interest in adoption and whether subsidies to encourage adoption would improve social welfare. These two questions are of course connected because unmeasured costs may be important deterrents to adoption and these costs will enter any social welfare calculation. We have not addressed either question because in each case further information is required.

The survey we conducted did query ranchers about the nature of constraints that they faced in the adoption decision (Che, Feng and Hennessy 2021), but did not request the sort of information that would be required to understand the shadow price of these constraints. That work pointed in particular to capital constraints as an impediment to practice adoption. However, given the detailed nature of the problem and the distinctiveness of each farming operation, a more personalized data gathering endeavor is needed. Doidge, Hennessy and Feng (2020) conducted focus group meetings for landowners in the same general area, along the James River east of the Missouri River in North and South Dakota, to collect data on private costs and benefits of converting grassland to cropland. Intensive data collection endeavors to cost impediments to embracing rotational grazing might best focus on costing out water availability, fencing costs and credit constraints.

The most problematic aspect of addressing whether subsidies directed at encouraging more intensive grazing would improve social welfare is addressing the nature and extent of environmental benefits likely to accrue as a result. A comprehensive accounting of these benefits would be a large-scale endeavor, accounting for local ecosystem effects, water quality consequences right through to lake and ocean levels, and greenhouse gas emission consequences. In addition, indirect land use effects may arise to the extent that the subsidies encourage grass-based agriculture instead of crop-based agriculture.

REFERENCES

REFERENCES

Alkemade, R., R.S. Reid, M. van den Berg, J. de Leeuw, and M. Jeuken. 2013. Assessing the Impacts of Livestock Production on Biodiversity in Rangeland Ecosystems. *Proceedings of the National Academy of Sciences* 110 (52): 20900–20905.

Arora, G., H. Feng, D.A. Hennessy, C.R. Loesch, and S. Kvas. 2021. The Impact of Production Network Economies on Spatially-Contiguous Conservation–Theoretical Model with Evidence from the US Prairie Pothole Region. *Journal of Environmental Economics and Management* 107: 102442.

Baerenklau, K.A. 2005. Toward an Understanding of Technology Adoption: Risk, Learning, and Neighborhood Effects. *Land Economics* 81 (1): 1–19.

Bandiera, O., and I. Rasul. 2006. Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal* 116 (514): 869–902.

Banerjee, A., A.G. Chandrasekhar, E. Duflo, and M.O. Jackson. 2013. The Diffusion of Microfinance. *Science* 341 (6144): 1236498–1236498.

Bénabou, R. 2015. The Economics of Motivated Beliefs. *Revue d'Économie Politique* 125 (5): 665–685.

Bertrand, M., E.F. Luttmer, and S. Mullainathan. 2000. Network effects and welfare cultures. *The Quarterly Journal of Economics* 115 (3): 1019–1055.

Beugnot, J., B. Fortin, G. Lacroix, and M.C. Villeval. 2019. Gender and Peer Effects on Performance in Social Networks. *European Economic Review* 113: 207–224.

Bollinger, B., and K. Gillingham. 2012. Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science* 31 (6): 900–912.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2009. Identification of Peer Effects through Social Networks. *Journal of Econometrics* 150 (1): 41–55.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2020. Peer Effects in Networks: A Survey. *Annual Review of Economics* 12 (1): 603–629.

Breza, E., and A.G. Chandrasekhar. 2019. Social Networks, Reputation, and Commitment: Evidence From a Savings Monitors Experiment. *Econometrica* 87 (1): 175–216.

Cai, J., A. de Janvry, and E. Sadoulet. 2020. Subsidy Policies and Insurance Demand. *American Economic Review* 110 (8): 2422–2453.

Carter, M., R. Laajaj, and D. Yang. 2019. Subsidies and the African Green Revolution: Direct Effects and Social Network Spillovers of Randomized Input Subsidies in Mozambique.

No. w26208, National Bureau of Economic Research. Available at: http://www.nber.org/papers/w26208.pdf [Accessed November 1, 2020].

Che, Y., H. Feng, and D.A. Hennessy. 2021. *Grazing Practice Choices, Capital Constraints, and the Environment.* Selected Paper for Lightning Session Presentation at AAEA Annual Meeting, Austin, TX, Aug. 1-3, 2021.

Conley, T.G., and C.R. Udry. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100 (1): 35–69.

Cowan, R., and P. Gunby, P.1996. Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies. *The Economic Journal* 106(436): 521-542.

Crawford, C.L., Z.M. Volenec, M. Sisanya, R. Kibet, and D.I. Rubenstein. 2019. Behavioral and Ecological Implications of Bunched, Rotational Cattle Grazing in East African Savanna Ecosystem. *Rangeland Ecology & Management* 72 (1): 204–209.

Derner, J.D., D.J. Augustine, D.D. Briske, H. Wilmer, L.M. Porensky, M.E. Fernández-Giménez, D.E. Peck, and J.P. Ritten. 2021. Can Collaborative Adaptive Management Improve Cattle Production in Multipaddock Grazing Systems? *Rangeland Ecology & Management* 75: 1–8.

Dillman, D.A., J.D. Smyth, and L.M. Christian. 2014. *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. John Wiley & Sons.

Doidge, M., D.A. Hennessy, and H. Feng. 2020. The Role of Economic Returns in Land Use Change: Evidence from Farm-Level Data in the US Northern Great Plains. *Journal of Soil and Water Conservation* 75(5): 669-679.

Dupas, P. 2014. Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment. *Econometrica* 82 (1): 197–228.

Epley, N., and T. Gilovich. 2016. The Mechanics of Motivated Reasoning. *Journal of Economic Perspectives* 30 (3): 133–40.

Feder, G., R.E. Just, and D. Zilberman. 1985. Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development & Cultural Change* 33 (2): 255–298.

Foster, A.D., and M.R. Rosenzweig. 1995. Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy* 103 (6): 1176–1209.

Gillespie, J.M., W. Wyatt, B. Venuto, D. Blouin, and R. Boucher. 2008. The roles of labor and profitability in choosing a grazing strategy for beef production in the U.S. Gulf Coast Region. *Journal of Agricultural & Applied Economics* 40 (1): 301–313.

Granovetter, M. 1985. Economic Action and Social Structure: The Problem of Embeddedness.

American Journal of Sociology 91 (3): 481–510.

Graziano, M., and K. Gillingham. 2015. Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment. *Journal of Economic Geography* 15 (4): 815–839.

Hawkins, H.J. 2017. A global assessment of Holistic Planned Grazing™ compared with season-long, continuous grazing: meta-analysis findings. *African Journal of Range & Forage Science* 34 (2): 65–75.

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

Jakoby, O., M.F. Quaas, S. Baumgärtner, and K. Frank. 2015. Adapting livestock management to spatio-temporal heterogeneity in semi-arid rangelands. *Journal of Environmental Management* 162: 179–189.

Keshk, O.M.G. 2003. CDSIMEQ: A Program to Implement Two-stage Probit Least Squares. *The Stata Journal* 3 (2): 157–167.

Kolady, D., W. Zhang, T. Wang, and J. Ulrich-Schad. 2020. Spatially Mediated Peer Effects in the Adoption of Conservation Agriculture Practices. *Journal of Agricultural & Applied Economics* 1–20.

Maddala, G.S. 1983. *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press.

Manski, C.F. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* 60 (3): 531–542.

Manson, S.M., N.R. Jordan, K.C. Nelson, and R.F. Brummel. 2016. Modeling the effect of social networks on adoption of multifunctional agriculture. *Environmental Modelling & Software* 75: 388–401.

McFadden, D. 1974. The Measurement of Urban Travel Demand. *Journal of Public Economics* 3 (4): 303–328.

Milgrom, P., and J. Roberts. 1990. Rationalizability, Learning, and Equilibrium in Games with Strategic Complementarities. *Econometrica* 58 (6): 1255–1277.

Munshi, K. 2004. Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution. *Journal of Development Economics* 73 (1): 185–213.

Munshi, K., and J. Myaux. 2002. Development as a Process of Social Change: An Application to the Fertility Transition. *University of Pennsylvania, mimeo*.

Nelson, K.C., R.F. Brummel, N. Jordan, and S. Manson. 2014. Social Networks in Complex Human and Natural Systems: The Case of Rotational Grazing, Weak Ties, and Eastern

US Dairy Landscapes. *Agriculture & Human Values* 31 (2): 245–259.

Park, J.Y., S. Ale, and W.R. Teague. 2017. Simulated Water Quality Effects of Alternate Grazing Management Practices at the Ranch and Watershed Scales. *Ecological Modelling* 360: 1–13.

Roche, L.M., B.B. Cutts, J.D. Derner, M.N. Lubell, and K.W. Tate. 2015. On-Ranch Grazing Strategies: Context for the Rotational Grazing Dilemma. *Rangeland Ecology & Management* 68 (3): 248–256.

Roe, B., E.G. Irwin, and J.S. Sharp. 2002. Pigs in Space: Modeling the Spatial Structure of Hog Production in Traditional and Nontraditional Production Regions. *American Journal of Agricultural Economics* 84(2): 259-278.

Rysman, M. 2019. The Reflection Problem in Network Effect Estimation. *Journal of Economics & Management Strategy* 28(1): 153-158.

Sampson, G.S., and E.D. Perry. 2019. The Role of Peer Effects in Natural Resource Appropriation – The Case of Groundwater. *American Journal of Agricultural Economics* 101 (1): 154–171.

Searchinger, T.D., S. Wirsenius, T. Beringer, and P. Dumas. 2018. Assessing the Efficiency of Changes in Land Use for Mitigating Climate Change. *Nature* 564 (7735): 249–253.

Singh, A., B. MacGowan, M. O'Donnell, B. Overstreet, J. Ulrich-Schad, M. Dunn, H. Klotz, and L. Prokopy. 2018. The Influence of Demonstration Sites and Field Days on Adoption of Conservation Practices. *Journal of Soil & Water Conservation* 73 (3): 276–283.

Steinfeld, H., P. Gerber, T.D. Wassenaar, V. Castel, M. Rosales, M. Rosales, and C. de Haan. 2006. *Livestock's Long Shadow: Environmental Issues and Options*. Food & Agriculture Org.

Teague, W.R., U.P. Kreuter, W.E. Grant, H. Diaz-Solis, and M.M. Kothmann. 2009. Economic Implications of Maintaining Rangeland Ecosystem Health in a Semi-arid Savanna. *Ecological Economics* 68 (5): 1417–1429.

Undersander, D.J., B. Albert, D. Cosgrove, D. Johnson, and P. Peterson. 2002. *Pastures for Profit: A Guide to Rotational Grazing*. Cooperative Extension Publications, University of Wisconsin-Extension.

USDA National Agricultural Statistics Service. 2017. NASS - Quick Stats. USDA National Agricultural Statistics Service. https://data.nal.usda.gov/dataset/nass-quick-stats. Accessed 2019-11-03.

Wang, T., H. Jin, U. Kreuter, H. Feng, D.A. Hennessy, R. Teague, and Y. Che. 2020. Challenges for Rotational Grazing Practice: Views from Non-adopters Across the Great Plains, USA. *Journal of Environmental Management* 256: 109941.

Wang, T., W. R. Teague, S.C. Park, and S. Bevers. 2018. Evaluating Long-term Economic and Ecological Consequences of Continuous and Multi-paddock Grazing - A Modeling Approach. *Agricultural Systems* 165: 197–207.

Windh, J.L., J.P. Ritten, J.D. Derner, S.I. Paisley, and B.P. Lee. 2019. Economic Cost Analysis of Continuous-Season-long versus Rotational Grazing Systems. *Western Economics Forum* 17 (1837-2019–947): 62–72.

Xiong, H., D. Payne, and S. Kinsella. 2016. Peer Effects in the Diffusion of Innovations: Theory and Simulation. *Journal of Behavioral & Experimental Economics* 63: 1–13.

CHAPTER 3 Will Adoption Occur if Viewed by a Decisionmaker as Win-Win for Profit and the Environment? An Application to a Rancher's Grazing Practice Choices

Abstract

There is a large literature on the "adoption gap" which describes the slow adoption of a technology that appears to be win-win technology for both profit and the environment. The extent of and reasons for such adoption gaps differ across technologies. We examine this gap in the context of rotational grazing. While rotational grazing has the potential to provide both economic and environmental benefits, the set of ranchers that adopts falls far short of the set that could potentially adopt. To investigate this gap and learn about both adoption decisions and motivations, we survey 874 ranchers on the U.S. Great Plains. In contradiction to basic economic reasoning, we find that the majority (57%) of surveyed ranchers who view rotational grazing as win-win for both profit and the environment do not adopt the practice. We also find that win-win non-adopters are a very constrained group for most potential challenges to rotational grazing adoption, especially high initial costs, water resource limitations, and ranch conditions. Some of these challenges could be relieved by capital; however, win-win non-adopters have limited borrowing capacity and constrained access to operating capital. They are more willing to adopt rotational grazing than others when a one-time hypothetical subsidy is offered, suggesting that win-win non-adopters hold promise as a target group for subsidies to reduce the cost of adoption. Consistent with the literature, our analysis shows the importance of understanding the specifics of the adoption gap for effective policymaking.

Introduction

Many conservation practices have been shown to enhance economic profits and improve the environment. They can reduce the negative effects of production on environmental conditions. For example, conservation tillage can enhance overall soil health as well as reduce fuel and labor costs (Hodde et al. 2019); nutrient management practices can mitigate nutrient loss to the environment; while cover crops can help to improve soil quality, alleviate drought stress, and reduce input costs (Bergtold et al. 2019). The U.S. federal government provides financial and technical assistance to promote conservation practice adoption through various programs such as Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP). Other government and nongovernmental entities also provide voluntary payment programs to support conservation practices (Claassen, Duquette and Smith 2018). Despite various efforts to encourage conservation practices, and despite a vibrant literature that addresses incentives for conservation practice adoption, there often remains a large "adoption gap" between the set that could potentially adopt a practice and the set that actually adopts (Prokopy et al. 2019). For example, the adoption of no-till farming presents a distinction between willingness to adopt and feasibility (Nowak 1992).

The adoption gap is not unique to the agriculture sector. A similar phenomenon exists in the energy sector, where a large literature documents the "energy efficiency gap," defined as the difference between actual energy use and optimal energy use (Allcott and Greenstone 2012; Gillingham and Palmer 2014). The gap is often defined more broadly as the slower than socially optimal diffusion rate of energy-efficient products. According to Gerarden, Newell and Stavins (2017), potential explanations for this gap fall into three categories, namely market failures, behavioral explanations, and model or measurement errors. Backlund et al. (2012) also summarize the barriers to energy efficiency, identifying limited access to capital, bounded rationality, and lack of information as potential barriers to energy efficiency technology diffusion.

Many studies have also explored the determinants of “adoption gap” related to conservation practices in agricultural contexts. Prokopy et al. (2019) conduct a comprehensive review of quantitative studies focusing on the adoption of agricultural conservation practices in the United States over 1982-2017. Factors found to be important include farmers’ attitudes toward the environment, attitudes towards a particular practice, previous adoption of other conservation practices, social networking, land quality, farm size, and farmer characteristics. Knowler and Bradshaw (2007) summarize the underlying factors in adoption decisions into three categories, namely farmer characteristics, farm biophysical and financial characteristics, and other factors including government support and price shocks. Other causes of adoption gaps relative to stated preferences include real options optimal delay strategies (Song, Zhao and Swinton 2011), transaction costs of participation in subsidy programs (Palm-Forster et al. 2016), and provision bias (Lloyd-Smith and Adamowicz 2018). However, no common explanation has emerged across different conservation practices for why the adoption gap exists. Carlisle (2016) points out that, in the context of soil health practices, the role of economic factors generally appeared to be secondary rather than primary. This research also notes that while economic factors are unlikely to motivate farmers’ adoption of practices, they could be important in removing barriers.

This paper focuses on rotational grazing, which is considered by many researchers to be a profit-increasing and environment-friendly conservation practice. Rotational grazing can address many of the concerns arising from traditional continuous grazing. Under rotational grazing, pastures are divided into multiple paddocks typically by temporary fencing. Livestock are rotated through paddocks with only one paddock grazed at a time while the other paddocks rest. Due to higher stocking density on each paddock being grazed, the livestock are forced to be less picky and will graze back, and discourage from proliferation, a higher proportion of less preferred plant species. The practice also protects from overgrazing the species that are more productive for beef enterprises and so improves ranch productivity (Chaubey et al. 2010; Teague, Grant and Wang 2015). In addition to environmental benefits, rotational grazing can provide higher profit when compared with traditional grazing practices (Teague et al. 2009; Jakoby 2015; Wang et al. 2018).

Despite the potential benefits, the rotational grazing adoption rate was only about 31% in 2017 (USDA NASS, 2017). There was also a declining trend in adoption, from 43% of all grazing enterprises in 2007 to 31% in 2017 (Table 3.1). At the same time, we can observe the number of rotational grazing operations decreased every five years from 2007 while the total operation number across cattle, goat, and sheep operations also decreased since 2002 but had a slight increase between 2012 and 2017. Similar phenomena can be found at the state level. As is shown in Figure 3.1, the rotational grazing adoption rates had a declining trend over 2007-2017 in the states of North Dakota, South Dakota, and Texas. Spatial variations also exist, and the practice has become popular over the decade on the small amounts of grassland along the northeastern coast (Figure 3.2). Figure 3.3 shows the percentage change in rotational grazing adoption rates between 2007 and 2017. Adoption rates have clearly declined in most counties in 2017 when compared with 2007.

Table 3.1 Rotational grazing operations and adoption rate in the selected states and the United States (USDA NASS 2017)

Year	Number of rotational grazing operations				Total number of cattle, goat, and sheep operations				Adoption rate			
	ND	SD	TX	U.S.	ND	SD	TX	U.S.	ND	SD	TX	U.S.
2002	N/A	N/A	N/A	N/A	8,249	13,537	143,016	914,205	N/A	N/A	N/A	N/A
2007	5,221	7,473	50,225	388,912	6,701	10,879	141,520	907,228	0.78	0.69	0.35	0.43
2012	3,270	4,485	41,401	288,719	5,447	9,900	144,883	826,719	0.60	0.45	0.29	0.35
2017	3,019	4,449	38,070	265,162	6,316	10,326	155,685	852,907	0.48	0.43	0.24	0.31

Note: The adoption rate is calculated by dividing the number of rotational grazing operations by the total number of cattle, goat, and sheep operations. “N/A” represents that data is not available.

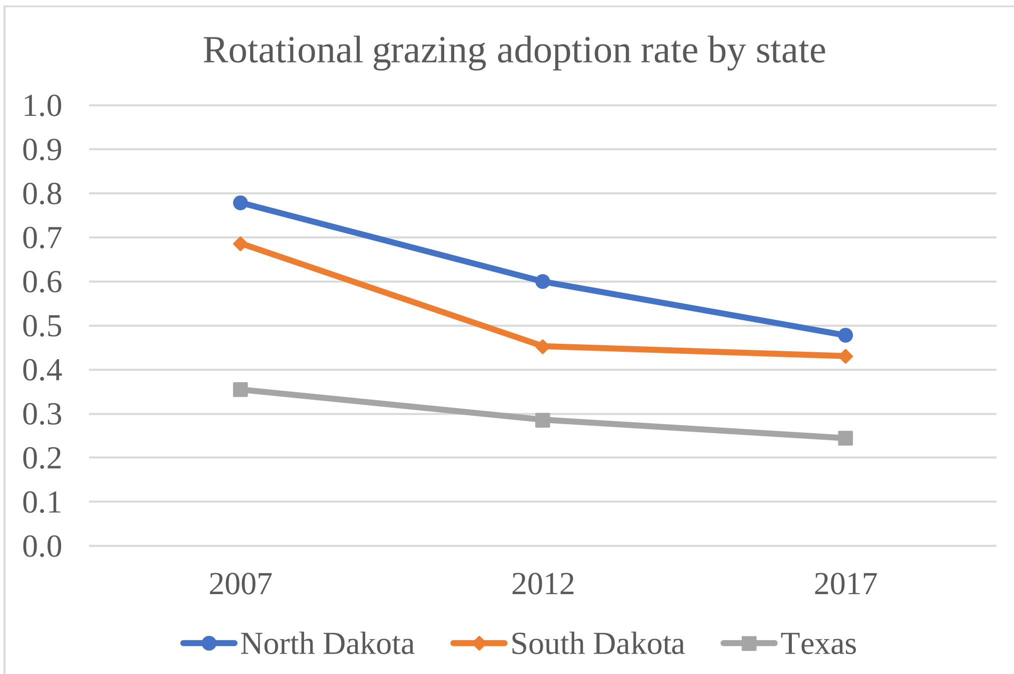


Figure 3.1 Recent rotational grazing adoption rates in North Dakota, South Dakota, and Texas
Note: Adoption rate is calculated by dividing the number of rotational grazing operations over the total number of cattle, goat, and seep operations within each state

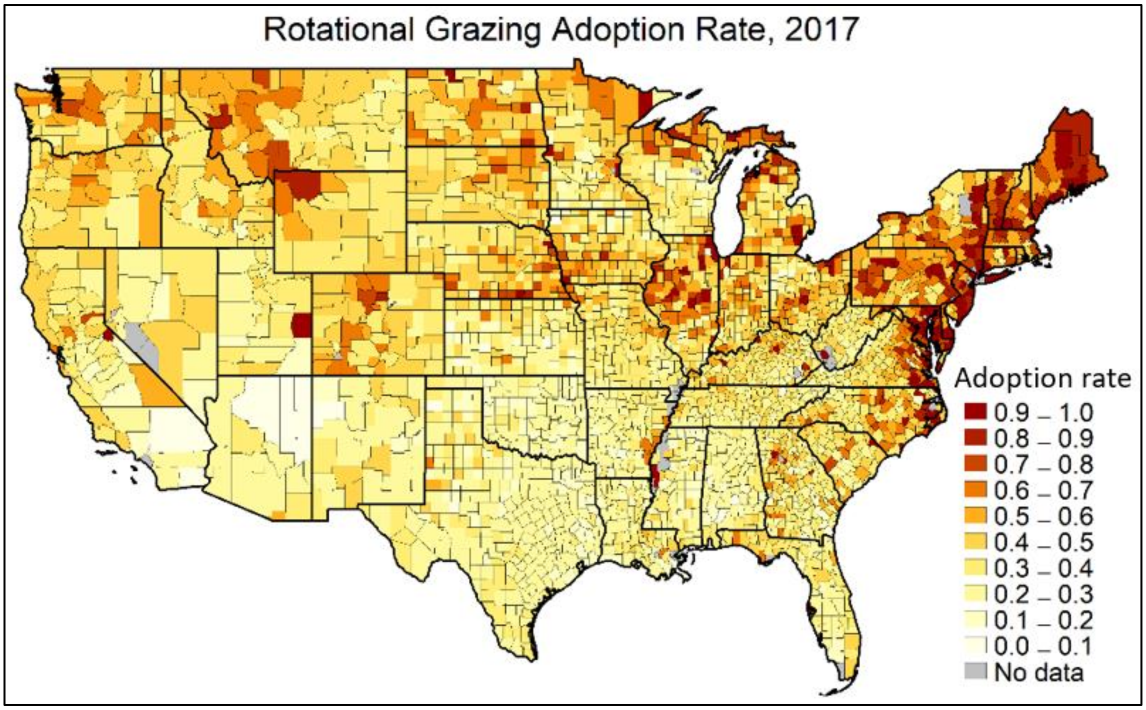


Figure 3.2 County-level rotational grazing adoption rates in 2017

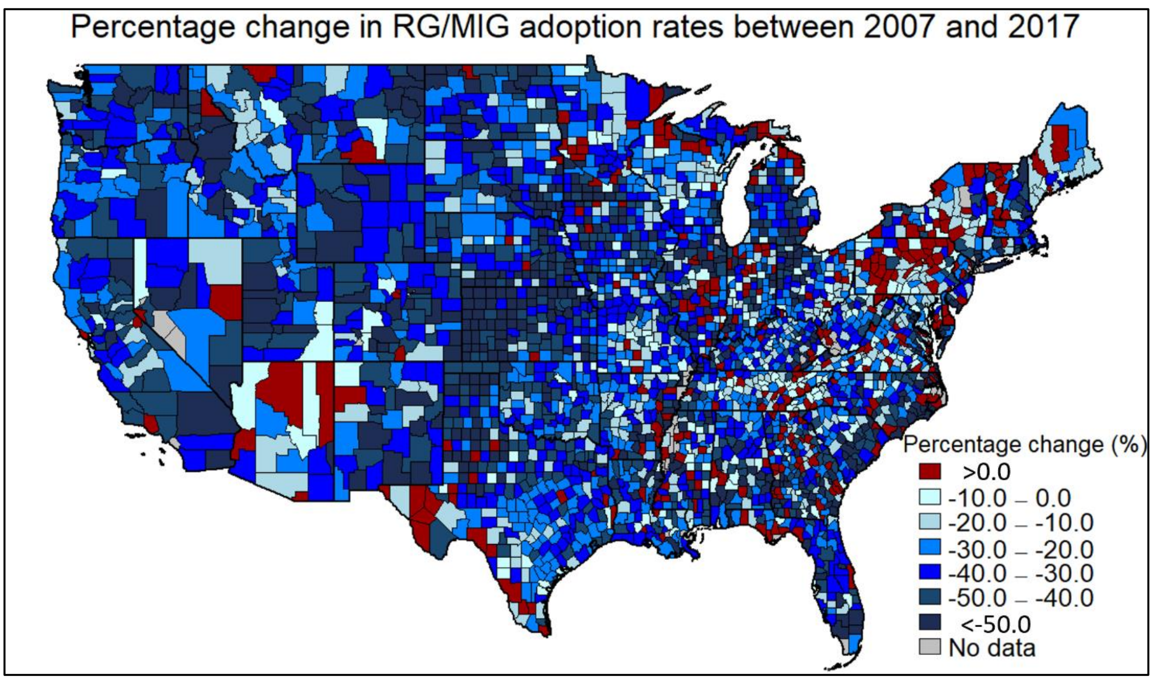


Figure 3.3 Percentage change in rotational grazing adoption rates between 2007 and 2017
Note: Percentage change is calculated by dividing the difference in adoption rates between 2017 and 2007 by the adoption rate in 2007

In order to investigate the reasons for low adoption rates and better understand rancher adoption decision processes, in early 2018 we sent out a survey to beef operators on the U.S. Great Plains. Contrary to basic economic reasoning we find from survey responses that many ranchers who viewed rotational grazing as a win-win practice for their own profit and environmental outcomes did not adopt it. The purposes of this paper are to investigate the factors that resulted in non-adoption decisions among these ranchers and to explore possible incentives approaches for encouraging them to adopt rotational grazing.

Our paper contributes to the literature in the following ways. First, from a conceptual perspective, we discuss a rancher's decision on whether to adopt rotational grazing when accounting for both economic profits and own environmental outcomes. The inclusion of these two attributes extends the literature that emphasizes only one of the two. For example, Basarir and Gillespie (2006) find that beef producers regard environmental goals to be more important than maximizing profit. Our conceptual framework also adds to the work by Kim, Gillespie and Paudel (2008), who apply a random utility model on rotational grazing adoption including both profit and environmental impacts, but they focus on the role of uncertainty in the adoption with a cost-share payment.

Second, we document the extent of the rotational grazing adoption gap and further assess the extent of win-win non-adoption in terms of profit and the environment. About 57% of non-adopters in our sample regarded rotational grazing as a win-win practice. It is important to note that the win-win views analyzed in our paper are those of the ranchers themselves, this is in contrast to the win-win characterization of a technology by researchers based on lab or field experiments. Given that the win-win views are decision-makers' own perceptions, not external data the decision-makers have learned about, it will be more remarkable if the decision-makers with win-win views do not adopt the technology.

Third, we use a relatively large survey sample to identify the main barriers that constrain win-win non-adopters and the factors that induce potential barriers. Other studies of rotational grazing have been much smaller, generally with a survey sample of less than 100 (Kim, Gillespie and Paudel 2008; Nelson et al. 2014; Manson et al. 2016). We also explore ranchers' opinions about rotational grazing using responses from open-ended survey questions rather than rely on secondary data sources. Finally, we investigate the effects of incentive programs on the adoption decisions of the win-win non-adopters in comparison with other non-adopters.

Our findings are as follows. First, a large proportion (56.5%) of non-adopters regarded rotational grazing as a win-win practice, while about 76.4% of adopters viewed rotational grazing to be a win-win practice. Second, win-win non-adopters were a very constrained group for most potential challenges to rotational grazing adoption, especially "high initial costs", "water resource constraint", and "ranch conditions." Most challenges could be relieved by capital; however, win-win non-adopters had limited borrowing capacity and constrained access to operating capital. Their concerns about costs and capital are also revealed through our analysis of open-ended comments. Further, we find that the win-win nonadopters reported themselves to be more willing to adopt rotational grazing than others when a one-time hypothetical subsidy was offered. The findings suggest that these win-win non-adopters may be a suitable target group for investment subsidies intended to effectively promote the adoption of rotational grazing, and that the policies will be more effective when they adequately address the costs and constraints that ranchers face.

In what follows, we provide a conceptual characterization of a rancher's decision to choose over a grazing practice in terms of both own profits and environmental outcomes. We then describe the survey's implementation and data. After that, we identify how potential barriers constrain win-win non-adopters and other groups. Next, we use open-ended comments to analyze the ranchers' views on rotational grazing. After comparing responses to hypothetical subsidies by win-win non-adopters and by other groups, we conclude with some brief comments on how our findings can be placed in the policy arena.

Conceptual Considerations

Let $A_i \in \{ext, \mathrm{int}\}$ denote the potential decision choice set, where *ext* represents continuous grazing practice, and *int* represents rotational grazing practice. We assume each grazing practice choice has two attributes, i.e., economic profit (π) and private environmental benefit (*E*). The utility function is given as $U(\pi(A_i), E(A_i))$ and is assumed to be monotonic in both arguments. Thus rancher indifference curves are downward sloping. Figure 3.4a depicts the two attributes along with an indifference curve that indicates the trade-off between profit and environmental benefits for an individual farmer. Suppose that the profit and environmental benefits of continuous grazing are located at point *x* in the figure. Then the whole area can be divided into four quadrants for rotational grazing in terms of profit and environmental outcomes, relative to those of continuous grazing: win-win, win-loss, loss-loss, loss-win. The four quadrants represent four possible cases with regard to ranchers' opinions and choices on rotational grazing. The decisions in the win-win case and the loss-loss case are clear while the decisions in the other two quadrants are less clear. We will describe each case below.

(1) Loss-loss case: If rotational grazing is a loss-loss practice in terms of profit and the environment compared to continuous grazing, then $U(\pi(ext), E(ext)) \geq U(\pi(\mathrm{int}), E(\mathrm{int}))$ holds for any utility function U , so ranchers will not switch from continuous grazing.

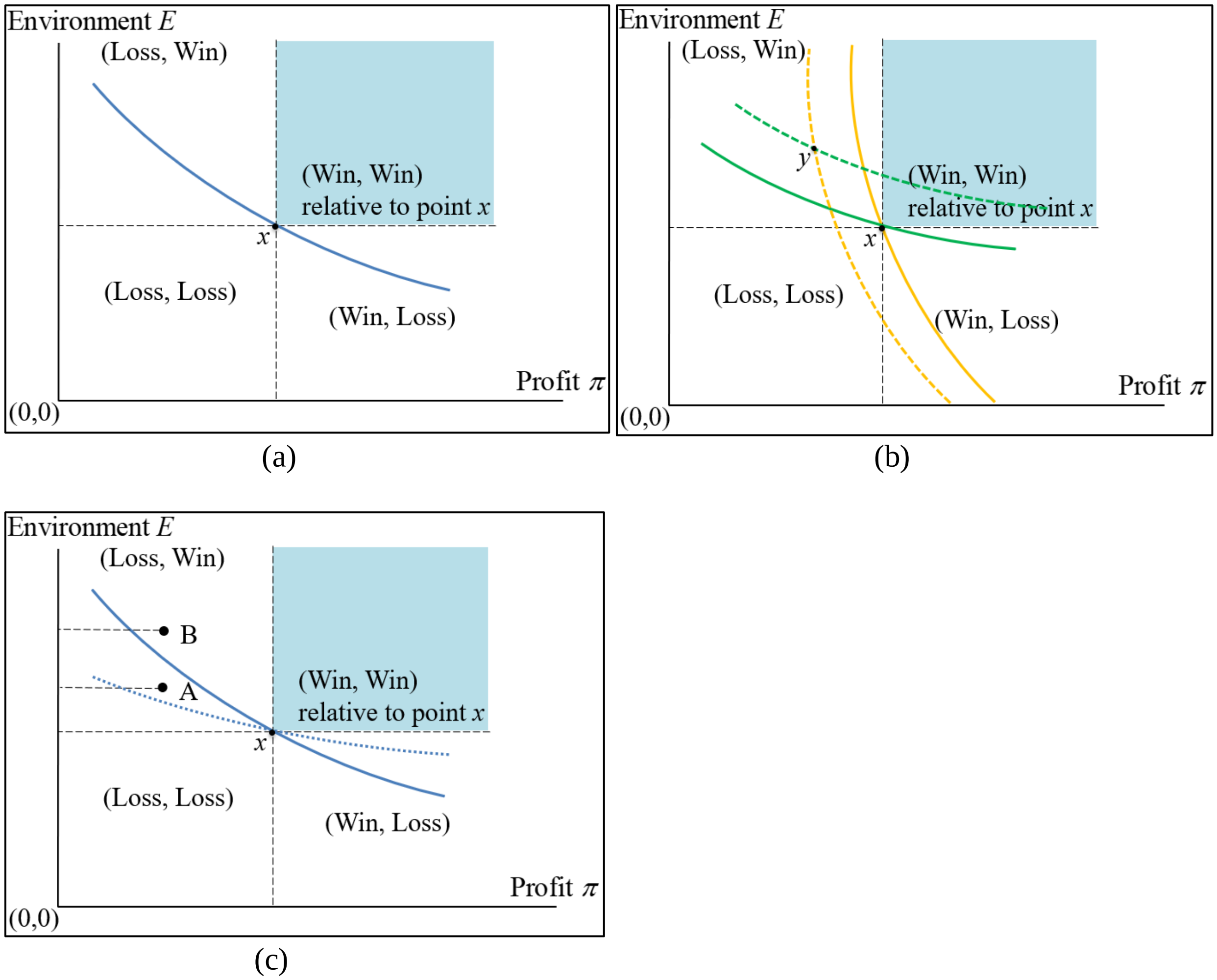


Figure 3.4 Profit-environment indifference between practices

(2) Loss-win case: If rotational grazing is a loss-win practice in terms of profit and the environment, then it is not clear whether a rancher will derive higher utility from rotational grazing and adopt it. Take point *y* as an example of rotational grazing in the loss-win case, the dashed lines represent indifference curves through point *y* (Figure 3.4b). The ranchers with green-colored indifference curves will be better off when choosing rotational grazing *y* compared to continuous grazing *x*. They put more weight on the environmental outcomes than profit with flatter indifference curves and will be more likely to choose rotational grazing. On the other hand, the ranchers with yellow-colored steeper indifference curves treat profit as more important than the environment and they will be worse when choosing rotational grazing *y* compared to *x*,

so they will be more likely to keep continuous grazing.

(3) Win-loss case: Contrary to the second case, when rotational grazing is a win-loss practice in terms of profit and environment, the region southeast of *x* applies. Still applying the indifference curve examples in Figure 3.4b, ranchers who put more weight on the environment than on profit will be more likely to keep continuous grazing. The corresponding indifference curves are just like the green-colored lines. Otherwise, those who treat profit as more important than the environment will be more likely to choose rotational grazing.

(4) If rotational grazing is a win-win practice for both profit and environment when compared with continuous grazing, then $U(E(ext),\pi(ext)) < U(E(\text{int}),\pi(\text{int}))$ holds for any utility function form. The rational choice by aware ranchers with monotone preferences should be rotational grazing. There can be a variety of reasons why aware, rational ranchers with win-win views will not adopt rotational grazing. These include (i) financial, physical, or other tangible constraints, (ii) measurement errors, or (iii) behavioral reasons. Measurement errors might be possible in our case because our measurement of win or loss is based on survey data that asked farmers to state the economic and environmental impacts. This subjective statement might exaggerate the actual benefits or losses. Behavioral reasons are not evident, which have many possibilities including ranchers' retirement status, or personality disposition of keeping the status quo. Ranchers who are about to retire, might not like to try a new practice due to potential uncertainties. In our paper, we focus on the likely effects of financial and physical constraints for not adopting decisions, because these constraints have traditionally been the focus of policy interventions and also because different types of research methods would be required to examine the other two reasons.

Turning to Figure 3.4c, with the blue solid indifference curve, the traditional theory would rancher preferring *x* to *A* where *A* is private (E, π) pair but society would prefer *B* to *x* where *B* is public (E, π) pair. For these two points, profits are the same as society place extra value only on the environment. The traditional policy would try to twist the indifference curve down so that *A* is preferred to *x*, just as changing from the blue solid line to the dashed one. Promoting environmental protection knowledge among ranchers might be one example. But if *A* is in the (Win, Win) quadrant then there is no need to shift the indifference curve. Other subsidized incentive policies might help in this regard.

Survey Description

In early 2018 we sent out a survey to beef operators in 49 North Dakota and 58 South Dakota counties as well as 81 counties in Central and North Texas. The areas were chosen because they are the northern and southern extremities of the U.S. Great Plains and incorporate a relatively higher proportion of livestock operations than does the Central Plains, where irrigated crop production dominates. The screening criterion for rancher selection is that each respondent operated at least 100 non-feedlot cattle.[21] We purchased contact information for 4,500 randomly selected ranchers in three states from Survey Sampling International.[22] The survey was implemented by following the Dillman mail survey administration method (Dillman, Smyth and Christian 2014). During the period from late January 2018 to early April 2018, we sent out an advance letter of notification, two survey questionnaire mailings, and two postcard reminders. In late June 2018, a final survey packet was re-sent to secure a higher response rate.

[21] To account for the differences in the number of qualified ranches in each county, we used proportional sampling to select 1,500 ranches in each state. The sample size for each county is obtained from multiplying 1,500 by a ratio, the ratio being the number of qualified farms for each county over the total number of qualified farms across all the selected counties in each state (Wang et al., 2020).

[22] The company has gone through a merger and re-branding, and it is now part of Dynata. https://www.dynata.com/press/announcing-new-name-and-brand-research-now-ssi-is-now-dynata/.

A total of 874 recipients completed and returned the survey questionnaires with an overall response rate of 20.6%. Among all respondents average grassland acres, both native rangeland and improved pastures, was about 2,807 and average cattle herd size was 364. The percentage of respondents' total household income from ranching operations was between 20% and 40% on average. About 59% of respondents were currently practicing rotational grazing while the residual had either never adopted or had discontinued the practice.

Ranchers were asked to indicate whether rotational grazing was a win-win practice in terms of its effects on both the economic profit and the environment. For economic profit, adopters were asked "How has your adoption of rotational grazing or MIG affected (or will likely affect) the economic profit of your ranch during the first 5 years?"; while non-adopters were asked "To what degree do you think that rotational grazing or MIG might affect the economic profit of your ranch in the first 5 years?". Both sets had five option choices with 1="significantly decrease", 2="slightly decrease", 3="no influence", 4="slightly increase", and 5="significantly increase." We encode as a "win" practice for the profit whenever the rancher chose "slightly increase" or "significantly increase" for the above questions.

For the environment, ranchers were asked "whether or not you have adopted, please indicate what you observe or expect regarding the following possible benefits associated with rotational grazing or MIG practices on your ranch or neighboring ranchers." The proposed potential benefits include "increased percentage of desirable grass", "decreased runoff and erosion", and "increased drought resilience/faster drought recovery." They were offered four option choices for each benefit with 1="none", 2="slight", 3="medium", and 4="significant." We encode as a "win" practice for the environment whenever the rancher chose "slight", "medium" or "significant" for any of the above three environmental benefits.

Data Analysis

Win-Win Non-Adopters and Their Constraints

Although adopters and non-adopters expressed diverse views on the profit effects of rotational grazing adoption, as shown in Figure 3.5 the majority in both groups were of the view that rotational grazing was a profit-increasing practice. Indeed, 57% of non-adopters perceived the practice as profit increasing. A greater proportion (83%) of non-adopters thought that rotational grazing would increase the required labor and management time than did adopters (61%). But different perceptions about grassland productivity impacts also explain the less enthusiastic views about practice profitability among non-adopters. Fewer non-adopters reported that rotational grazing would prolong the grazing season, increase stocking rate capacity, increase livestock weight gain, and improve livestock health than adopters (Figure 3.6). For example, about 96% of adopters and 83% of non-adopters reported that rotational grazing would increase livestock weight gain while about 92% of adopters and 73% of non-adopters reported that rotational grazing would improve livestock health.

Most adopting (99%) and non-adopting (89%) respondents agreed that rotational grazing would improve the environment by increasing desirable grass production, decreasing runoff and erosion as well as improving drought resilience and recovery (Figure 3.6). A greater proportion of adopters regarded the above environmental benefits to be significant when compared with non-adopters. Table 3.2 shows that perceptions about economic and environmental effects align well. Most adopters (76%) regarded rotational grazing as a win-win practice. Among non-adopters, about 57% thought rotational grazing to be a win-win practice. Therefore, ranchers did not adopt rotational grazing not because they had not perceived the potential economic and environmental benefits but because there were other possible reasons that we will discuss later.

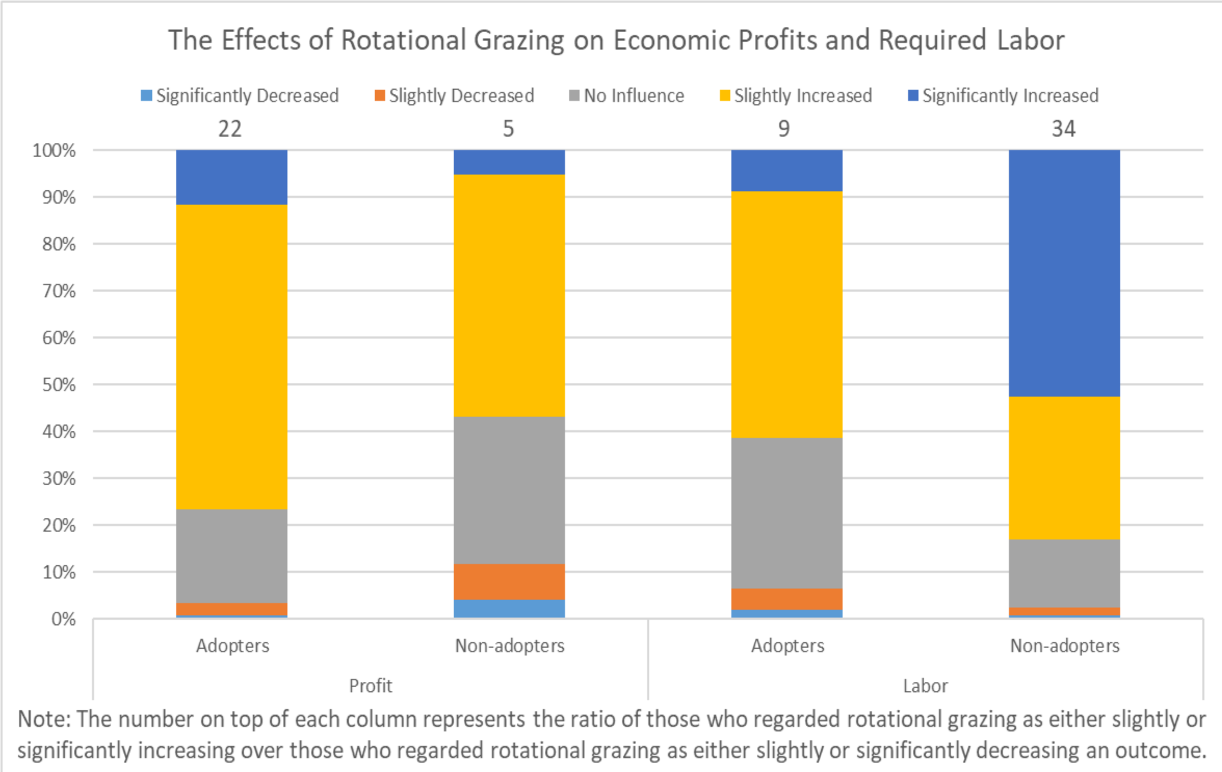


Figure 3.5 Adopter and non-adopter opinions about the effects of rotational grazing adoption on the ranch profit during the first five years, and on the needed labor and management time

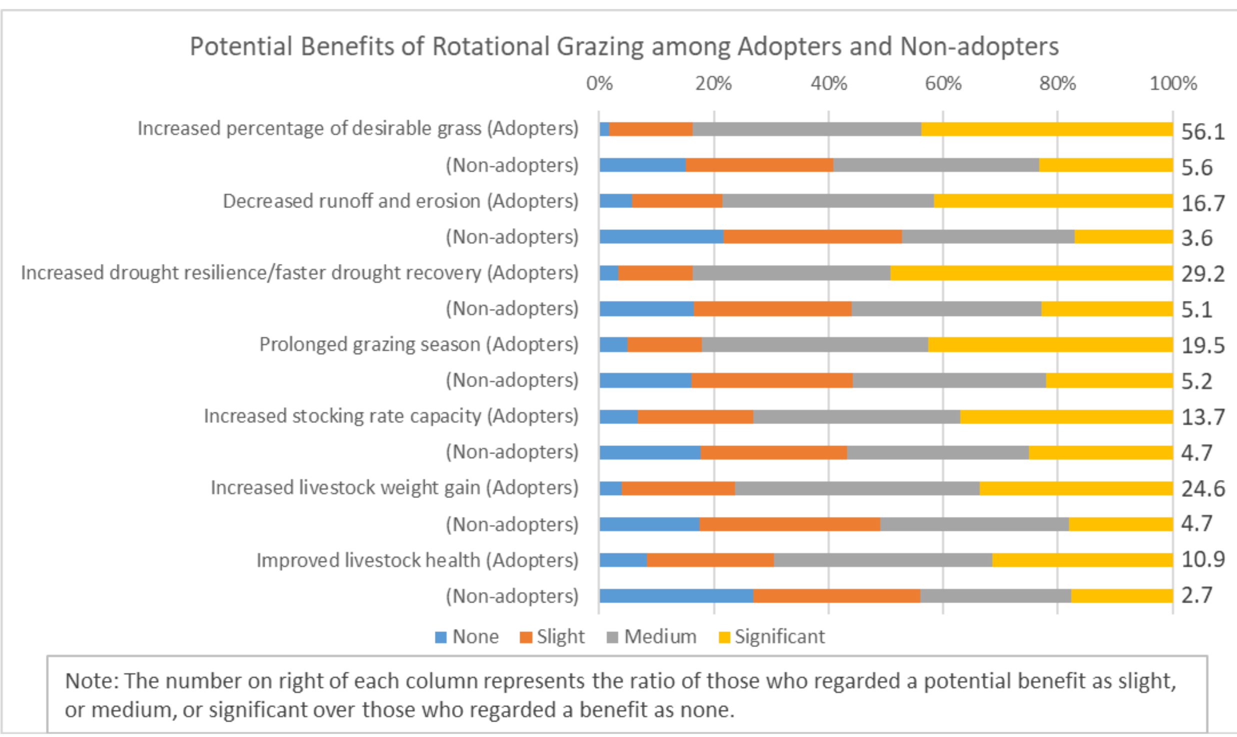


Figure 3.6 The potential benefits associated with rotational grazing practices among adopters and non-adopters

Table 3.2 Economic and environmental outcomes of rotational grazing adoption

Adopters		Economic Profit		
		Improved	*Worsened*	*No impact*
Environmental Outcomes	*Improved*	(Win, Win) 76.4%	(Win, Loss) 3.5%	(Win, No change) 19.5%
	No impact	(No change, Win) 0.2%	(No change, Loss) 0.0%	(No change, No change) 0.4%

Non-adopters		Economic Profit		
		Improved	*Worsened*	*No impact*
Environmental Outcomes	*Improved*	(Win, Win) 56.5%	(Win, Loss) 9.7%	(Win, No change) 23.0%
	No impact	(No change, Win) 1.8%	(No change, Loss) 2.2%	(No change, No change) 6.8%

It is intuitive that a rancher seeking to stay in business may not adopt a practice whenever environmental gains are not accompanied by profit. However, the finding that many ranchers viewed rotational grazing as both profit-increasing and environment friendly yet did not adopt goes against basic economic reasoning. To better understand the decision by win-win non-adopters, we first assess how this group compares with win-win adopters in terms of some basic demographic characteristics unless their response entailed a suppressed qualification, perhaps about unstated constraints. As is shown in Table 3.3, the mean ages were about 66 and 62 for win-win non-adopters and adopters, so non-adopters were slightly older. Win-win non-adopters managed ranches with average grazing acres of about 2,200, which were much smaller than adopters' ranches with average grazing acres of about 3,100. In addition, within a 1-mile radius of the rancher's location, 44% and 47% of acres had LCC I and II soils, respectively, while 44% and 38% of the area had slopes less than or equal to 3% for win-win non-adopters and adopters, respectively.

Table 3.3 Rancher and ranch characteristics summary

	Win-win adopters				Win-win non-adopters			
Variable	Obs	Mean	Min	Max	Obs	Mean	Min	Max
Age	336	62.07	30	90	160	65.52	19	91
Operating years	338	34.75	2	68	158	37.32	1	67
Education	340	3.26	1	5	160	3.23	1	5
Liability ratio	327	2.65	1	6	152	2.63	1	6
Grazing acres	330	3,078	0	55,075	156	2,167	0	41,000
% Grazing land	328	0.69	0	1	156	0.66	0	1
Lease ratio	327	0.36	0	1	155	0.29	0	1
LCC I & II	341	46.93	0	100	159	43.84	0	100
Slope ≤ 3%	341	37.84	0	100	159	44.01	0	100
Distance	336	11.15	0	200	156	10.29	0	200
Latitude	341	42.14	30.71	48.84	159	40.59	30.52	48.98
Longitude	341	-99.40	-103.76	-95.87	159	-99.22	-103.49	-95.77
TX	342	0.27	0	1	161	0.40	0	1

We asked adopters to rate the potential challenges that they had encountered when practicing rotational grazing, and we also asked non-adopters how these challenges were hindering their adoption decisions. We compared the responses across win-win non-adopters and other non-adopters, and the t-test results are shown in Table 3.4. The three most challenging constraints for both win-win non-adopters and other non-adopters were the same “high installation cost”, “water source constraint”, and “labor/management time constraints.” However, adopters ranked “water resource” as the most severe constraint and “labor or management time” as third-most while non-adopters reversed this ordering. These findings are consistent with previous study findings which concluded that implementing rotational grazing requires additional infrastructure and possibly also additional labor when compared to traditional continuous grazing (Gillespie et al. 2008; Windh et al. 2019). Turning to Table 3.5, most of these potential challenges are viewed as more constraining for win-win non-adopters than for win-win adopters. One noticeable phenomenon is that win-win adopters ranked “weather/climate factors” as the second greatest challenge, while non-adopters only ranked as sixth greatest in the order.

Table 3.4 Mean values and t-tests for the importance of potential barriers among non-adopters

Potential Challenges	Win-win non-adopters Mean	Win-win non-adopters Ranking	Other non-adopters Mean	Other non-adopters Ranking	t-test t	t-test Pr(|T| > |t|)
High installation cost	3.555	2	3.188	2	-2.379	0.018
Water source constraint	3.648	1	3.162	3	-2.958	0.003
Labor/management time constraints	3.552	3	3.313	1	-1.527	0.128
Cash flow constraints	2.945	5	3.031	5	0.536	0.592
Uncertain outcomes	2.785	7	2.924	7	0.888	0.375
Rental agreement restrictions	2.314	8	2.376	8	0.35	0.727
Lack of information/education/support	2.155	9	2.254	9	0.655	0.513
Ranch conditions	3.418	4	3.039	4	-2.226	0.027
Unfavorable neighborhood opinions	1.455	11	1.603	11	1.215	0.225
Unwillingness to take on leadership in new practices adoption	1.819	10	1.896	10	0.551	0.582
Weather/climate factors	2.876	6	2.945	6	0.39	0.697

Table 3.5 Mean values and t-test for the importance of potential barriers between win-win adopters and win-win non-adopters

Potential Challenges	win-win adopters Mean	win-win adopters Ranking	win-win non-adopters Mean	win-win non-adopters Ranking	t-test t	t-test Pr(|T| > |t|)
High installation cost	2.850	3	3.555	2	6.668	0.000
Water source constraint	3.206	1	3.648	1	3.802	0.000
Labor/management time constraints	2.832	4	3.552	3	6.417	0.000
Cash flow constraints	2.524	6	2.945	5	3.779	0.000
Uncertain outcomes	2.080	7	2.785	7	6.562	0.000
Rental agreement restrictions	1.994	8	2.314	8	2.468	0.014
Lack of information/education/support	1.737	9	2.155	9	4.319	0.000
Ranch conditions	2.761	5	3.418	4	5.514	0.000
Unfavorable neighborhood opinions	1.346	11	1.455	11	1.317	0.188
Unwillingness to take on leadership in new practices adoption	1.465	10	1.819	10	4.141	0.000
Weather/climate factors	2.911	2	2.876	6	-0.257	0.798

The above differences between win-win non-adopters and other groups are also supported by cumulative percentage response curves to different rating levels of the top challenges.[23] Taking "water resources constraint" as an example in Figure 3.7, the cumulative percentage lines show win-win non-adopters to be lower than the other three groups, indicating that win-win non-adopters were the most water source constrained group. Similar results can be found for other constraints. Although to some extent high initial costs, water resource constraints, and ranch conditions could be relieved by capital, win-win non-adopters are still more constrained by cash flow. These findings reveal that more constrained situations are one possible reason for not adopting rotational grazing among win-win non-adopters.

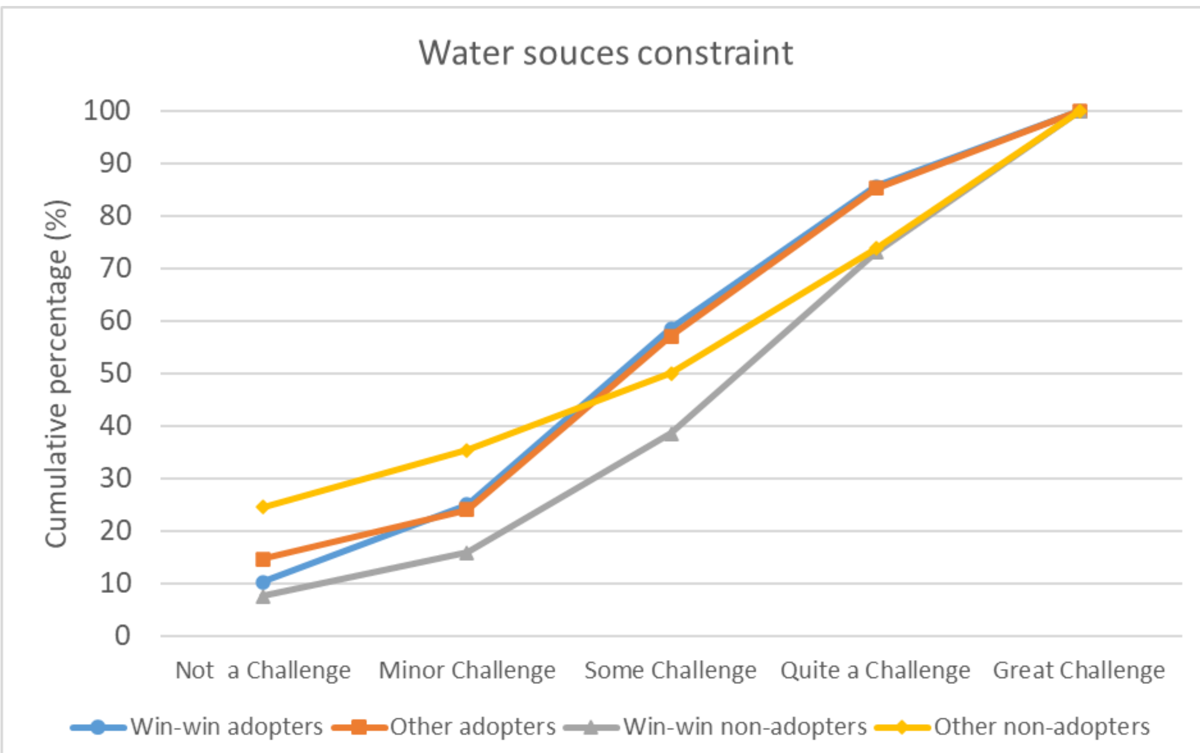


Figure 3.7 Cumulative percentage of responses to different challenge levels of "water sources constraint" among four groups of ranchers

[23] More figures for cumulative percentage response curves to different rating levels of top challenges can be found in the Appendix B.

Ordered Logit Estimations for the Constraints among Different Groups of Ranchers

In this section, we examine how perceived constraints for adoption might be affected by rancher and ranch characteristics. As responses to the constraint variables take five ordinal categories (1="not a challenge", 2="minor challenge", 3="some challenge", 4="quite a challenge", and 5="great challenge"), the ordered logit model is an appropriate modeling choice. We examine the factors that affect each of the eight most serious challenges. The estimated coefficients are presented in Tables 3.6-3.9. Generally, for win-win non-adopters, education, liability ratio, lease ratio, land quality, and longitude emerged as important factors. To be specific, win-win non-adopters with a higher liability ratio tended to perceive "high installation cost", "cash flow constraints", "weather and climate factors", and "uncertainty outcomes" to be the most challenging barriers. A higher liability ratio implies a more limited capacity to borrow from lenders and, therefore, restricts the ability to overcome the potential challenges that a new practice presents. Therefore, the capital constraint might aggravate the potential barriers and prevent the adoption of rotational grazing among win-win non-adopters.

Similarly, a higher lease ratio was associated with stronger views that win-win non-adopters' perceptions about "water source", "labor or time management", "ranch conditions", and "rental agreement restrictions" are indeed constraining. Lessees had little incentive to develop water resources, improve ranch conditions, increase labor inputs on land they did not own and were, therefore, more likely to perceive rental agreement restrictions as challenging when compared to ranchers who own land. By contrast when non-adopting ranchers had a higher percentage of high-quality land, as indicated by increased proportion of land with LCC I & II, then perceptions that "labor or management time constraint", "weather or climate factors", and "rental agreement restrictions" were challenges decline.

Table 3.6 Ordered logit estimated coefficients for “water source constraint” and “high installation cost”

	Water source constraint			High installation cost		
VARIABLES	Win-win adopters	Win-win non-adopters	Other non-adopters	Win-win adopters	Win-win non-adopters	Other non-adopters
Operating years	-0.019**	0.014	0.007	-0.012	0.011	0.012
Education	-0.056	0.352*	0.418*	-0.079	-0.032	0.499**
Liability ratio	0.017	-0.141	-0.136	0.016	0.355**	0.004
Grazing acres	0.000	0.000	0.000	-0.000	0.000	0.000
% Grazing land	-1.522***	-0.959	-3.060***	-0.771	0.024	-2.079**
Lease ratio	0.449	1.762***	0.489	0.394	0.367	0.470
LCC I & II	-0.000	-0.005	-0.007	0.001	-0.008	-0.004
Slope ≤ 3%	0.000	-0.007	-0.014**	-0.002	-0.007	-0.010
Distance	0.004	-0.002	0.015	0.001	-0.004	0.009
Latitude	-0.049	0.151	0.236	-0.039	0.076	0.024
Longitude	-0.259***	0.209	-0.101	-0.246***	0.333**	-0.038
TX	0.233	1.276	3.095	0.372	0.737	0.818
Observations	311	127	94	310	128	97

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.7 Ordered logit estimated coefficients for "Labor management constraint" and "Ranch conditions"

	Labor management constraint			Ranch conditions		
VARIABLES	Win-win adopters	Win-win non-adopters	Other non-adopters	Win-win adopters	Win-win non-adopters	Other non-adopters
Operating years	-0.018*	0.023	0.015	-0.003	0.012	0.009
Education	0.060	0.136	0.603**	0.092	0.190	0.453*
Liability ratio	0.130	0.100	-0.184	0.079	0.132	-0.255
Grazing acres	-0.000	0.000	0.000	0.000	0.000	-0.000
% Grazing land	-1.221**	0.149	-2.919***	-0.885*	-0.433	-1.913**
Lease ratio	0.144	1.962***	0.491	0.261	1.490***	0.938
LCC I & II	0.001	-0.013**	-0.008	0.003	-0.006	-0.010
Slope ≤ 3%	0.002	-0.006	-0.007	0.003	-0.006	-0.012*
Distance	0.004	-0.008	0.018*	-0.000	-0.002	0.011
Latitude	-0.060	0.203	0.073	-0.114	0.143	-0.036
Longitude	-0.211***	0.202	-0.162	-0.311***	0.252*	-0.385**
TX	-0.704	0.669	1.151	-0.860	1.483	-0.200
Observations	310	126	94	310	128	94

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.8 Ordered logit estimated coefficients for "Cash flow constraint" and "Weather/Climate factors"

	Cash flow constraints			Weather/Climate factors		
VARIABLES	Win-win adopters	Win-win non-adopters	Other non-adopters	Win-win adopters	Win-win non-adopters	Other non-adopters
Operating years	-0.016*	-0.003	0.024	0.001	0.010	0.031*
Education	0.062	0.072	0.136	0.211*	-0.084	-0.138
Liability ratio	0.139*	0.431***	-0.001	0.001	0.560***	-0.317**
Grazing acres	0.000	-0.000	0.000	0.000	0.000	0.000
% Grazing land	-0.680	1.036	-1.437	0.108	0.229	-0.418
Lease ratio	-0.039	0.650	0.459	-0.228	-0.309	-0.154
LCC I & II	-0.000	-0.008	-0.004	0.004	-0.013**	-0.005
Slope ≤ 3%	0.002	-0.001	-0.014**	0.004	-0.006	-0.002
Distance	0.007	-0.002	0.018*	-0.002	-0.006	0.008
Latitude	-0.073	-0.118	0.263	-0.146*	0.139	0.179
Longitude	-0.096	-0.101	-0.051	-0.288***	0.280*	-0.145
TX	-0.894	-2.022	3.611*	-1.104	1.538	2.544
Observations	311	127	94	308	127	93

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.9 Ordered logit estimated coefficients for "Uncertain outcomes" and "Rental agreement restrictions"

	Uncertain outcomes			Rental agreement restrictions		
VARIABLES	Win-win adopters	Win-win non-adopters	Other non-adopters	Win-win adopters	Win-win non-adopters	Other non-adopters
Operating years	0.001	0.003	0.030*	-0.013	0.012	0.015
Education	0.084	-0.005	0.119	-0.149	-0.205	0.129
Liability ratio	0.138	0.561***	-0.142	0.022	0.112	-0.268
Grazing acres	-0.000	-0.000	-0.000	0.000	0.000	-0.000
% Grazing land	-0.669	-0.424	-1.113	-0.758	-0.298	-1.830*
Lease ratio	-0.527	-0.178	0.927	1.064***	1.406**	1.330**
LCC I & II	0.005	-0.004	-0.002	0.004	-0.014**	-0.011
Slope $\leq$ 3%	0.004	-0.006	-0.006	-0.001	-0.008	-0.002
Distance	0.001	-0.008	0.017	0.009**	-0.000	0.018*
Latitude	-0.121	-0.116	-0.004	-0.007	0.080	-0.029
Longitude	-0.276***	-0.032	-0.274*	-0.040	0.245	-0.089
TX	-0.980	-1.279	0.297	-0.090	-0.141	0.398

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

“Water source constraint” was listed by both win-win adopters and win-win non-adopters as the most challenging issue. Specifically, many ranchers had commented on water-related constraints, such as lack of water, high costs of drilling new wells. Higher lease ratios were associated with stronger win-win non-adopter perceptions about water sources as a constraint. Lessees had little incentive to develop water resources on land that they did not own, so they were more likely to perceive water resources as a constraint. Especially, when the lease ratio increased by 1 standard error, non-adopters became, respectively, 7.1% and 30.8% more likely to perceive water resource as “quite a challenge” and “great challenge.” They became, respectively, 15.7%, 10.8%, 11.3% less likely to perceive it as “some challenge”, “minor challenge”, and “not a challenge” (Table 3.10).

Comments Analysis

In our survey, in addition to requesting ratings of potential challenges we solicited general open-ended comments about rotational grazing practices. Specifically, ranchers were asked “Please record any further comments you have regarding rotational grazing or MIG practices”, after which ranchers were presented with space for any related comments. We categorized these comments into thirteen general themes, relating to (1) water; (2) fencing; (3) cost; (4) labor; (5) government support; (6) rent; (7) retirement and age; (8) environmental benefits; (9) land characteristics; (10) ranch scale; (11) neighborhood; (12) other cattle type; (13) other comments. Appendix C provides a comment classification rubric as well as example comments in each category.

Table 3.10 Marginal effects and standard errors for win-win non-adopter perceived water constraint model

	Not a challenge		Minor challenge		Some challenge		Quite a challenge		Great challenge	
	ME	SE	ME	SE	ME	SE	ME	SE	ME	SE
Operating years	-0.001	0.001	-0.001	0.001	-0.001	0.001	0.001	0.001	0.002	0.003
Education	-0.022	0.014	-0.022	0.013	-0.031*	0.018	0.014	0.010	0.061*	0.035
Liability ratio	0.009	0.009	0.009	0.009	0.013	0.012	-0.006	0.006	-0.025	0.024
Grazing acres	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
% Grazing land	0.061	0.047	0.059	0.045	0.086	0.062	-0.039	0.033	-0.168	0.118
Lease ratio	-0.113**	0.049	-0.108**	0.044	-0.157***	0.054	0.071*	0.038	0.308***	0.098
LCC I & II	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	-0.001	0.001
Slope ≤ 3%	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	-0.001	0.001
Distance	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001
Latitude	-0.010	0.008	-0.009	0.008	-0.014	0.011	0.006	0.006	0.026	0.022
Longitude	-0.013	0.010	-0.013	0.009	-0.019	0.013	0.008	0.007	0.037	0.025
TX	-0.082	0.094	-0.079	0.089	-0.114	0.126	0.051	0.061	0.223	0.247

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.11 summarizes the frequency of comments in each of the above categories. Of the 392 comments made, and setting aside the category of other comments, the largest set (70, about 18% of all comments) mentioned water and related water resource concerns. Other comment categories that featured prominently were fencing, cost, labor, government support, rent, and retirement each made up 5-11% of total comments. The most commonly mentioned comment categories were consistent with our findings on potential challenges.

Table 3.12 compares the comment count in each category among win-win adopters, win-win non-adopters, and other non-adopters. There were no significant differences in the frequency of comments between win-win non-adopters and other non-adopters. However, win-win non-adopters provided comparatively more cost-related comments than did win-win adopters, with respective averages of 0.2 and 0.086 per respondent. Win-win non-adopters were less likely than adopters to cite government support and environmental benefits as important comments about rotational grazing practice.

Table 3.11 Frequency of comments made in 13 categories

	Comment frequency	
Category	Total comments	Ranchers making at least one comments in category
Water	70	61
Fencing	42	39
Cost	30	29
Labor	23	22
Government support	23	22
Rent	22	18
Retirement or age	20	18
Environment benefits	9	9
Land characteristics	8	8
Ranch scale	6	6
Neighborhood	4	4
Other cattle type	46	46
Other	152	124
Total	392	283

Table 3.12 Frequency of comments, by different groups of ranchers.

Category	Win-win adopters	Win-win non-adopters	Win-win non-adopters	Other non-adopters
Water	0.190	0.244	0.244	0.140
Fencing	0.164	0.133	0.133	0.093
Cost	0.086^{**}	0.200^{**}	0.200	0.116
Labor	0.086	0.111	0.111	0.070
Government support	0.121^{**}	0.000^{**}	0.000	0.000
Rent	0.112	0.089	0.089	0.023
Retirement or age	0.052	0.067	0.067	0.116
Environment benefits	0.069^{*}	0.000^{*}	0.000	0.000
Land characteristics	0.009^{***}	0.089^{***}	0.089	0.023
Ranch scale	0.000^{***}	0.067^{***}	0.067	0.070
Neighborhood	0.017	0.000	0.000	0.023

Note: *, **, *** denote response frequencies are different between win-win adopters and win-win non-adopters, as well as between win-win non-adopters and other non-adopters at the 10%, 5%, and 1% significance levels.

In addition to comparing comment frequency, we investigate the relationship between respondents' comments and adoption decisions in the win-win group. We generate a binary variable to indicate the adoption decision within the win-win group (i.e., 1=win-win adopters, 0=win-win non-adopters). Comment frequencies and rancher-specific characteristics are included as independent variables. The logit regression results in Table 3.13 show that there is a significant relationship between adoption decisions and cost-related comments, which support the idea that high installation cost is a great constraint for win-win non-adopters. In addition, win-win non-adopters made more comments related to land characteristics than did win-win adopters, which is also consistent with the finding that win-win non-adopters were more constrained by ranch conditions.

Table 3.13 Regression results on each comment frequency on adoption decisions (win-win adopters vs win-win non-adopters)

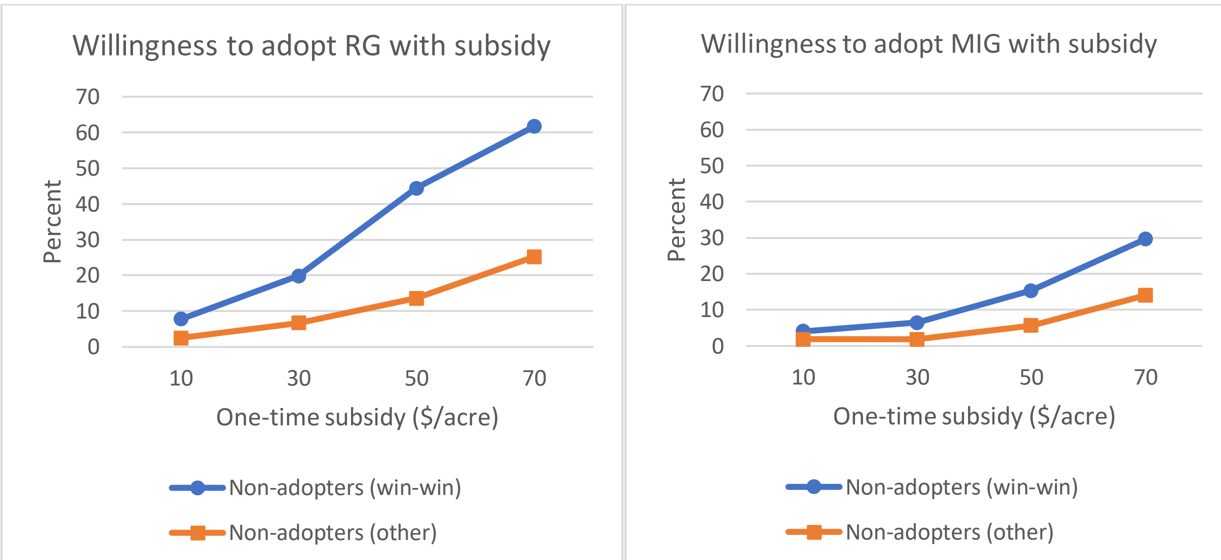
VARIABLES	Adoption (1)	(2)
Water	0.004	0.068
Fencing	0.556	0.439
Cost	-0.462	-0.573^{*}
Labor	-0.068	-0.104
Government support	-ǂ	-ǂ
Rent	0.910	0.162
Retirement	0.034	-0.238
Environment benefits	-ǂ	-ǂ
Land characteristics	-2.128^{**}	-1.661^{**}
Ranch scale	-ǂ	-ǂ
Neighborhood	-ǂ	-ǂ
Other control variables	Yes	No
Observations	128	135

Note: *** p<0.01, ** p<0.05, * p<0.1.
ǂ The variables are omitted due to probability being perfectly predicted.
"Adoption" is a binary variable (win-win adopters=1; win-win non-adopters=0).
"Other control variables" include rancher and ranch characteristics.

Subsidy Responses

The findings in the earlier sections indicate that win-win non-adopters belong to a very constrained group when faced with potential barriers to rotational grazing, especially for high initial costs, water resource constraints, and ranch conditions. These constraints are particularly severe for ranchers with a greater liability ratio. Therefore we conjecture that win-win non-adopters are more sensitive to subsidies which would relieve some of the more pecuniary potential constraints.

In this section, we first compare the willingness to adopt RG and MIG between win-win non-adopters and other non-adopters when a hypothetical one-time subsidy is offered. Then we further examine the subsidy responses within these two groups. As is shown in Figure 3.8, win-win non-adopters were more willing to adopt both RG and MIG than were other non-adopters when offered a one-time subsidy. To be specific, there was a 1.5% increase in the win-win non-adopters who were willing to adopt RG due to a 1% increase in a one-time subsidy, and the corresponding change among other non-adopters was about 1.2%. There was a 1.1% increase in the win-win non-adopters who were willing to adopt MIG due to a 1% increase in a one-time subsidy, and the corresponding change among other non-adopters was about 0.7%.



(a) (b)

Figure 3.8 Willingness to adopt RG and MIG with a one-time subsidy among non-adopters

We also apply a logit model to examine how non-adopters' willingness to adopt RG or MIG was affected by initial costs, labor requirements, and farmer and farm characteristics when a one-time subsidy is provided (Table 3.14). When compared with other non-adopters, win-win non-adopters' adoption decisions were significantly affected by initial costs, which is consistent with the finding that win-win non-adopters were more constrained by high installation costs. The capital constraints associated with potential barriers can be relieved by the incentive subsidies. In addition, win-win non-adopters were more likely to adopt RG and MIG when a lower proportion of their ranch consisted of good-quality soil and flatter lands. This suggests that these ranchers were more willing to improve the ranch conditions and cared more about the environmental outcomes of grazing operations. Consistent with this finding, Basarir and Gillespie (2006) emphasized that beef producers regard environmental goals as an important factor influencing decision making. Fewer operating years were also associated with a stronger willingness to adopt RG, so the incentive subsidies will be more effective among the relatively new grazing operators. Therefore, these findings suggest that win-win non-adopters may be a suitable target group for incentive subsidy programs to increase the adoption rate of rotational grazing, especially those with poor soil conditions and shorter operating years.

Table 3.14 Logit regression results of future adoption with one-time subsidy among non-adopters

VARIABLES	Non-adopters (win-win) RG adoption	Non-adopters (other)	Non-adopters (win-win) MIG adoption	Non-adopters (other)
Subsidy	0.055***	0.063***	0.059***	0.092***
Initial costs	-0.232**	-0.207	-0.769***	0.188
Labor	-0.066	-0.284	0.009	0.044
Operating years	-0.018*	-0.034**	0.009	-0.003
Education	0.185	0.285	0.054	0.324
Grazing acres	0.000*	0.000	0.000	-0.000
LCC I & II	-0.011**	0.007	0.014	0.005
Slope $\leq$ 3%	-0.009***	-0.006	-0.016***	0.000
Distance	0.008	0.002	0.014	-0.097*
Latitude	-0.051	0.461**	0.193	0.037
Longitude	0.045	-0.120	0.422**	-0.312
TX	-0.936	5.850**	4.790**	-1.156
Observations	493	303	407	262

Note: *** p<0.01, ** p<0.05, * p<0.1

Conclusion

The phenomenon that many non-adopters view a practice as win-win is not unique to rotational grazing. It has been commonly found that there often remains a large gap between optimal and actual adoption of conservation technology. Energy efficiency technologies are examples, and an energy efficiency gap exists between actual energy use and optimal use (Backlund et al. 2012; Gerarden, Newell and Stavins 2017). To promote conservation technology adoption, it is important to identify whether the practice is actually win-win for potential adopters. If the practice can provide economic and environmental benefits under certain conditions, then win-win non-adoption might be caused by some constraints. By understanding win-win non-adopters' decision mechanisms and potential barriers to adoption, targeted incentive policies can be proposed to realize the win-win possibilities for more ranchers. Our analysis has not addressed whether subsidy cost is justified by the environmental benefit gains and we do not focus on that, but it is important and relevant for policy proposals.

This work first identifies a large proportion of non-adopters who regarded rotational grazing as a win-win practice. Our survey sample allows us to identify the main barriers that constrained win-win non-adopters, including high installation costs, water resource constraints, and ranch conditions. These constraints were challenging since the non-adopters in question likely had limited borrowing capacity and little access to operating capital. Our open-ended comments analysis also reveals their concerns about costs and limited capital. We also explore how the win-win non-adopters responded to a hypothetical one-time subsidy program. They were more likely to adopt rotational grazing when the subsidies were provided, especially those with poor soil conditions and shorter operating years.

Our findings provide some policy implications. First, incentive policies are likely to be more effective in changing decisions when they adequately address the costs and operational constraints that ranchers face. Second, those promoting strategies will be better able to reach and persuade ranchers when the factors that ranchers consider and the specific circumstances they face are commonly understood. Third, win-win non-adopters may be a suitable target group for investment subsidies intended to ultimately realize the win-win possibilities for more ranchers. Finally, beyond grazing practices on the U.S. Great Plains, our findings could apply to many other landscapes where livestock production is prevalent. Our research also provides a basis for other research aimed at identifying the factors that generate the adoption gap and at promoting adoption of conservation practices or technologies in a broader field.

APPENDICES

APPENDIX A: Questions in Survey Instrument

This section contains images of main survey questions used in this essay.

18. Whether or not you have adopted, please indicate what you observe or expect regarding the following possible benefits associated with rotational grazing or MIG practices on your ranch or neighboring ranches.

Potential Benefits	None	Slight	Medium	Significant
Increased percentage of desirable grass	☐	☐	☐	☐
Decreased runoff and erosion	☐	☐	☐	☐
Increased drought resilience/faster drought recovery	☐	☐	☐	☐
Prolonged grazing season	☐	☐	☐	☐
Increased stocking rate capacity	☐	☐	☐	☐
Increased livestock weight gain	☐	☐	☐	☐
Improved livestock health	☐	☐	☐	☐

Figure 3A.1 Question about environmental outcomes of rotational grazing

19. Please rate the challenges that you have encountered when practicing rotational grazing or MIG, or how these challenges are hindering your adoption decisions.

Potential Challenges	**Not a Challenge**	**Minor Challenge**	**Some Challenge**	**Quite a Challenge**	**Great Challenge**
High installation cost	☐	☐	☐	☐	☐
Water source constraint	☐	☐	☐	☐	☐
Labor/management time constraints	☐	☐	☐	☐	☐
Cash flow constraints	☐	☐	☐	☐	☐
Uncertain outcomes	☐	☐	☐	☐	☐
Rental agreement restrictions	☐	☐	☐	☐	☐
Lack of information/education/support	☐	☐	☐	☐	☐
Ranch conditions (e.g., size and water availability issues)	☐	☐	☐	☐	☐
Unfavorable neighborhood opinions	☐	☐	☐	☐	☐
Unwillingness to take on leadership in new practices adoption	☐	☐	☐	☐	☐
Weather/climate factors	☐	☐	☐	☐	☐

For other challenges not listed above, please describe and rate them here: ________________________________

________________________________.

Figure 3A.2 Question about potential challenges of rotational grazing adoption

27. How has your adoption of rotational grazing or MIG affected (or will likely affect) the economic profit of your ranch **during the first 5 years?**

Effect on profitability in the first 5 years	**Significantly Decreased**	**Slightly Decreased**	**No Influence**	**Slightly Increased**	**Significantly Increased**
Rotational grazing	☐	☐	☐	☐	☐
MIG	☐	☐	☐	☐	☐

Figure 3A.3 Question about economic profit of rotational grazing for adopters

33. To what degree do you think that rotational grazing or MIG might affect the economic profit of your ranch in the first 5 years?

Effect on profitability in the first 5 years	**Significantly Decrease**	**Slightly Decrease**	**No Influence**	**Slightly Increase**	**Significantly Increase**
Rotational grazing	☐	☐	☐	☐	☐
MIG	☐	☐	☐	☐	☐

Figure 3A.4 Question about economic profit of rotational grazing for non-adopters

37. If a one-time subsidy were available to those willing to adopt rotational grazing or MIG practices, then would you adopt?

One-time Subsidy	37a. **Rotation grazing adoption**			37b. **MIG adoption**		
	Yes	No	Not sure	Yes	No	Not sure
$10/acre	☐	☐	☐	☐	☐	☐
$30/acre	☐	☐	☐	☐	☐	☐
$50/acre	☐	☐	☐	☐	☐	☐
$70/acre	☐	☐	☐	☐	☐	☐

Figure 3A.5 Question about non-adopters’ willingness to adopt with a one-time subsidy

APPENDIX B: Cumulative Percentage of Responses to Potential Challenge

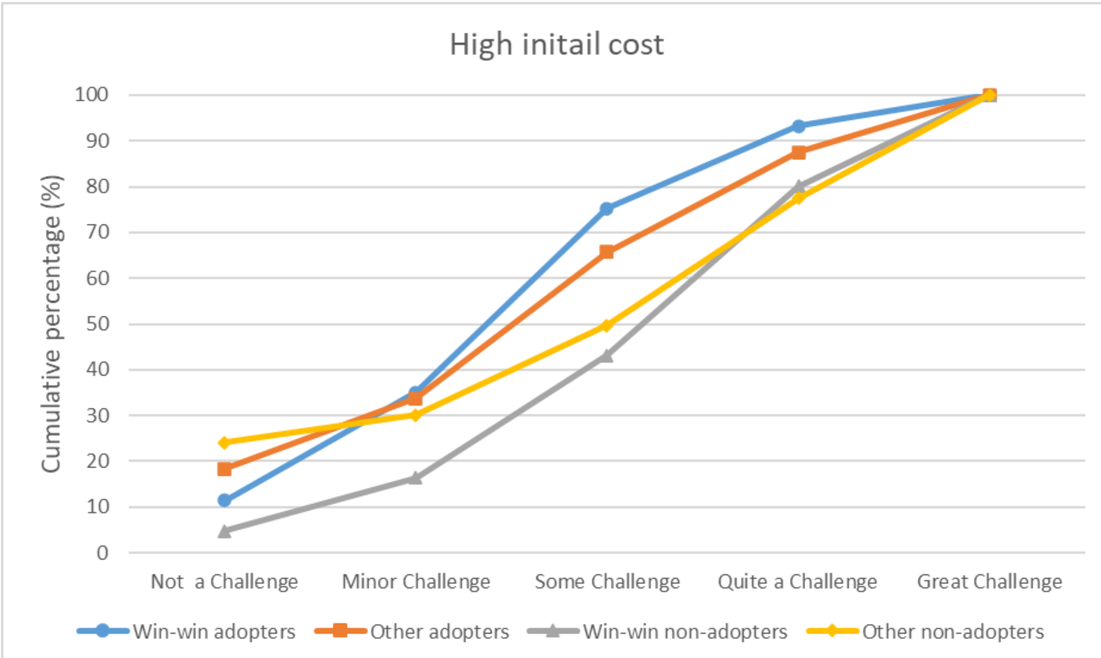


Figure 3B.1 Cumulative percentage of responses to different challenge levels of "high initial cost" among four groups of ranchers

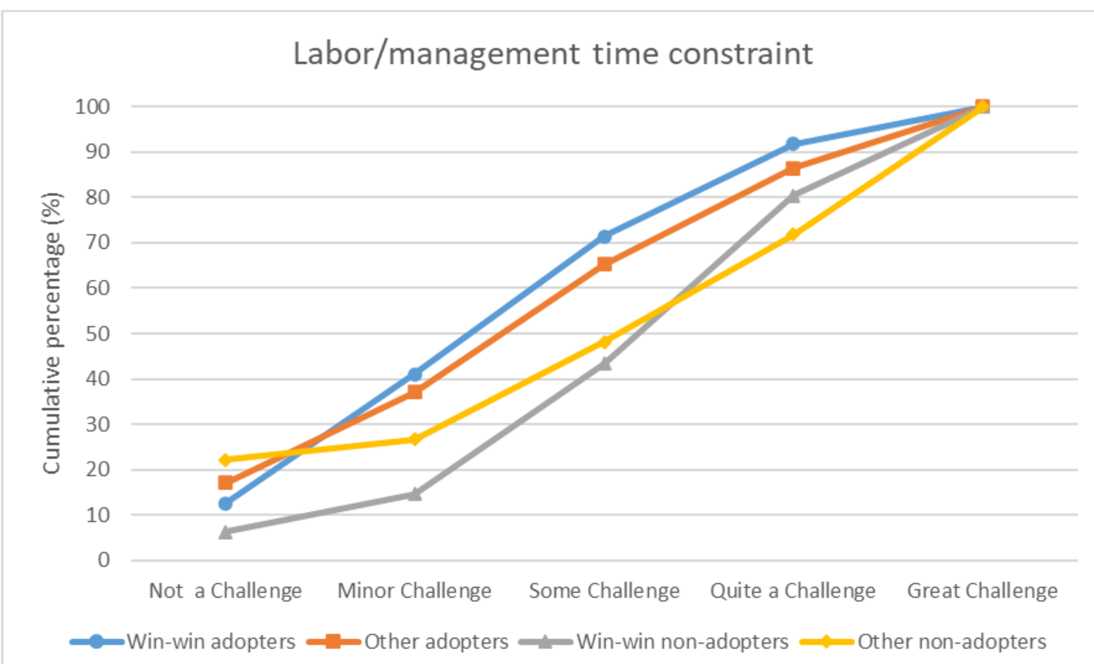


Figure 3B.2 Cumulative percentage of responses to different challenge levels of "labor/management time constraint" among four groups of ranchers

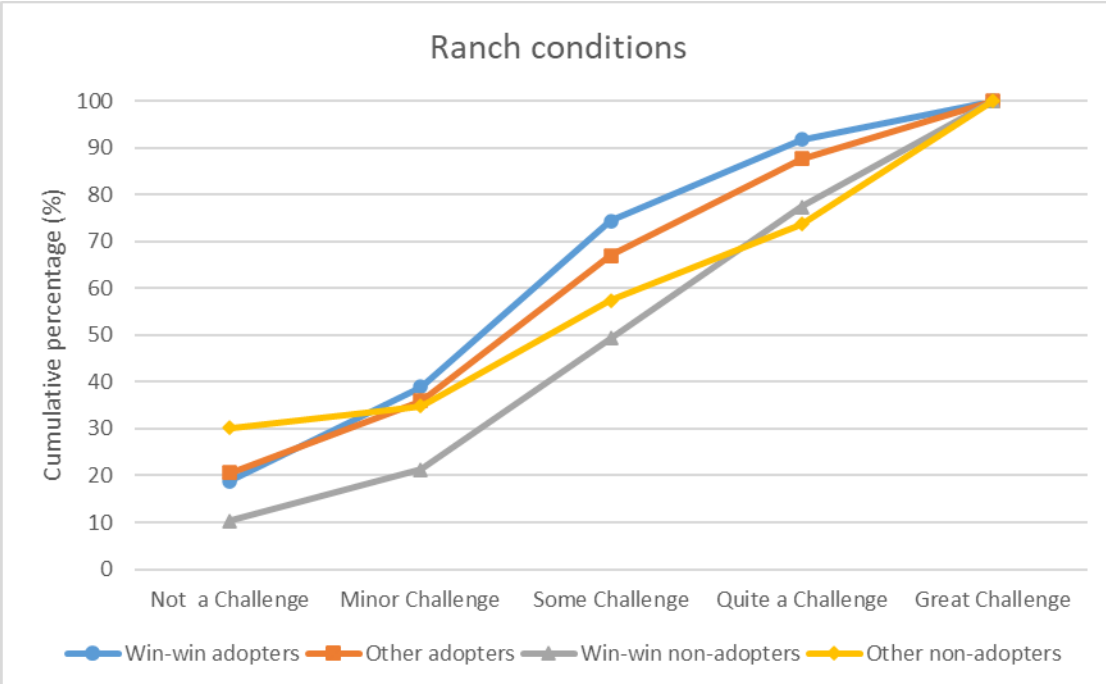


Figure 3B.3 Cumulative percentage of responses to different challenge levels of “ranch conditions” among four groups of ranchers

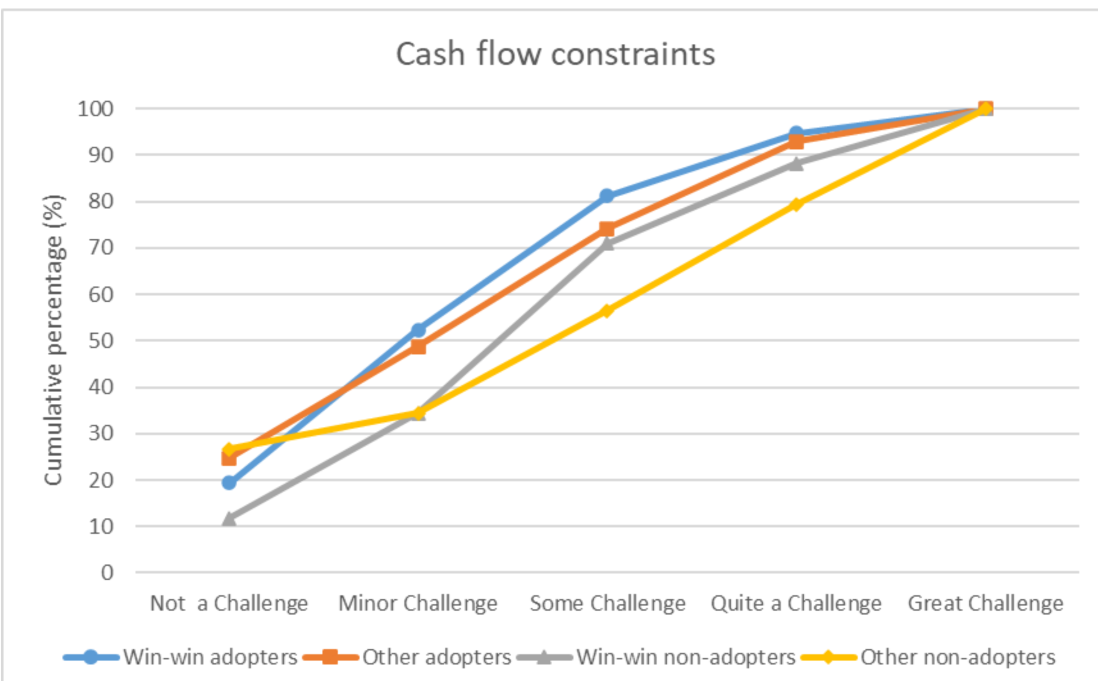


Figure 3B.4 Cumulative percentage of responses to different challenge levels of “cash flow constraints” among four groups of ranchers

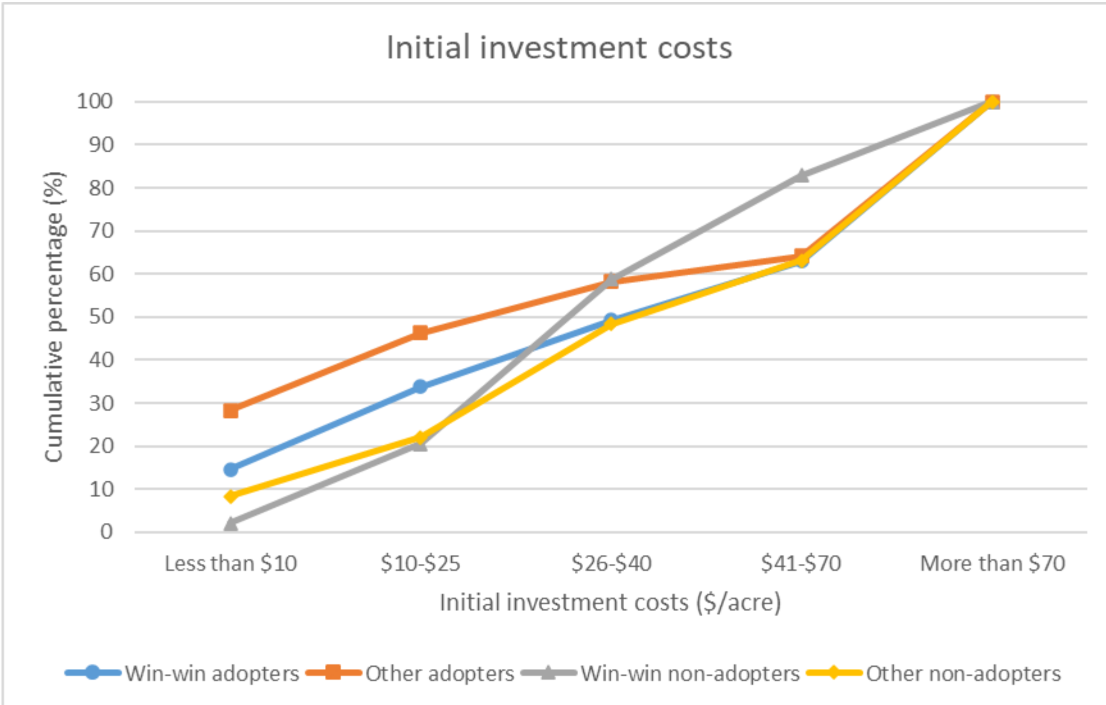


Figure 3B.5 Cumulative percentage of responses to different levels of “initial investment costs” among four groups of ranchers

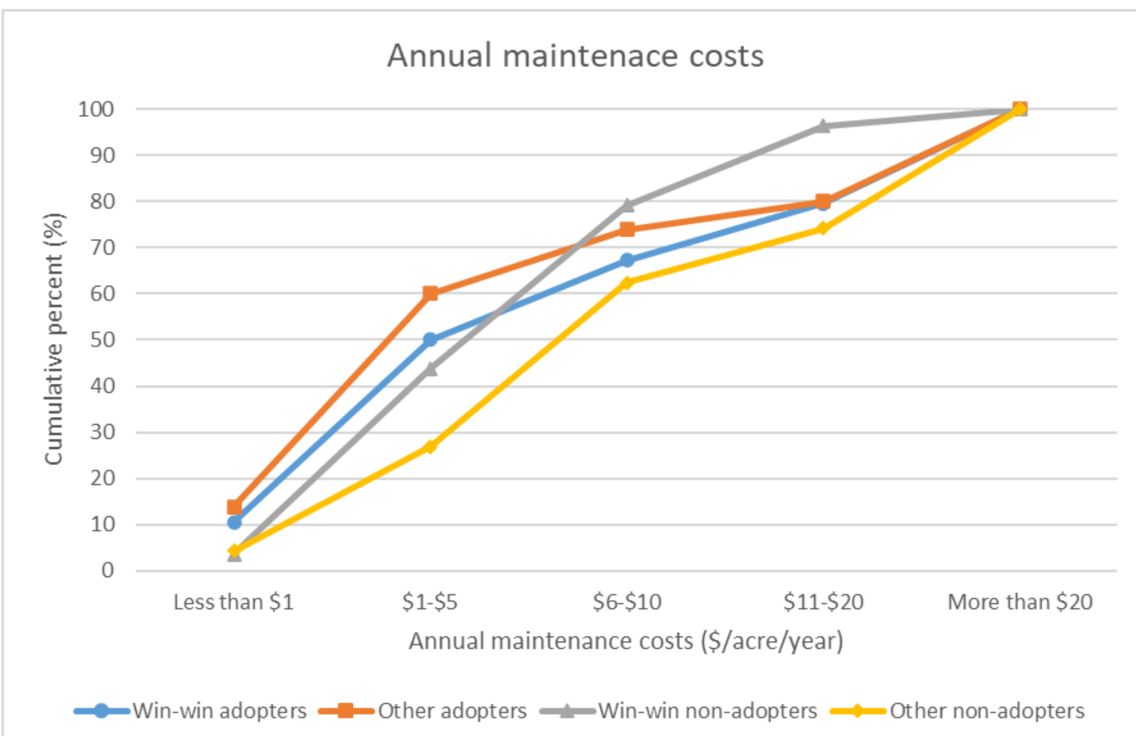


Figure 3B.6 Cumulative percentage of responses to different levels of “annual maintenance costs” among four groups of ranchers

APPENDIX C: Supplemental Tables

Table 3C.1 Mean values and t-test of initial investment costs and annual maintenance costs by group

Category	Win-win adopters	Win-win non-adopters	Win-win non-adopters	Other non-adopters
Initial investment costs	3.393	3.355	3.355	3.579
Annual maintenance costs	2.925	2.770	2.770***	3.323***

Note: *, **, *** denote response frequencies are different at the 10%, 5%, and 1% significance levels.

Table 3C.2 Mean values and t-test of the importance of management goals by group

Management goals	Win-win adopters	Win-win non-adopters	Win-win non-adopters	Other non-adopters
Maintain high economic returns	4.136	4.064	4.064	4.110
Breed high-quality stock	4.299	4.234	4.234	4.100
Improve soil/grassland quality	4.222*	4.082*	4.082	3.944
Improve water quality/wildlife habitat	3.884**	3.667**	3.667	3.586
Be considered one of the best ranchers	2.703	2.748	2.748	2.746
Achieve a desirable work-life balance	3.781	3.748	3.748	3.613

Note: *, **, *** denote response frequencies are different at the 10%, 5%, and 1% significance levels.

Table 3C.3 Mean values and t-test of potential benefits by group

Potential Benefits	Win-win adopters	Win-win non-adopters	Win-win non-adopters	Other non-adopters
Increased percentage of desirable grass	3.330***	3.019***	3.019***	2.331***
Decreased runoff and erosion	3.181***	2.689***	2.689***	2.161***
Increased drought resilience/faster drought recovery	3.363***	2.988***	2.988***	2.265***
Prolonged grazing season	3.298***	3.000***	3.000***	2.235***
Increased stocking rate capacity	3.196	3.100	3.100***	2.191***
Increased livestock weight gain	3.173***	2.851***	2.851***	2.181***
Improved livestock health	2.997***	2.652***	2.652***	2.044***

Note: *, **, *** denote response frequencies are different at the 10%, 5%, and 1% significance levels.

Table 3C.4 Classification rubric for ranchers' comments regarding their ranching practices

Category	Comments containing or pertaining to					Typical comment
Water	water Water moisture	Drought dry	Rainfall Rain			"There is no underground water resources" "Limited by access to water" "The uncertain rainfall and unpredictability of rain hinders MIG"
Fencing	fencing	fence	fences	wire	electronic	"Maintaining fences and water gaps" "Not enough water and cost of fencing"
Cost	cost costs costly	costly expensive extra	money pay	initial	maintenance	"Fencing is expensive, labor is expensive" "I like some rotational grazing but the MIG is too much labor and cost"
Labor	time	labor	management	work		"I don't think MIG would be practical for my situation because of lack of labor. "It is good for land but takes extra work"
Government or agency	government	cost-share	NRCS			"Cost-share agreement uncertainty and speculations and meeting deadlines quite a challenge." "I may do more rational grazing if cost-share programs improve."
Rent	rent	rented	leases	leased	landowner	"Hard to improve rented grow because of cost no long-term leases"
Retirement	renting retired	renters old	leasing age	contract	landlords	"I am reducing herd size and acres because of retirement." "We are too old."

Table 3C.4 (cont'd)

Category	Comments containing or pertaining to					Typical comment
Environment benefits	Better grass	Weed control	good for land			"I have always used rotational grazing, as a management tool for better grass" "It is good for land"
Land characteristics	hilly	steep	soil	rocky	stony	"Our big pastures are on steep river bottom ground which is tough to work with, great challenge." "We own and rent pastures that are located in rough terrain hill."
	sandy	terrain	ground	rough		
Ranch scale	size	enough	small	larger	herd	"The size of my pastures is small (Great Challenge)." "I think rotational grazing can have benefits but the size of your pastures have to be fairly large for the costs to be feasible"
Neighborhood	neighbors	other	neighborhood	neighbor		"neighbors' bulls are great challenge" "unfavorable opinion by other ranch partners."

REFERENCES

REFERENCES

Allcott, H., and M. Greenstone. 2012. Is There an Energy Efficiency Gap? *Journal of Economic Perspectives* 26 (1): 3-28.

Backlund, S., P. Thollander, J. Palm, and M. Ottosson. 2012. Extending the Energy Efficiency Gap. *Energy Policy* 51:392-396.

Basarir, A., and J.M. Gillespie. 2006. Multidimensional Goals of Beef and Dairy Producers: An Inter-Industry Comparison. *Agricultural Economics* 35(1):103–114.

Bergtold, J.S., S. Ramsey, L. Maddy, and J.R. Williams. 2019. A Review of Economic Considerations for Cover Crops as a Conservation Practice. *Renewable Agriculture and Food Systems* 34(1):62–76.

Carlisle, L. 2016 Factors Influencing Farmer Adoption of Soil Health Practices in the United States: A Narrative Review. *Agroecology and Sustainable*. *Food Systems* 40(6): 583-613.

Chaubey, I., L. Chiang, M.W. Gitau, and S. Mohamed. 2010. Effectiveness of Best Management Practices in Improving Water Quality in a Pasture-Dominated Watershed. *Journal of Soil and Water Conservation* 65(6):424–437.

Claassen, R., E.N. Duquette, and D.J. Smith. 2018. Additionality in U.S. Agricultural Conservation Programs. *Land Economics* 94(1):19–35.

Dillman, D.A., J.D. Smyth, and L.M. Christian. 2014. *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. John Wiley & Sons.

Gerarden, T.D., R.G. Newell, and R.N. Stavins. 2017. Assessing the Energy-Efficiency Gap. *Journal of Economic Literature* 55(4):1486–1525.

Gillespie, J.M., W. Wyatt, B. Venuto, D. Blouin, and R. Boucher. 2008. The Roles of Labor and Profitability in Choosing a Grazing Strategy for Beef Production in the U.S. Gulf Coast Region. *Journal of Agricultural and Applied Economics* 40 (1): 301–313.

Gillingham, K. and K. Palmer. 2014. Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence. *Review of Environmental Economics and Policy* 8(1,): 18-38.

Hodde, W., J. Sesmero, B. Gramig, T. Vyn, and O. Doering. 2019. The Predicted Effect of Projected Climate Change on the Economics of Conservation Tillage. *Agronomy Journal* 111(6):3130–3139.

Jakoby, O. 2015. Adapting Livestock Management to Spatio-Temporal Heterogeneity in Semi-Arid Rangelands. *Journal of Environmental Management*11.

Kim, S.-A., J.M. Gillespie, and K.P. Paudel. 2008. Rotational Grazing Adoption in Cattle Production Uuder a Cost-Share Agreement: Does Uncertainty Have a Role in Conservation Technology Adoption? *Australian Journal of Agricultural and Resource Economics* 52(3):235–252.

Knowler, D., and B. Bradshaw. 2007. Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research. *Food Policy* 32(1):25–48.

Lloyd-Smith, P., and W. Adamowicz. 2018. Can Stated Measures of Willingness-to-accept be Valid? Evidence from Laboratory Experiments. *Journal of Environmental Economics and Management* 91:133-149.

Manson, S.M., N.R. Jordan, K.C. Nelson, and R.F. Brummel. 2016. Modeling the Effect of Social Networks on Adoption of Multifunctional Agriculture. *Environmental Modelling & Software* 75: 388–401.

Max, R., and H. Ritchie. 2013. *Technological Progress.* Published Online at ourworldindata.org. Retrieved From: https://ourworldindata.org/technological-progress.

Nelson, K.C., R.F. Brummel, N. Jordan, and S. Manson. 2014. Social Networks in Complex Human and Natural Systems: The Case of Rotational Grazing, Weak Ties, and Eastern US Dairy Landscapes. *Agriculture and Human Values* 31 (2): 245–259.

Nowak, P. 1992. Why Farmers Adopt Production Technology. *Journal of Soil and Water Conservation* 47(1):14-16.

Palm-Forster, L.H., S.M. Swinton, F. Lupi, and R. Shupp. 2016. Too Burdensome to Bid: Transaction Costs and Pay-for-Performance Conservation. *American Journal of Agricultural Economics* 98(5):1314-1333.

Prokopy, L.S., K. Floress, J.G. Arbuckle, S.P. Church, F.R. Eanes, Y. Gao, B.M. Gramig, P. Ranjan, And A.S. Singh. 2019. Adoption of Agricultural Conservation Practices in the United States: Evidence from 35 Years of Quantitative Literature." *Journal of Soil and Water Conservation* 74(5):520–534.

Song, F., J. Zhao, and S.M. Swinton. 2011. Switching to Perennial Energy Crops under Uncertainty and Costly Reversibility. *American Journal of Agricultural Economics* 93(3):768–783.

Teague, R., B. Grant, and H.-H. Wang. 2015. Assessing Optimal Configurations of Multi-Paddock Grazing Strategies in Tallgrass Prairie using a Simulation Model. *Journal Of Environmental Management* 150:262–273.

Teague, W.R., U.P. Kreuter, W.E. Grant, H. Diaz-Solis, and M.M. Kothmann. 2009. Economic Implications of Maintaining Rangeland Ecosystem Health in a Semi-Arid Savanna. *Ecological Economics* 68(5):1417–1429.

USDA National Agricultural Statistics Service. 2017. NASS - Quick Stats. USDA National

Agricultural Statistics Service. https://data.nal.usda.gov/dataset/nass-quick-stats. Accessed 2021-06-06.

Wang, T., H. Jin, U. Kreuter, H. Feng, D.A. Hennessy, R. Teague, and Y. Che. 2020. Challenges for Rotational Grazing Practice: Views from Non-Adopters across the Great Plains, USA. *Journal Of Environmental Management* 256:109941.

Wang, T., W. R. Teague, S.C. Park, and S. Bevers. 2018. Evaluating Long-Term Economic and Ecological Consequences of Continuous and Multi-Paddock Grazing - A Modeling Approach. *Agricultural Systems* 165:197–207.

Windh, J.L., J.P. Ritten, J.D. Derner, S.I. Paisley, and B.P. Lee. 2019. Economic Cost Analysis of Continuous-Season-Long versus Rotational Grazing Systems. *Western Economics Forum* 17 (1837-2019–947): 62–72.

CHAPTER 4 Plant Architecture and Seeding Rate Responses to Markets, Resources, and Technologies

Abstract

Corn and soybean seeding rates in the United States have moved in opposite directions over recent decades, with the former trending upward and the latter trending downward. Both seed markets have experienced similar market, technological and environmental shocks over that time. This paper aims to better understand how farmers make seeding rate choices and why corn and soybean seeding rates have trended in opposite directions. We develop a model of seeding rate choices by incorporating a resource budget trade-off between more seeds and fewer resources allocated to each seed. With a unique detailed U.S. farm-level market data, consisting of more than 600,000 plot-level choices over 1995-2016 for corn and 1996-2016 for soybean, we assess how farmers' seeding rate choices respond to markets, resources, and technologies. We find that the soybean seeding rate choice to be more price elastic than that for corn, i.e., seed companies are likely to have less power in the soybean seed market. Furthermore, most inputs that are endowed with the land, and so are shared across all seeds, increase both corn and soybean seeding rates; while inputs that come with the seed increase corn rates but decrease soybean rates. Focus group participants reveal some different ideas and they rely most heavily on their own experience when deciding on seeding rate choices. The difference in price elasticities across crops due to different plant architectures has implications in various aspects including the division of economic surplus and the mitigation of negative ecological impacts.

Introduction

Seed rate choices have played a critical role in enhancing productivity and ensuring sufficient food supply for a rapidly growing population. Corn and soybean yields have significantly increased since the 1930s when hybrid varieties were commercialized. These increasing trends have been attributed to complex interactions among genetic improvement, advanced plant breeding, and improved agricultural management (Duvick 2005; Assefa et al. 2016; Assefa et al. 2018). However, no consensus has emerged on the exact yield contribution of seeding rates (i.e., seeds per acre). A literature in agronomy argues that, at least for corn, crop yield increases have been directly linked to increases in seeding rate over time (Stanger and Lauer 2006; Assefa et al. 2017; DeBruin et al. 2017; Assefa et al. 2018), while other agronomic literature indicates that higher seeding rates do not affect yields and can even reduce yields due to more competition among plants for the available soil nutrients (Hashemi, Herbert and Putnam 2005; Ciampitti et al. 2013; Assefa et al. 2016). Thus seeding rate may have positive, neutral, or negative effects on crop yield (Assefa et al. 2016). Despite the increasing trends in corn and soybean yields, seeding rate trends for these two crops have been very different. Therefore, understanding the factors that affect farmers' seeding rate choices and induce the different corn and soybean seeding rate patterns is of great importance to productivity gains.

Notwithstanding seeding rates' productivity-enhancing potential, seed input costs comprise a large proportion of production costs with technologies changing continuously. Soybean seed costs about $50 per acre while corn seed costs about $100 per acre[24], clearly large expenses for an enterprise. These seed markets are oligopolies (Ciliberto, Moschini and Perry 2019) where supplier market power is further strengthened through possession of germplasm

[24] Estimated seed costs are obtained from Estimated Costs of Crop Production in Iowa – 2021 at https://www.extension.iastate.edu/agdm/crops/html/a1-20.html.

foundation lines and patents on seed traits. Seeding rates may also be affected by the choice of biotechnology trait. Seed varieties have changed quickly with a commercial life of about 4.6 years for corn (Perry, Hennessy and Moschini 2018) and about 3.5 years for soybean (Zhang and Bellaloui 2014). Technology trait endowed seeds are more costly, suggesting that growers will seek to economize on seeding rates when planting these seeds. Alternatively, the traits may promote healthier plants so that the ground can sustain a denser stand.

Seeding rate and variety choice decisions are made by farmers at the start of planting season when they face uncertainty. Corn seeding rates play a role in the magnitude of climate-change-induced risks (Aglasan 2020). Specifically, Aglasan (2020) finds that the magnitude of warming-related crop insurance losses becomes more severe at higher seeding rates due to the inter-plant competition for nutrients and moisture. These losses escalate under severe heat stress and higher seeding rates. However, the use of varieties that are potentially more resilient to warming can alleviate such loss increasing effects and so allow for high seeding rates (Aglasan 2020).

Seeding rate choices are also related to environmental concerns that are raised by the widely-used chemical coatings on seeds. The chemical coating can protect the seedling during germination and establishment but may have negative environmental implications (Perry and Moschini 2020). Higher seeding rates will impose a larger chemical load on the environment. For example, neonicotinoids are applied on more than 90% of corn acres (Perry and Moschini 2020) and more than 50% of soybean acres in the United States (Hurley and Mitchell 2017). Although neonicotinoids can reduce crop loss risks, residues from seed-applied neonicotinoid insecticides persist in the soil and water and pose a threat to many non-target plants. These chemicals can have negative effects on the abundance of birds (Li, Miao and Khanna 2020), bees

(Rundlöf et al. 2015), and butterflies (Van Deynze 2020). Notwithstanding a literature on the environmental risks of neonicotinoid applications, little is known about the seeding rate choices that determine the amount of these chemicals that enter the environment. Therefore, a better understanding of farmers' seeding rate choices has significant implications for our capacity to appropriately manage farm profits and the environment.

In this paper, we investigate how seeding rate choices respond to market, resource, and technology factors and why corn and soybean seeding rates are different. We first develop a conceptual model of seeding rate choices by incorporating a resource budget trade-off between more seeds and fewer land-based resources allocated to each seed. The seeding rate input is a distinctive choice. While more seed on unlimited land resources should increase yield output, as with other inputs, an increase in the seeding rate rations fixed land and associated resources over more plants. Exogenous shocks have different effects on this trade-off depending on whether these shocks primarily affect plant profitability or resources available per acre. From the perspective of plant architecture, corn varieties have been bred to grow straight and tall rather than branch sideways; while soybeans are short and can readily branch laterally. In comparison with corn, the laterally growing soybean plant is better positioned to expand or contract when seeking to optimally gather sunlight and soil nutrients at varying seeding rates.

To conduct our empirical analysis, we draw on a large, unique farm-level dataset of more than 600,000 U.S. seeding rate choices. The data spans the period 1995-2016 for corn and 1996-2016 for soybean and contains information on the specific hybrid planted, seed price, and farmer-chosen seeding density. We control for unobserved confounders through both hybrid and farm-level fixed effects. We obtain two main findings based on farm-level market data. First, the soybean seeding rate choice is more price elastic than corn. Second, most land endowment inputs increase corn and soybean seeding rates; while seed endowment inputs increase corn seeding rates but decrease soybean seeding rates. In addition, we also collect seeding rate choice responses from corn and soybean growers and consultants through focus group meetings. They reveal some distinct viewpoints on seeding rate choices and also indicate that farmers rely most heavily on their own experiences when deciding on seeding rate choices. Finally, we discuss how the difference in price elasticities across crops has implications in various aspects, especially the division of economic surplus and the mitigation of negative ecological impacts. We develop a rough estimate on how targeted tax or price policies will mitigate neonicotinoid-related ecological impacts. Taking grassland birds as an example, a 10% tax on corn (or soybean) seed or decrease in corn (or soybean) price will induce a 0.6% (or 3.6%) increase in the bird population.

Our paper contributes to the literature in the following ways. We are the first to develop a model that considers a resource budget trade-off between more seeds and few resources allocated to each seed. To our best knowledge, no existing work has explored why corn and soybean seeding rates respond so differently to different stimuli. Most previous work that has addressed seeding rate choices has typically done so with one kind of crop and from a purely agronomic viewpoint. Second, our findings also contribute to the literature on input choices and food production. Seed costs are very expensive and account for about 14% of total production costs for corn and about 10% for soybean.[25] Corn and soybean are the two most important field crops and key commodities for food production in the United States and, together with wheat and rice, are among the four most important globally. Our findings highlight features of the seeding rate choices that distinguish between corn and soybean. Third, our paper contributes to the literature

[25] Cost proportion calculations are based on Estimated Costs of Crop Production in Iowa – 2021 at https://www.extension.iastate.edu/agdm/crops/html/a1-20.html.

on agricultural production and environmental risks. Most seeds are treated by chemical coating such as neonicotinoids, so our paper provides a new perspective on mitigating environmental concerns through seeding rate adjustments. Fourth, we explain why seed own-price elasticity of demand for soybean is likely to be more negative than that for corn, our analysis adds to the work by Ciliberto, Moschini and Perry (2019), who estimate a larger absolute value of seed own-price elasticity for aggregate corn seed products than for aggregate soybean seed products and also find that the seed industry extracts more surplus from corn products than from soybean products. Our finding of the difference across crops in elasticities of crop yield to seeding rate is of great consequence for the division of economic surplus, and also for the magnitude of that surplus.

In what follows we briefly summarize the agronomy and economics of corn and soybean seeding rate choices in the United States. Then we develop a model incorporating a trade-off between more seeds and fewer land-based resources allocated to each seed. Next we explain market data, focus group participants' responses, and other external data that we analyze and we also explain the variables that we construct. We then examine plant elasticity or plant rigidity by seed trials data and also study factors that determine commercial seeding rates by market data. Moreover, we report and analyze market estimation results and further discuss the different opinions from focus group participants. Further, we explore the potential implications of the difference in seed price elasticities across crops. We also conduct a rough estimate on the ecological effects of price changes through seeding rate adjustments. After reporting and analyzing the results, we conclude with a summary and some comments on policy implications.

Background on Seeding Rates

Corn seeding rates have increased dramatically (from about 26,000 seeds per acre in 1995 to about 32,000 seeds per acre in 2016), while soybean seeding rates have declined (from about 181,000 seeds per acre in 1996 to about 157,000 seeds per acre in 2016), which is shown in Figure 4.1. These trends are also reflected in the cumulative distribution function (CDF) of seeding rates in some representative years in Figure 4.2.[26] The CDF lines of corn seeding rates shifted right from 1996 to 2016 while the lines of soybean seeding grates shifted towards the left. The temporal pattern in the national-wide level is also reflected at the state level even though different states have different seeding rates (Figure 4.3).

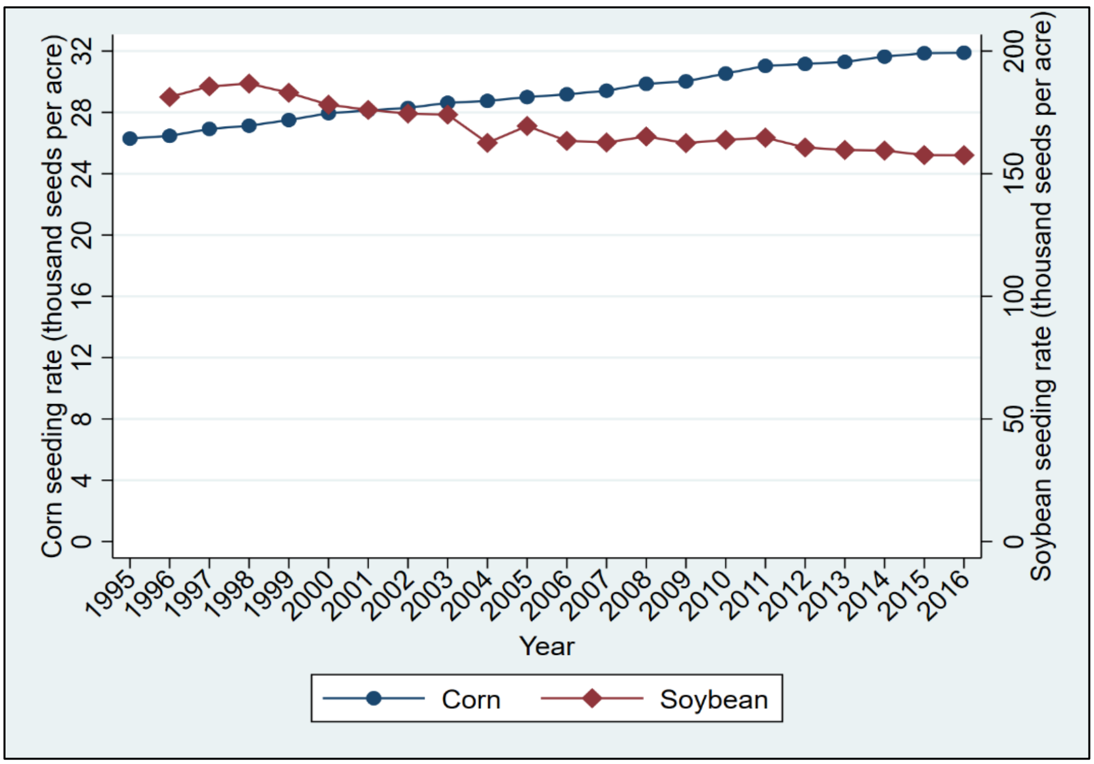
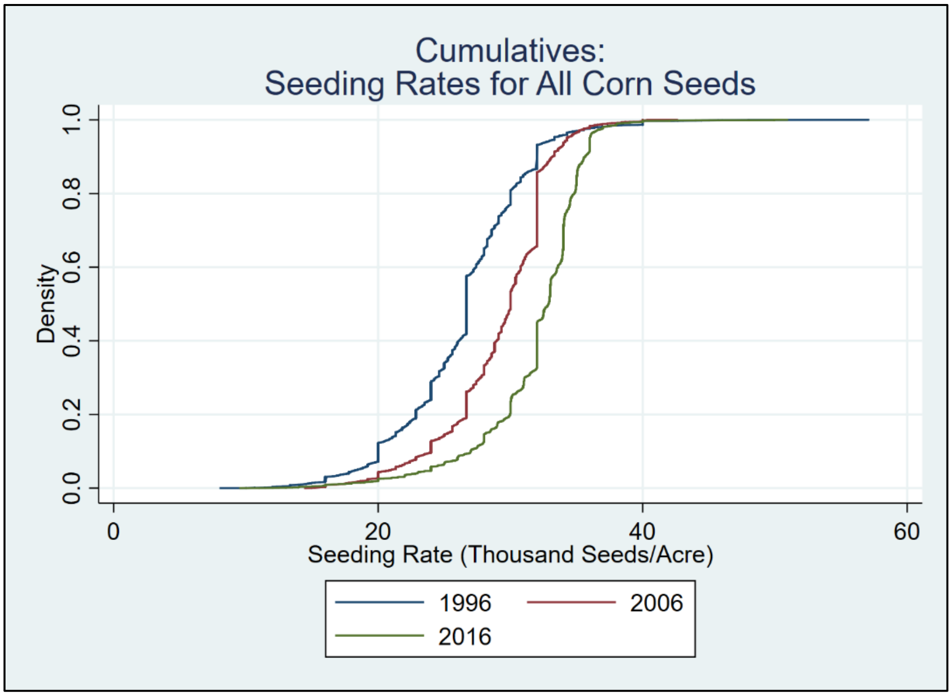
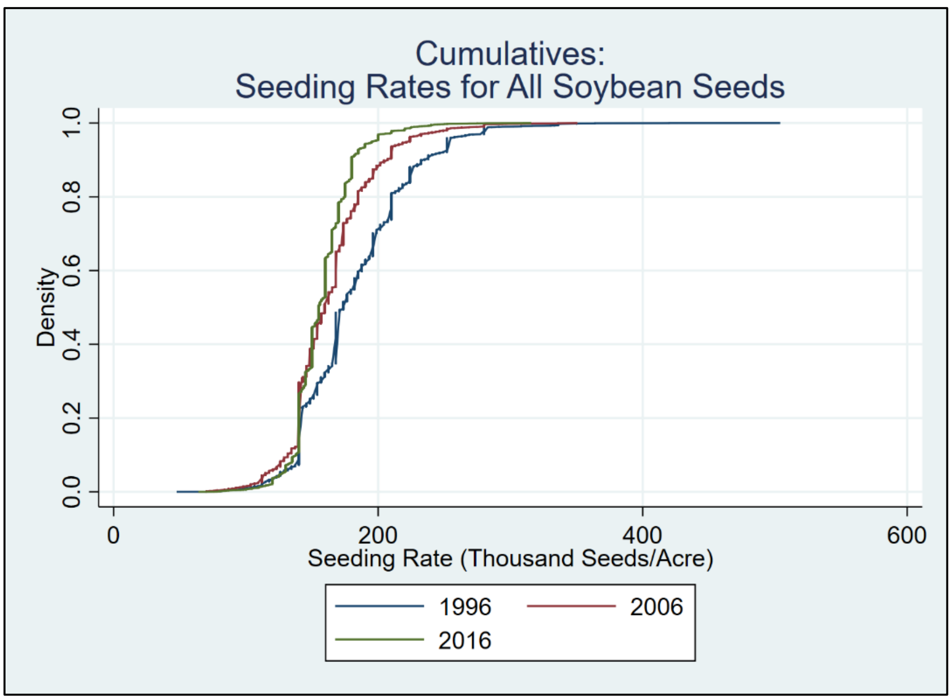


Figure 4.1 Average seeding rates for corn (1995-2016) and soybean (1996-2016) in the United States (Kynetec data)
Note: In the TraitTrak® dataset, prior to 2010, soybean units are reported in the unit of 50 lb bags, while all soybean units are converted to 140,000 seed bags since 2010. Thus, we convert soybean planting rates prior to 2010 by multiplying 2,800 seed/lb to uniform the measurement scale over 2001-2016.

[26] Detaied about cumulative distribution function of seeding rates can be found in the Appendix A.



(a) Corn



(b) Soybean

Figure 4.2 Cumulative distribution for corn and soybean seeding rates in representative years[27]

[27] Details on cumulative distribution can be found in the Appendix A.

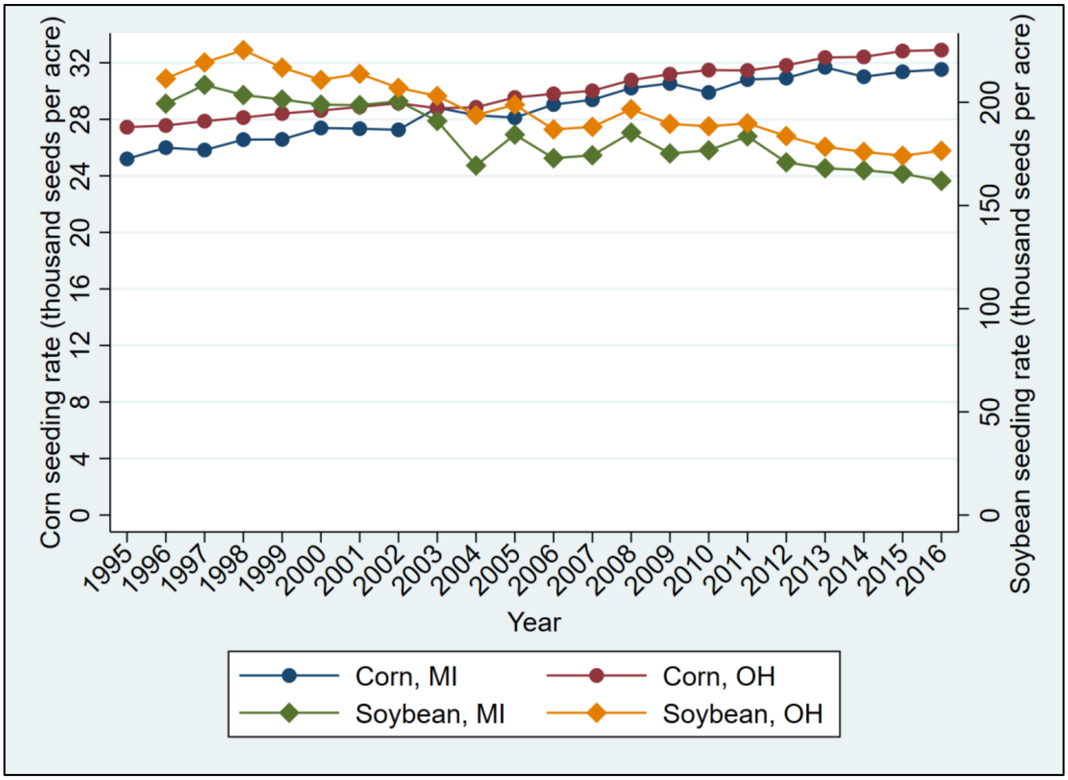
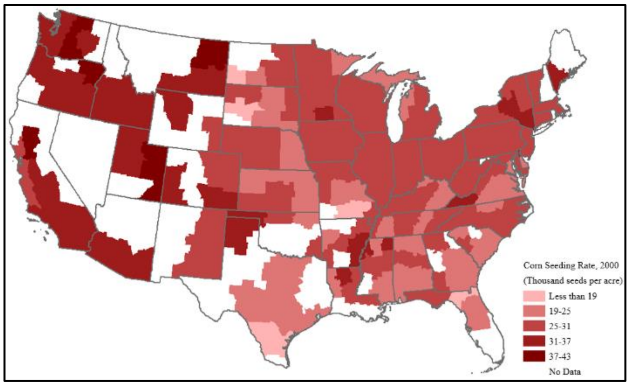
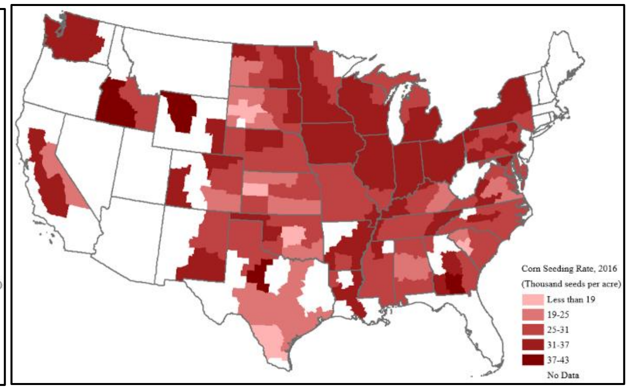


Figure 4.3 Average seeding rates for corn (1995-2016) and soybean (1996-2016) in Michigan and Ohio (Kynetec data)

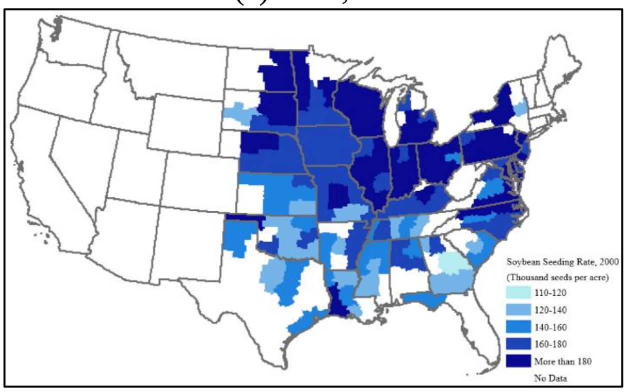
In addition to temporal differences, seed rates will differ geographically because higher latitude locations need short-season varieties, more arid locations need drought-tolerant varieties and varieties perform differently on different soils. Corn and soybean seeding rates are known to vary considerably, even in a locality. As depicted in Figure 4.4, which provides the seeding rates distribution by crop reporting district (CRD) in 2000 and 2016 for both corn and soybean, corn seeding rates were higher in 2016 when compared with 2000 in most districts. For a given year, corn seeding choices varied spatially in the United States, generally being highest in the Cornbelt and Great Lakes Region. By contrast, soybean seeding rates were lower in 2016 compared with 2000 in most districts and were greater in the Eastern Cornbelt and Northern Great Plains than in the Western Cornbelt.



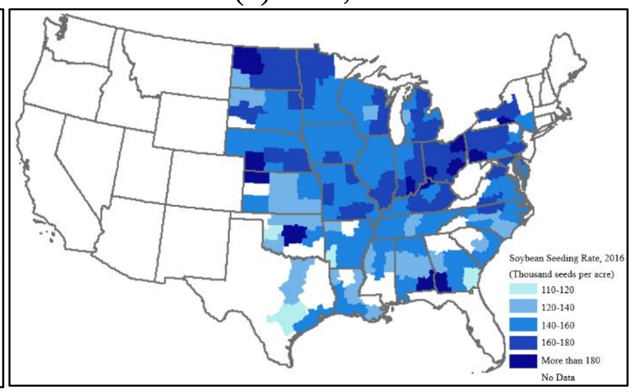
(a) Corn, 2000



(b) Corn, 2016



(c) Soybean, 2000



(d) Soybean, 2016

Figure 4.4 Seeding rates (thousand seeds/Acre) for corn and soybean by crop reporting district (CRD) in 2000 and 2016 (Kynetec data)

Many researchers have studied corn yield and seeding rate relationships and optimal seeding rate choices (Assefa et al. 2016; Assefa et al. 2018; Lindsey, Thomison and Nafziger 2018; Schwalbert et al. 2018). When considering technology only, corn optimal seeding rates should be determined by interaction effects between genotype (*G*), environment (*E*), and management (Assefa et al. 2016). Complementary management technologies such as insect resistant varieties (Ruffo et al. 2015), increased use of inorganic fertilizer (Ruffo et al. 2015; Assefa et al. 2016), irrigation, and enhanced weed and pest control techniques (Assefa et al. 2016) have been found to be critical factors for successfully increasing both plant density and corn yield. However, Assefa et al. (2018) have shown that higher seeding rates do not improve corn yield when they are planted on poor land with inadequate nutrition and water. Similarly, in the more humid parts of the world, research trials show that yield per acre responds positively to plant density but this is not true in arid environments (Haarhoff and Swanepoel 2018).

Many studies have also been conducted on soybean seeding rate choices and yields (Thompson et al. 2015; Ferreira et al. 2016; Corassa et al. 2018). Similar to corn, soybean seed yield potential is also associated with genetic attributes, environmental conditions, and management practices, and their interactions (Corassa et al. 2018). However, soybean plants are more flexible with a wide range of seeding rates. For example, soybean plants can produce more branches and pods at low seeding rates while they can produce fewer branchers and pods at higher seeding rates. Due to this flexibility, soybean varieties can efficiently respond to their environment through branching (Singh 2021).

Genetically engineered (GE) crop varieties play an important role in seeding rate choices and yield potential. GE varieties, first introduced commercially in 1996, exploit the recombinant DNA tools of modern biotechnology (Moschini 2008). These tools are used to insert one or more foreign genes into the plant's genome to express desirable traits. Two sets of attributes, herbicide tolerance in corn and soybeans and insect resistance in corn only, have dominated commercial GE corn and soybean offerings.[28] Herbicide tolerant crops are mostly tolerant to glyphosate, and insect resistance crops embed one or more genes from the bacterium *Bacillus thuringiensis* (*Bt*), which emit proteins that are toxic to certain insects. GE crops were originally offered as single trait varieties, but by 2010 corn seed with multiple GE traits had come to dominate the U.S. seed corn market. Figure 4.5 presents the diffusion pattern of GE varieties, which have accounted for the majority of U.S. corn and soybean in recent years.

[28] As of 2021, drought tolerance and other traits have not yet proven to be so popular.

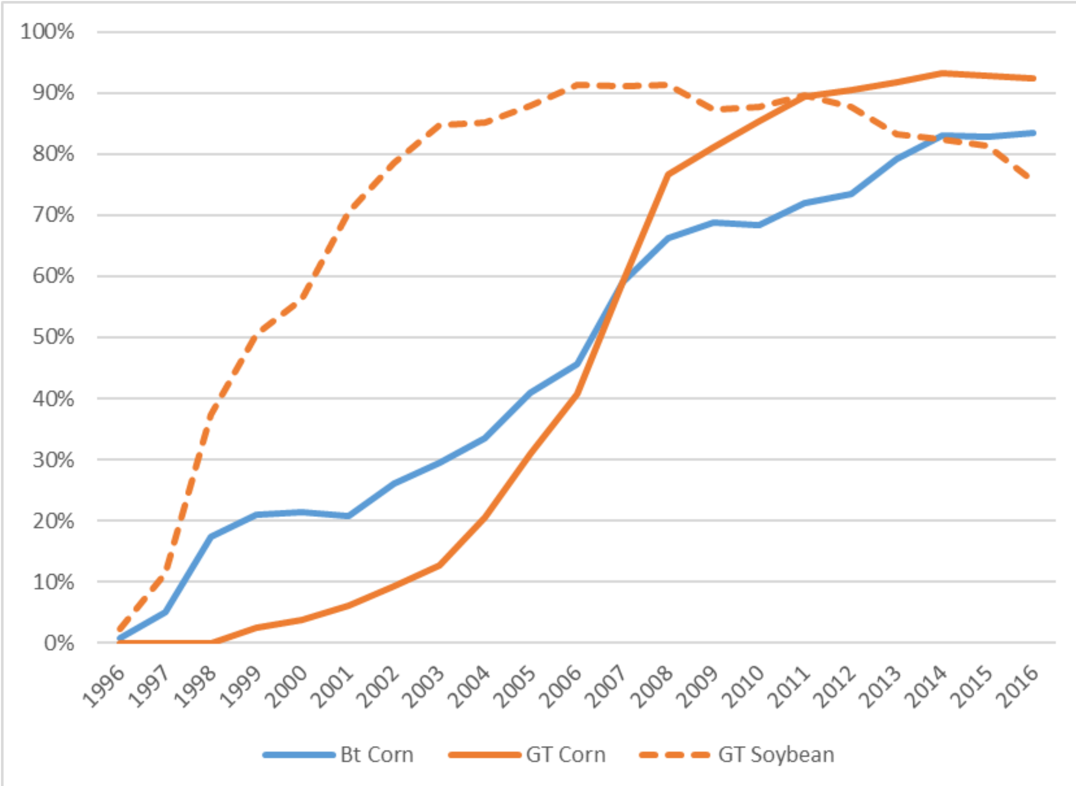


Figure 4.5 Area percentage of GE corn and soybean in the United States, 1996-2016
Note: Acre percentage is calculated based on Kynetec data. "*Bt* Corn" refers to corn varieties with *Bt* trait alone or in combination with other traits, "GT Corn" refers to corn varieties with GT trait alone or in combination with other traits, and "GT Soybean" refers to soybean varieties with GT trait.

Conceptual Model

We model profit-maximizing crop production, and our calculations will be for one land unit, which we will refer to as an acre. Let $s \in [0, \infty)$ represent seeding rate (i.e., seeds per acre). We consider two technology or resource related inputs: per acre land endowments τ divided across *s* seeds per acre, and per seed endowments θ. Examples of τ include better quality land and a new drainage technology, which improve resources per unit land area and not per seed. Examples of θ include seed coating or innovations in genetics, which improve resources per seed and not per unit land. Yield per seed is given generically as a function $y(s, \tau, \theta)$, which is decreasing in *s* and increasing in both τ and θ. With more seeds per acre, the available area and resources will decrease for each plant.[29] Given seeds per acre, endowment inputs will increase yield per seed. This yield function is assumed to be twice continuously differentiable where function derivatives are represented by appropriately subscripted variables. The function is also assumed to satisfy the boundedness constraint $\lim_{s\to\infty} y(s,\tau,\theta)s \to K$ with $K > 0$ for any τ and θ. For the sake of simplicity, germination rate is assumed to be 100%. Yield per acre is, therefore, seeding rate times yield per seed, $Y(s,\tau,\theta) = y(s,\tau,\theta)s$ so that the boundedness constraint merely requires finite limit on yield per acre as seeding rate increases to infinity.

Price Effects

With price per seed as *w* and output price as *p*, profit per plant is $py(s,\tau,\theta) - w$ and profit per acre (PPA) is

(4.1) $$\pi(s,\tau,\theta) = py(s,\tau,\theta)s - ws,$$

with first-order optimality condition

(4.2) $$\frac{d\pi(s,\tau,\theta)}{ds} = py(s,\tau,\theta) - w + py_s(s,\tau,\theta)s = 0,$$

and solution s^*. The second derivative of the PPA function is

(4.3) $$\frac{d\pi^2(s,\tau,\theta)}{ds^2} = 2py_s(s,\tau,\theta) + py_{ss}(s,\tau,\theta)s.$$

Notice that, $d\pi^2(s,\tau,\theta)/ds^2|_{s=s^*} = 2py_s(s,\tau,\theta)|_{s=s^*} + py_{ss}(s,\tau,\theta)s|_{s=s^*} < 0$ with the assumption that $2y_s(s,\tau,\theta) + sy_{ss}(s,\tau,\theta) < 0$ for any *s*, τ and θ, so the PPA function is locally concave in seeding rate at any maximum or minimum point. Consequently, there can be only one

[29] At a later juncture well will impose the resource budget constraint by setting $y(s,\tau,\theta) \equiv F(\tau/s,\theta)$, but for now we consider only the generic specification.

interior solution s^* to (4.2) and it must maximize profit. However, profit needs not be globally concave on $s \in \mathbb{R}_+$. Considering (4.1) further, if $p \lim_{s\to\infty} y(s,\tau,\theta) < w$, then $\lim_{s\to\infty} \pi(s,\tau,\theta) \to -\infty$. Given that the yield function is bounded, it follows that $\lim_{s\to 0} \pi(s,\tau,\theta) \to 0$. If $\pi(s,\tau,\theta)\big|_{s=s^*} > 0$, then continuity requires that $\pi(s,\tau,\theta)$ be convex somewhere on $s \in (0, s^*)$.

Returning to first-order condition (4.2), we have

$$(4.4) \qquad y(s,\tau,\theta)\,|_{s=s^*}\left[1+\frac{y_s(s,\tau,\theta)\,|_{s=s^*}\; s^*}{y(s,\tau,\theta)}\,|_{s=s^*}\right] = y(s^*,\tau,\theta)\left[1+\frac{d\ln[y(s,\tau,\theta)\,|_{s=s^*}]}{d\ln(s)}\right] = \frac{w}{p},$$

where $d\ln[y(s,\tau,\theta)\,|_{s=s^*}]/d\ln(s) < 0$ as resources per plant decline. Alternatively, as area scales with s^{-1} or $a \sim s^{-1}$,

$$(4.5) \qquad y(s^*,\tau,\theta)\left[1-\frac{d\ln[y(s,\tau,\theta)\,|_{s=s^*}]}{d\ln(a)}\right] = \frac{w}{p}.$$

Were yield per plant invariant to area per plant then we would have $y(s^*,\tau,\theta) = w/p$. However, just as price per unit declines with an increase in quantity chosen in the monopoly problem we have seeding rate set at a quantity such that $y(s^*,\tau,\theta) = w/p$ whenever yield per plant is insensitive to area available. We take $B(s,\tau,\theta) = d\ln[y(s,\tau,\theta)]/d\ln(a) \in [0,1]$ to be a measure of ‘plant elasticity’ and $R(s,\tau,\theta) = 1 - B(s,\tau,\theta) \in [0,1]$ to be a measure of ‘plant rigidity’. If $B(s,\tau,\theta)$ is close to 1, so that little yield is lost per acre by scaling back on seeds, then seed use will differ greatly from that defined by $y(s,\tau,\theta)\,|_{s=s^*} = w/p$. Figure 4.6 provides a characterization.

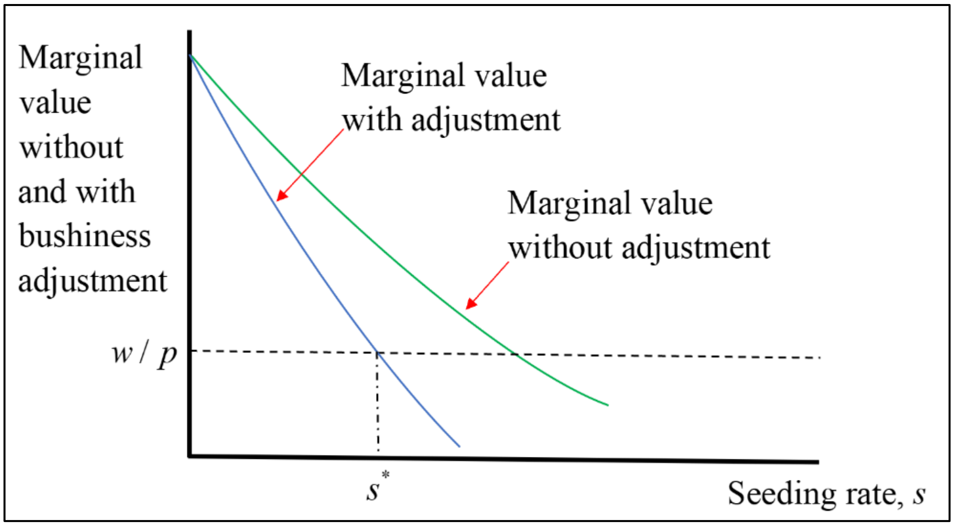


Figure 4.6 Optimal seeding choice and plant architecture

One interpretation of (4.5) is that there are two ways in which seeding rate changes the marginal value of seed. One is to change production per plant, through $y(s,\tau,\theta)$, and the other is to affect responsiveness to the area resource. A parameterization will illustrate. Notice that were $y(s,\tau,\theta)=s^{\varepsilon(\tau,\theta)}$ with $\varepsilon(\tau,\theta)\in(-1,0)$ then $B(s,\tau,\theta)=-\varepsilon(\tau,\theta)$ and $R(s,\tau,\theta)=1+\varepsilon(\tau,\theta)$ where each is independent of seeding rate for this technology. Therefore we can write $R(s,\tau,\theta)=\hat{R}(\tau,\theta)=1+\varepsilon(\tau,\theta)$ for this technology.

When $\varepsilon(\tau,\theta)\approx -1$ then yield per plant is more space elastic but $Y(s,\tau,\theta)=y(s,\tau,\theta)s$ is space inelastic. When $\varepsilon(\tau,\theta)\approx 0$ then yield per plant is insensitive to seeding rate and area available, i.e., the plant is rigid so that responsiveness to the area resource is constant (up to some external effect θ that might include genetics) and only the effect of seeding rate on production per plant matters.

For this technology,

$$(4.6)\qquad y(s,\tau,\theta)|_{s=s^*}\left[1+\frac{y_s(s,\tau,\theta)|_{s=s^*}\,s^*}{y(s,\tau,\theta)|_{s=s^*}}\right]=(s^*)^{\varepsilon(\tau,\theta)}[1+\varepsilon(\tau,\theta)]=\frac{w}{p},$$

and we have optimal seeding rate as

$$(4.7) \qquad s^* = \left(\frac{w}{p[1+\varepsilon(\tau,\theta)]} \right)^{1/\varepsilon(\tau,\theta)} = \left(\frac{w}{p\hat{R}(\tau,\theta)]} \right)^{1/\varepsilon(\tau,\theta)}.$$

Notice that plant rigidity separates the price ratio from the effective price ratio where the effective ratio is larger. When the plant becomes less rigid, or more elastic with respect to space, then the effective price ratio faced increases so that the absolute value of own-price elasticity will increase as the plant becomes more space elastic.

Figure 4.7 depicts responsiveness at the extreme when $\varepsilon(\tau,\theta) \approx 0$. We see this picture as representing the corn plant (Tian et al. 2011; Andorf et al. 2019) in which yield per acre is very elastic with respect to seeding rate when spare ground is available but inelastic when this ground has been filled. Thus when the input to output price ratio w/p is sufficiently low then the absolute value of own-price elasticity of demand for seed is very low.

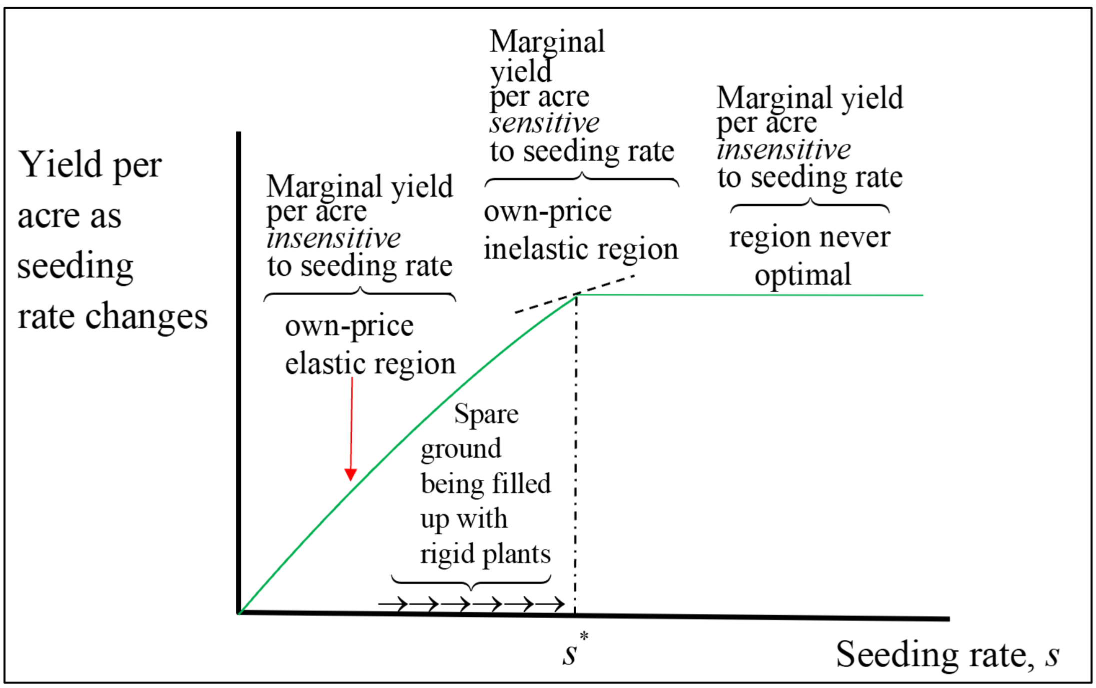


Figure 4.7 Yield as a function of seed under rigid plant architecture

Thus, we have our first hypothesis,

Hypothesis 1: H1) For given prices and seeding rate, the more elastic the plant, the more elastic the seed own-price demand curve.

This perspective then supports the idea that the corn seed market is vulnerable to high mark-ups. The infertility of highly productive hybrids curtail the option of saving seed from past harvests and, in addition, farmers cannot respond at the intensive margin to higher prices by spreading seed over larger areas.

External Shocks

We turn next to understanding the effects of an external shock, be it technology shock or change in natural resources available. Given the resource budget constraint, yield per seed is $y(s,\tau,\theta) = F(\tau/s,\theta)$, which is increasing in both arguments. We denote $F_1(\cdot) \equiv dF(\cdot)/d(\tau/s) > 0$ and $F_2(\cdot) \equiv dF(\cdot)/d\theta > 0$, while the function as a whole is assumed to be twice continuously differentiable and concave. PPA is $\pi(s,\tau,\theta) = pF(\tau/s,\theta)s - ws$

with optimality condition

(4.8) $$F\left(\frac{\tau}{s},\theta\right)|_{s=s^*} - \frac{\tau}{s^*}F_1\left(\frac{\tau}{s},\theta\right)|_{s=s^*} = \frac{w}{p},$$

and cross derivatives

(4.9)

(4.9*a*) $$\frac{d^2\pi(\cdot)}{dsd\tau} = -\frac{\tau}{(s^*)^2}F_{1,1}\left(\frac{\tau}{s},\theta\right)|_{s=s^*} > 0;$$

(4.9*b*) $$\frac{d^2\pi(\cdot)}{dsd\theta} = F_2\left(\frac{\tau}{s},\theta\right)|_{s=s^*} - \frac{\tau}{s^*}F_{1,2}\left(\frac{\tau}{s},\theta\right)|_{s=s^*} = F_2(\cdot)\left[1 - \frac{\tau}{s^*}\frac{F_{1,2}(\cdot)}{F_2(\cdot)}|_{s=s^*}\right] \overset{\text{sign}}{=} 1 - \frac{d\ln[F_2(\cdot)|_{s=s^*}]}{d\ln(\tau/s)}.$$

Derivative (4.9*a*) asserts that an increase in per acre resources complements seed use and so optimal seed use should increase with an increase in this form of endowments, $ds^*/d\tau > 0$.

Derivative (4.9*b*) cannot be so readily signed. If resources provided to each plant substitute for resources provided to each acre then optimal seed use should increase with an increase in endowment provided per plant, $ds^* / d\theta > 0$. This is because an increase in endowments per plant will then decrease the marginal value of endowments per acre where value can be restored by reducing resources per plant, i.e., increasing seeding rate. More generally, if the marginal value of resources per plant is inelastic with respect to resources per acre then an increase in resources per plant will increase seeding rate. An example where the two resources are likely to substitute is when resources per plant come in the form of genetics to protect against drought and the endowment per acre is soil moisture. Then the drought tolerance trait would provide confidence to the farmer that sharing water endowments over more seed will be beneficial. An example where two resources are likely to complement is when herbicide tolerant seed releases nutrients, sunlight and other land resources that would have been consumed by weeds for use by the plant.

Our second hypothesis is then

Hypothesis 2: H2*i*) The optimal seed rate will increase with an increase in per acre endowments for any plant architecture. **H2*ii*)** Whenever the marginal value of resources per plant is elastic (respectively, inelastic) with respect to resources per acre, then optimal seeding rate will decrease (respectively, increase) in response to an increase in resources per plant.

Both Hypothesis 1 and Hypothesis 2 provide avenues for empirical scrutiny, and it is to testing these hypotheses that we now turn.

Data Description

We first bring together data from several sources to construct a unique farm-year panel dataset, which includes information about seeding rate choices, spatial locations, prices, soil conditions, agricultural practices, and genetic technologies. We also collect seeding rate choice responses from corn and soybean growers and consultants through focus group meetings that occurred in 2018.

Market Data

The main econometric analysis that we perform relies on the TraitTrak® dataset, which contains a large sample of farm-level data for land sown to corn and soybean. The TraitTrak® dataset is constructed by a market research company Kynetec USA, Inc., which collected data from annual surveys from randomly sampled farmers in the United States. The sampled farmers were designed to be representative at the crop reporting district (CRD) level. CRDs are USDA-designated groupings of counties with similar geography, climate, and cropping practices. Data collected are reviewed and verified by specially trained analysts to ensure accuracy, high completion levels, internal consistency, and compatibility with external information sources. The unit of observation is land tract level so that each surveyed farmer may report multiple corn and soybean plantings in a given year. Each surveyed farmer was asked to specify their seeding rate, seed trait, seed cost, and genetic technology choices during the previous growing season.

The original dataset reports 442,803 corn seed observations over 1995-2016 and 213,062 soybean seed observations over 1996-2016 across 235 CRDs in 31 states, where each observation is a unique combination of the year, farmer, and seed variety. We also include a tillage variable (i.e., the share of farms with conventional tillage at the CRD level) in some specifications. The tillage data is obtained from another dataset AgroTrak®, which is also constructed by Kynetec. Each plot is identified as using one of three following alternatives: "Conventional Tillage", "Conservation Tillage", or "No-Till". We treat conventional tillage as a distinct category and calculate the share of conventional tillage at the CRD level.[30]

At the time when farmers make seeding rate choice decisions, post-harvest-time market crop prices are not yet realized and each crop's futures prices are used to represent farmers' expectations of postharvest prices. To be specific, we incorporate monthly average pre-planting settlement price in February of each year's December Futures contract for corn (Chicago Board of Trade or CBOT) and November contract for soybean (CBOT).[31]

Location, Soil and Weather Data

Seeding rates differ geographically and so including location variables can capture climate-related effects and spatial variations. Latitude and Longitude coordinates are obtained from the 2018 Census U.S. Gazetteer files for counties.[32] Land capability classification (LCC) are from National Resource Inventory files. We use LCC to denote the fraction of land in a county that is best for crop production, namely land capability categories I or II among the eight categories available where only categories I through IV are suitable for cropping. The Palmer's Z (PZ) index measures soil moisture availability for crop growth (Heim 2002) by accounting for evapotranspiration, soil water storage capacity, and precipitation (Karl 1986). National Oceanic and Atmospheric Administration (NOAA) files[33] provide monthly PZ values for climate divisions in the conterminous United States. Each climate division contains multiple counties where some counties overlap with multiple climate divisions. To project these climate division data to the county-level of analysis, we calculate the intersection area between climate divisions

[30] Details about data screening are available at the Appendix B.
[31] Futures prices for commodities are downloaded from https://www.quandl.com/.
[32] Latitude and longitude information are available at https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.2018.html.
[33] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/, last accessed June 16, 2021.

and each county and then calculate area-weighted PZ values. Since PZ values have been normalized to zero on average in that location (Xu et al. 2013), we transform PZ values to capture moisture stress from dryness ($PZ \leq 0$, DRY) and wetness ($PZ \geq 0$, WET). Our wetness and dryness calculations are applied to March PZ values, the time when farmers begin to make seeding rate decisions.

Agricultural Practice and Seed Trial Data

Advances in crop management techniques such as increased irrigation area are critical factors for increase in both seeding rate and yield and available irrigation is correlated to water supply for crop growth (Assefa et al. 2016; Brown 1986). We calculate the ratio of irrigated harvested acres to total harvested acres, which is denoted by IR. County-level irrigated harvested acres and total harvested acres are from the National Agricultural Statistics Service (NASS).

Agronomic optimal seeding rates vary with planting dates, and delayed planting would result in an increase in optimal seeding rates for certain varieties (Lindsey and Thomison 2016; Van Roekel and Coulter 2011). We obtain the median planting date (*MPD*) from NASS. We detrend *MPD* and include the deviation of detrended *MPD* from its mean value across all the study period as an explanatory variable.[34] In addition, trial data including information on crop yield, seed treatment, and seeding rate are obtained from seed trial reports or extension reports of land grant universities.[35]

The definitions of variables in the market estimation can be found in Table 4.1, in which we classify the variables into the following group: seeding rate choices, prices, land endowment

[34] Details on median planting dates are included in the Appendix C.
[35] Detailed information about seed trial reports or extension reports can be found at https://agcrops.osu.edu/on-farm-research and https://webdoc.agsci.colostate.edu/csucrops/reports/corn/cornreport_2018.pdf.

factors, seed endowment factors, and other controls. Table 4.2 shows the corresponding variable descriptive statistics for corn and soybean. Table 4.3 reports the mean values of yield and area per plant by crop and region in the trial datasets.

Table 4.1 Definition of variables

Category	Variable	Description	Data Source
Seeding choices	*s*	Seeding rate (thousand seeds per acre)	TraitTrak®
Prices	PR	The ratio of seed costs over crop futures prices	TraitTrak®, Quandl
Land endowment	LCC	The fraction of land in a county that is in land capability categories I or II	NRI
	WET	The maximum among 0 and the Palmer Z in March	NOAA
	DRY	Negative value of the minimum among 0 and the Palmer Z in March	NOAA
	TI	Fraction of farms with conventional tillage by CRD	AgroTrak®
Seed endowment	GT	An indicator function for corn and soybean seeds where GT=1 whenever seed trait is glyphosate tolerance	TraitTrak®
	BT	An indicator function for corn seed where BT=1 whenever seed trait is either rootworm resistant or cornborer resistant or both	TraitTrak®
Controls	IR	The ratio of irrigated harvested acres to total harvested acres by CRD	NASS
	PD	The deviation of detrended median planting date (MPD) from the mean value of MPD during all the study years	NASS
	t	Time trend variable centered at the year 2007	
	LAT	The latitude of a county's internal point, the greater the north towards	Gazetteer files
	LON	Absolute value of longitude of a county's internal point, the greater the west towards	Gazetteer files

Table 4.2 Variable descriptive statistics

Crop	Variable	Obs	Mean	Std. Dev.	Min	Max
Corn	*s*	403,262	29.532	4.509	8.000	57.143
	PR	403,262	40.405	14.909	0.000	114.490
	LCC	402,807	0.490	0.229	0.000	0.935
	WET	403,262	0.539	0.998	0.000	9.240
	DRY	403,262	0.842	0.960	0.000	5.890
	TI	360,529	0.406	0.187	0.000	1.000
	GT	403,262	0.499	0.500	0	1
	BT	403,262	0.503	0.500	0	1
	IR	401,949	0.121	0.212	0.001	1.430
	PD	383,073	0.097	1.263	-3.053	6.674
	t	403,262	-0.577	6.237	-12	9
	LAT	403,262	41.422	2.699	26.083	48.831
	LON	403,262	91.235	6.365	68.722	124.148
Soybean	*s*	187,776	168.761	34.446	14.000	504.000
	PR	187,776	3.818	1.381	-0.938	9.566
	LCC	187,721	0.506	0.221	0.000	0.935
	WET	187,776	0.521	1.030	0.000	9.240
	DRY	187,776	0.857	0.950	0.000	5.290
	TI	172,829	0.360	0.178	0.000	1.000
	GT	187,776	0.744	0.436	0	1
	IR	187,059	0.070	0.145	0.000	0.822
	PD	181,043	-2.635	1.091	-5.164	1.065
	t	187,776	-0.712	6.110	-11	9
	LAT	187,776	40.879	3.185	28.288	48.828
	LON	187,776	90.864	5.274	73.656	106.352

Table 4.3 The mean of yield and area per plant by crop and region

Variable	Corn OH	Corn CO	Soybean OH	Soybean MI
Yield per Plant (×1,000)	6.510	6.435	0.455	0.551
Area per Plant (×1,000)	0.033	0.041	0.008	0.009
Seeding rate range (×1,000)	[22, 47]	[8, 37]	[50, 300]	[80, 160]
Obs	113	193	191	516

Focus Group Meeting Data

We implemented three focus group meetings with corn and soybean growers and consultants in August 2018, during which participants were asked about their opinions about seeding rate choices. We chose participants who varied in their farm size, soil types and were at various stages of incorporating precision agriculture technology into their farm operations. Three meetings were held on August 13 in East Lansing, Michigan, August 20 in Fulton, Ohio, and August 21 in Columbus, Ohio. The meetings were held at university offices and respondents generally resided within 30 miles of the meeting place. Each meeting lasted about 3.5 hours, and about 1.5 hours were required to complete the survey instruments which were available in paper format. A Michigan State University extension educator with a precision agriculture background led a presentation to help participants work through the instrument.

We received 14 responses from East Lansing attendees, 21 from Fulton attendees, and 14 from Columbus attendees. Of the 49 respondents who completed the questionnaire, 37 were operators and 12 were either crop consultants or suppliers. The average operated acres in our sample were about 1,100 acres in Wauseon, 1,800 acres in Columbus, and 3,200 acres in East Lansing, which were much higher than the average operated acres (441 acres) in the United States (USDA-NASS 2019). Our sample farms covered a large proportion of farmland. The 2017 Agricultural Census data reveals that the largest 8% of farms in the United States (1,000 or more acres) controlled 71% of all farmland (USDA-NASS 2019) while most farms in the United States are not commercially viable (Hoppe, MacDonald and Korb 2010). In Table 4.4 we compare the mean values for each surveyed grower response with average values for growers in the corresponding CRD. Although surveyed growers were younger and had operated farms for fewer years than those in the area, a greater share operated farms as their principal occupation.

Table 4.4 Grower characteristics by location

	East Lansing, MI	CRD 80, MI	Wauseon, OH	CRD 10, OH	Columbus, OH	CRD 50, OH
Mean years as grower	19	25	22	26	26	24
Mean age	46	57	45	57	45	57
Share who farm as principal occupation	0.75	0.41	0.60	0.38	0.50	0.39

Note: In "mean years as grower", we record 15 years for one operator in East Lansing who reported "15+" years, and 12.5 years for another in Wauseon who reported "10-15" years. Area comparisons are from the 2017 Agricultural Census.

The focus group meetings provided information about how farmers adjust corn and soybean seeding rate choices when faced with changes in tillage type, planting date, soil moisture, soil quality, chemical treatment, and genetic technology. Moreover, the meetings also explored how much impact different market or human influences had on seeding rate choices and what the most important factors were.

Empirical Methods

Plant Architecture Estimation

Based on our measures of plant elasticity and rigidity in the conceptual model, we further explore whether corn and soybean present different plant architectures by examining crop yield responses to area per plant with seed trial data. Letting *y* denote yield per plant *a* denote area per plant, we apply a simple log-log ordinary least squares (OLS) regression model with year-fixed, county-fixed, and variety-fixed effects. The estimation equation is

(4.10) $$\ln(y^{l}_{c,t}) = \alpha_0 + \alpha_1 \ln(a^{l}_{c,t}) + \psi_t + b_c + d_v + \xi_{c,t},$$

where *c* denotes county, *t* denotes year, *l* denotes crop (i.e., corn or soybean) and *v* denotes variety. The term ψ_t represents year-fixed effects, which can capture the influence in the aggregate time trends and also annual weather effects; b_c represents county-fixed effects, which capture some unobserved factors, idiosyncratic to each county; d_v represents variety-fixed effects, which control for some specific factors within each variety; and $\xi_{c,t}$ represents error term.

Market Estimation

After examining the difference in plant architecture between corn and soybean, we turn to explore how crop seeding rate choices respond to price changes, land endowment and seed endowment inputs. The main estimation equation is

$$(4.11)\quad \begin{aligned} s_{i,t}^{l} &= \beta_0 + \beta_1 PR_{i,t}^{l} + \beta_2 LE_{i,t}^{l} + \beta_3 SE_{i,t}^{l} + \beta_4 AG_{i,t}^{l} + \beta_5 t + \beta_6 LOC_{i,t} + \beta_7 t * LOC_{i,t} \\ &\quad + \delta_f^{l} + h_v^{l} + \varepsilon_{i,t}^{l} \end{aligned}$$

where each farm is denoted as i, each farmer who may own one or multiple farms is denoted as f, seed variety is denoted as v, and the time indicator is denoted as t. The dependent variable is $s_{i,t}^{l}$, the seeding rate (thousand seeds per acre) for farm i and crop l in time t. The main independent variables of interest are grouped into several vectors. *PR* is the ratio of observed seed purchase costs over the harvest-time crop contract futures price quoted at planting time. *LE* is the set of land endowment inputs including LCC, *WET*, DRY, and *TI* (the share of farms with conventional tillage in the total number of farms at CRD). *SE* is a set of seed endowment inputs, such as genetic technologies including *GT* and *Bt* for corn and only GT for soybean. *AG* is the set of agricultural inputs or practices as control variables, which contains the percent of irrigated acres on total harvested acres (IR), the deviation of detrended *MPD* from the average value of *MPD* (PD). *LOC* is the set of location variables including latitude (LAT), longitude (LON).

The remaining terms are farmer-specific effects denoted by δ_f^l, variety-fixed effects denoted by h_v^l, and the error term denoted by $\varepsilon_{i,t}^l$. The presence of farmer-specific fixed effects in the model is intended to control for unobserved factors, idiosyncratic to the farmers, and so account for any omitted variables such as education, age, and other personal characteristics, that are correlated with seeding rate choices. The presence of variety-specific fixed effects controls for the impact of excluded factors that could conceivably affect seeding rate choices but that may be presumed to be reasonably constant within a given variety.

Results and Analysis

In this section, we first present results for plant architecture estimations and compare the difference in plant elasticity and rigidity between corn and soybean. We then present results for market estimations on seeding rate responses to price changes, land endowment and seed endowment inputs. We then turn to discuss focus group participants' opinions about seeding rate responses to land and seed endowments, and also summarize the social factors that affect seeding rate choices. Finally, we explore the potential implications of price elasticity differences across crops in the division of economic surplus and the mitigation of negative ecological impacts. We conduct a rough estimate of how price changes affect ecological outcomes through neonicotinoid-treated seeds.

Plant Architecture

Table 4.5 shows the equation (4.10) regression results of plant yield responses to area per plant for corn and soybean in some representative states. Comparing the coefficients of area per plant in log form, we find that soybean yield per plant is more elastic than corn with regard to the change in area per plant, i.e., the soybean plant is more elastic than corn. This finding is consistent with the intuition that soybeans are short and space elastic and can readily branch laterally, while corn is tall and rigid. Compared with corn, the soybean plant can more readily utilize the resources made available with more area, i.e., at a lower seeding rate. The difference in plant architecture among crops provides potential explanations for diverse seeding rate choices. We also test the hypothesis that coefficients of area per plant in the log form equal to one so that does not matter within a range. The null hypothesis is rejected for corn in OH and CO and for soybean in CO at 1% significance level and for soybean in OH at 10% significance level.

Table 4.5 Regression of yield per plant on area per plant with fixed effects

Variable	Corn OH Log (Yield per Plant)	Corn CO	Soybean OH	Soybean MI
Log (Area per Plant)	0.896***	0.335**	0.970***	0.943***
	(0.0198)	(0.131)	(0.0153)	(0.0108)
Year FE	Yes	No	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Variety FE	Yes	Yes	Yes	Yes
Constant	3.814***	-2.126*	3.471***	3.286***
	(0.210)	(1.203)	(0.187)	(0.127)
Observations	113	193	191	513
R-squared	0.981	0.921	0.985	0.964
	H_0: coefficients of log (Area per Plant) equal to 1			
F statistics	27.89	25.69	3.86	27.61
Prob>F	0.000	0.000	0.051	0.000

Note: Standard errors in parentheses, *** p<0.01, **p<0.05, * p<0.1

Price Effects on Seeding Rate Choices

Table 4.6 reports equation (4.11) market estimation results for four specifications, each differing by crop and the type of fixed effects included. For each crop we chose as our reference model the estimation with variety fixed effects. We find price ratio (i.e., ratio of seed costs over crop future prices) to be statistically significant with an expected negative coefficient value in all the specifications. Recall that sample average price ratio values are approximately 40.4 and 3.8 for corn and soybean, respectively. Hence, a 10% increase in seed prices or a 10% decrease in corn prices, given the estimated coefficient in column 2, would reduce corn seeding rates by less than 3% of the average seeding rate.

Table 4.6 Regression results with fixed effects for corn and soybean (Kynetec data)

	Corn		Soybean	
	(1)	(2)	(3)	(4)
Variable	*s* (thousand seeds per acre)			
PR	-0.000962**	-0.00203***	-1.106***	-0.758***
	(0.000387)	(0.000470)	(0.0590)	(0.0714)
LCC	1.643***	1.383***	-2.414	0.214
	(0.216)	(0.224)	(3.527)	(3.751)
WET	-0.0148***	-0.0118**	-0.506***	-0.456***
	(0.00535)	(0.00569)	(0.0719)	(0.0779)
DRY	0.0386***	0.0218***	0.0123	0.0659
	(0.00556)	(0.00606)	(0.0826)	(0.0897)
TI	0.589***	0.538***	6.564***	3.373***
	(0.0545)	(0.0579)	(0.807)	(0.866)
GT	0.208***	0.312	-3.742***	-4.941***
	(0.0146)	(0.293)	(0.190)	(1.431)
BT	0.156***	0.329		
	(0.0101)	(0.218)		
PD	0.0162***	0.000469	0.356***	0.557***
	(0.00388)	(0.00428)	(0.0694)	(0.0756)
IR	-0.832***	-0.999***	-5.843	-1.431
	(0.266)	(0.284)	(3.999)	(4.483)
t	0.647***	0.313***	-6.605***	-7.145***
	(0.0261)	(0.0338)	(0.351)	(0.519)
LAT	0.0274	0.0744**	0.776	0.319
	(0.0332)	(0.0346)	(0.525)	(0.571)
LON	-0.0858***	-0.102***	-1.407***	-1.015***
	(0.0157)	(0.0171)	(0.289)	(0.312)
*t**LAT	0.00478***	0.0142***	-0.138***	-0.100***
	(0.000529)	(0.000712)	(0.00700)	(0.0109)
*t**LON	-0.00665***	-0.00751***	0.121***	0.110***
	(0.000244)	(0.000279)	(0.00397)	(0.00471)
Farmer FE	Yes	Yes	Yes	Yes
Variety FE	No	Yes	No	Yes
Constant	35.34***	35.02***	272.0***	254.4***
	(1.573)	(1.703)	(29.02)	(31.94)
Observations	342,794	333,237	163,316	157,225
R-squared	0.775	0.796	0.636	0.678

Note: Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

By contrast, soybean seeding rates would decrease by 18% of the average seeding rate if there is a 10% increase in seed prices or a 10% decrease in soybean prices, given the estimated coefficient in column 4. This indicates that the demand for soybean seed is more price elastic than that for corn, which supports hypothesis H1 in our conceptual model. We also calculate the seed own-price elasticities by year (Table 4.7). Although price elasticities change over time, their absolute values are relatively larger in most recent years for both corn and soybean.

Table 4.7 How seeding rate changes with a 10% increase in seed price or a 10% decrease in crop price

Year	Corn	Soybean
1998	-2.15%	-9.74%
1999	-2.53%	-13.76%
2000	-2.41%	-14.09%
2001	-2.50%	-17.14%
2002	-2.69%	-18.99%
2003	-2.66%	-16.87%
2004	-2.40%	-16.01%
2005	-2.98%	-21.20%
2006	-2.92%	-20.41%
2007	-1.98%	-15.86%
2008	-1.93%	-10.47%
2009	-3.19%	-20.72%
2010	-3.41%	-21.12%
2011	-2.28%	-14.51%
2012	-2.65%	-17.42%
2013	-2.87%	-18.31%
2014	-3.62%	-21.46%
2015	-3.97%	-25.90%
2016	-4.20%	-28.00%

Land Endowment and Seed Endowment Effects

In addition to price effects, seeding rate choices are affected by a complex combination of land endowment and seed endowment and other control variables. Land endowment includes better quality land, suitable soil moisture, and beneficial agricultural practices which can improve resources per acre. Seed endowment includes genetically engineered seed varieties adoption (e.g., GT and *Bt*) which will improve resources per seed.

Table 4.6 also reports seeding rate responses to land endowment and seed endowment. For land endowment, we find that corn seeding rates will be higher on the lands with better qualities, but the effects of land quality on soybean seeding rate choices are not clear. The deviation from expected soil moisture can affect corn and soybean seeding rates. Specifically, severe wetness induces a seeding rate decline for both crops, since too much moisture or flooding can take away valuable plant-available nutrients and organic matters. At the same time, we observe dryness can increase corn seeding rates but it does not have much impact on soybean seeding rates.

Turning to tillage, conventional tillage usually incorporates most of crop residue into soil, and so more nutrients per acre are released into soil compared to conservation tillage or no-till. Estimation results show that a larger proportion of conventional tillage will increase seeding rates for both corn and soybean, which is consistent with our H2*i*. Although conventional grazing can release more resources to land, it could induce soil erosion and soil moisture loss in the long run. There has been a shift away from conventional tillage for soybean, so it is reasonable to see a decline in soybean seeding rate over time. For other agricultural practices such as irrigation and planting date, we do not know their exact roles on seeding rate choices and we include them as control variables.

As stated in the background section, genetically engineered seed varieties have been widely adopted in U.S. corn and soybean production. We find farmers choose lower soybean seeding rates with GT. For corn, we observe farmers increase seeding rates with GT or *Bt* treatment when only farmer-fixed effects are included. This increasing effect disappears after including variety-fixed effects since variety-fixed effects capture the GT and *Bt* impacts. Thus these findings are consistent with H2*ii* in the conceptual model. To be specific, GT corn increases resources per plant by better controlling resource consuming weeds, which will provide confidence to farmers that sharing resources over more seed will be beneficial. As corn is rigid the best way to use these resources is to increase the seeding rate. The soybean plant, however, can expand to consume these resources.

Focus Group Participants' Opinions about Seeding Rate Choices

Table 4.8 presents how farmers' seeding rate choices respond to land endowment and seed endowment inputs across market estimation results and focus group meeting responses. Focus group participants in Ohio and Michigan differ in some regards with what market data convey. For land endowment, corn seeding rates increased when soil quality was better, soil moisture was higher, and soil varied smaller. Soybean seeding rates increased with higher soil moisture. These seeding rate responses are consistent with our H2*i*. However, soybean seeding rates did not respond to soil quality and variation as expected. We do not observe the increasing effects of more intensive tillage on seeding rates as revealed by market estimations. Turning to seed endowments, corn seeding rates would decrease if insect protection above and below ground trait was changed from yes to no, but seeding rates still increased when chemical treatment was changed from yes to no. For soybean, as expected seeding rates would increase when chemical treatment was changed from yes to no and would decrease when treatment was changed in the opposite direction.

Table 4.8 How seeding rates choices are affected by different environmental changes or agricultural practices

	Environmental changes or agricultural practices	Corn		Soybean	
		Market regression	Focus groups	Market regression	Focus groups
Land endowment	Soil quality was better.	R^a	R^a	L	L^a
	Soil moisture was higher.	L^a	R^b	L^a	R^b
	Soil moisture was lower.	R^a	L^b	L^a	R^c
	Soil varied greater.		L^a		R^a
	Tillage choice would be changed to be more intensive.	R^a	L	R^a	L^a
	Tillage choice would be changed to be less intensive.	L^a	R^b	L^a	R^a
Seed endowment	Chemical treatment was changed from Yes to No.		R^c		R^a
	Chemical treatment was changed from No to Yes.				L^b
	Insect protection above ground trait choice was changed from Yes to No.		L^c		
	Insect protection above ground trait choice was changed from No to Yes.		E		
	Insect protection below ground trait choice was changed from Yes to No.		L		
	Insect protection below ground trait choice was changed from No to Yes.		R		
	GT was adopted.	R^a		L^a	
	Bt was adopted.	R^a			
Other agricultural practices	Planting date was earlier.	R	R^a	L	L
	Planting date was later.	L	L^a	R	R^a
	The share of irrigated acres in harvested acres was greater.	L^a		L	
	Tile drained was changed from Yes to No.		L		R
	Tile drained was changed from No to Yes.		R^b		L^b

Note: L denotes farmers would like to lower seeding rates; R means farmers would like to raise seeding rate; E means farmers would not change seeding rates. Red color means the responses are consistent with our hypotheses. Standard errors are at the significance levels: ^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1.

Figures 4.8 and 4.9 present the most important factors that affect corn and soybean seeding rate choices from focus group participants' view, which are also discussed by Hennessy et al. (2021). Farmers rely most heavily on their own experience when making seeding rate choices. The second-order important factors are dealer, agronomy consultant, and university or extension recommendations. Peer farmer experience has little influence on seeding rate choices. Although price changes affect seeding rate choices, surveyed farmers claim that seed prices and crop expected prices are not major drivers in the decision process.

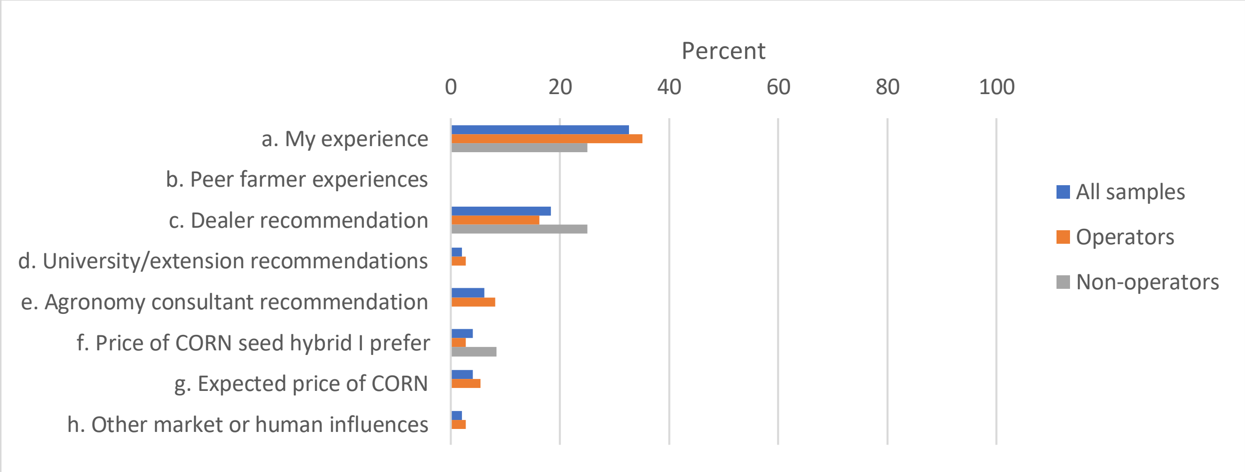


Figure 4.8 The most important factor that affects corn seeding rate choices from the focus group participants' view
Note: Fifteen participants did not answer this question.

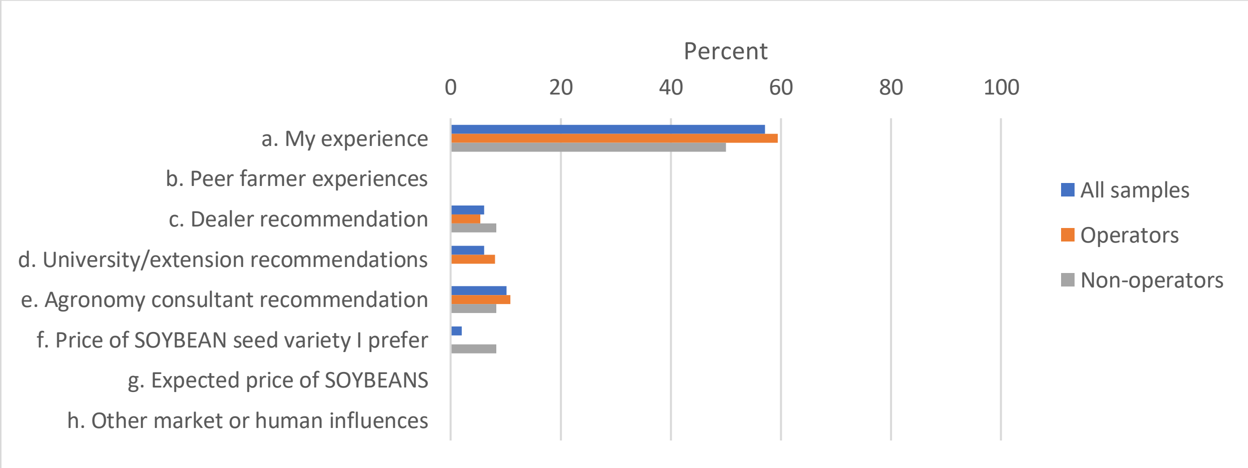


Figure 4.9 The most important factor that affects soybean seeding rate choices from the focus group participants' view
Note: Ten participants did not answer this question.

Implications of Seed Price Elasticities

The difference in seed price elasticities across crops is important in various aspects. First, the difference in elasticities determines a company's capacity to extract surplus through pricing power. Both corn seed and soybean seed industries are oligopolistic where the same firms are active in both markets. The corn seed industry has competed intensively on product quality since the advent of commercialized hybrids in the 1920s. The seed had in-built intellectual property protection because saved seed from hybrid variety crop was not very productive. Soybean seed savings undermined innovation in that market until technological developments during the past 25 years have made seed saving unprofitable for farmers. Farmers can still undermine oligopolistic pricing power through spreading seed more sparingly were price to increase. As our analysis shows, this can be done less loss to revenue for soybean than for corn. Ciliberto, Moschini and Perry (2019) apply discrete choice market demand analysis to show that corn seed demand is comparatively less elastic than is soybean seed, but do not discuss why this is so. A consequence of this difference in elasticities, as estimated in Ciliberto, Moschini and Perry (2019), is that the division of surplus from genetically engineered varieties favored the seed industry over farmers for corn and farmers over the seed industry for soybeans. How the partitioning of surplus affects the rate of innovation is an issue that has not received attention. Our claim here is that the difference across crops in the elasticity of crop yield to space available (or seeding rate) is of great consequence for the division of economic surplus, and also for the magnitude of that surplus.

Second, seed price elasticities can be applied to mitigate neonicotinoid-related ecological impacts. The use of chemical coating on seeds is known to improve germination (Sharma et al. 2015; Afzal et al. 2020) and also cause negative environmental damages (Rundlöf et al. 2015; Li, Miao and Khanna 2020; Van Deynze 2020). Given that the majority of corn and soybean seeds are coated with neonicotinoids (Hurley and Mitchell 2017), higher seeding rates will impose a larger chemical load on the environment. We develop rough conservative estimates of ecological effects resulting from farmers' seeding rate responses to price changes, by drawing upon values from the literature on neonicotinoid and biodiversity.

An increase in a seed tax or lower commodity price would also reduce acres allocated to that crop and so lower seed demand that way. To simplify the calculation, we assume crop acres will not change due to tax on seeds. In addition, we also assume that the potential tax does not differentiate among different types of seeds, and the tax is applied on general seeds rather than just chemical-coated seeds. Thus farmers' seed choices will not change toward seed without chemical coats.

To calculate how prices affect bird biodiversity through seeding rate and neonicotinoid, we rely on the semi-elasticities with respect to neonicotinoid use as reported by Li, Miao and Khanna (2020). They report the percentage impact of a 100kg increase (which represents a 12% increase on average) in neonicotinoid use on bird diversity measures. The three measures of bird biodiversity applied in their study are (1) bird population, measured by the number of birds observed; (2) species richness, measured by the number of bird species observed; and (3) species evenness, measured by the Shannon index, which takes the relative abundances of different species into account. Based on their semi-elasticities of bird biodiversity on neonicotinoid and our own price elasticity estimates of seed demand, we calculate how seed or crop price changes will affect bird biodiversity.

We find that a tax on seed or a decrease in crop price would increase the population of four groups of birds (Table 4.9). For example, a 10% soybean seed tax or a 10% decrease in soybean price contributes to a 3.6% increase in the grassland bird population and a 3.0% increase in the non-grassland bird population. This tax or price change also increases the insectivorous bird population by 3.4% and the non-insectivorous bird population by 3.0%. In addition, this price change also leads to an increase in the species richness and evenness of four groups of birds. More specifically, a 10% tax on soybean seed or a 10% decrease in soybean price causes about 0.05% increase in grassland and non-grassland bird species richness (roughly 0.002 species) and a 0.09% increase in grassland bird species evenness (measured by Shannon index).[36] Compared with soybean, a 10% tax on corn seed or a 10% decrease in corn price can also improve bird biodiversity, but the magnitude of effects is smaller.

Table 4.9 Price effects on bird biodiversity through neonicotinoid use and seeding rate choice

% change in bird diversity	Grassland bird	Non-grassland bird	Insectivorous bird	Non-insectivorous bird
Due to 10% tax on corn seed or 10% decrease in corn price				
Population	0.6%	0.5%	0.6%	0.5%
Species richness	<0.01%	<0.01%	<0.01%	0.02%
Shannon index	0.02%	<0.01%	<0.01%	<0.01%
Due to 10% tax on soybean seed or 10% decrease in soybean price				
Population	3.6%	3.0%	3.4%	3.0%
Species richness	0.05%	0.05%	0.05%	0.09%
Shannon index	0.09%	<0.02%	<0.02%	<0.02%

Conclusions and Discussions

Seed rate choice possesses a distinctive technological feature as reflected by the constraint that resources available to each plant decrease as seeding rate increases. This paper seeks to better understand how farmers make seeding rate decisions, as well as how and why corn and soybean seeding rates trend differently over time. We develop a theoretical model to understand the trade-off between within-plot extensive margin (more plants) and intensive margin (more resources to a given plant), in which we account for how elastic yield per plant is

[36] The negative effects of neonicotinoid used on species evenness reflects heterogeneous impacts of neonicotinoids on different types of grassland species (Li, Miao and Khanna 2020).

to greater area availability where corn and soybean are very different. With a large sample of farm-level market data and a survey dataset from focus group meetings, we examine how farmers' seeding rate choices respond to market, resource, and technology changes.

We find that, first, soybean seeding rate choice is more price elastic for corn, i.e., seed companies are likely to have less power in the soybean seed market. Second, our market estimations provide evidence that better soil quality would increase corn seeding rates, and more conventional tillage would increase corn and soybean seeding rates. These findings support our H2*i* that the optimal seeding rate will increase with an increase in per acre endowments. However, the effects of soil moisture on seeding rates are not clear. Third, for seed endowments, we find GT and *Bt* traits will increase corn seeding rates without variety-fixed effects, while soybean seeding rates decrease with GT traits. This finding supports our H2*ii* that optimal seeding rate responses to an increase in resources per plant depend on the elasticity of the marginal value of resources per plant with respect to resources per acre.

Our findings have implications in managing economic surplus and mitigating environmental risks beyond just documenting the different seeding rate patterns between corn and soybean. First, the difference in elasticities determines a company's capacity to extract surplus through pricing power. Second, our rough estimates reveal that a tax on seed or a decrease in crop prices has a positive effect on bird biodiversity through reducing seeding rates and mitigating neonicotinoids' adverse impacts, and this effect is more responsive for soybean than corn. Due to limited data availability, we cannot quantify the possible price effects on other neonicotinoid-influenced animals including butterflies, honey bees, wild bees, and mammals. However, adjusting seeding rates through targeted tax or price policies provides a new perspective on managing the ecological risks that neonicotinoids pose for biodiversity, with particularly negative effects directly coming from the consumption of coated crop seeds.

More efforts should be taken to conduct a comprehensive study of seeding rate choices in the future. One matter is that our analysis has not sought to quantify how seeding rate changes would affect social welfare, especially the effects of a tax on seed and economic welfare. Further analysis needs to obtain data on market values and also to conduct parameter calibrations.

A further matter is whether seeding rate choices are affected by behavioral factors since many researchers think that soybean seeding rates chosen by farmers might be excessive for profit maximization (Rees et al. 2019). Discrepancies between our market estimations and surveyed farmers' responses also suggest the farmers may not be fully rational. Some economic inquiries have found evidence that farmers misjudge their input choices, be it for crop insurance (Du, Feng and Hennessy 2017), pesticides (Perry, Hennessy and Moschini 2019), or nitrogen (Babcock 1992; Davidson et al 2011; Passeport et al 2013). These misjudges will lead to inefficiency (i.e. farmers lose some profits) and a better understanding of these behavioral factors will help improve policy designs and restore efficiency.

Externality is another important matter to consider. Some input applications will generate externalities and there will be a welfare loss if all farmers maximize their own profits. Taking nitrogen as an example, fertilizer use should consider the conflict between the need to use nitrogen and the need to protect groundwater quality (Huang and Lantin 1993). The decision will be more complicated when uncertainty about weather or soil nitrogen levels appears (Babcock 1992). Similarly, seeding rate choices also encounter the trade-off between farm profits and ecological risks as well as unpredictable climate and environmental changes. Seeding rates if excessive, especially chemical-coated seeds, have a negative externality. Possible behavioral drivers may provide an opportunity to adjust seeding rates and achieve social optimal.

APPENDICES

APPENDIX A: Cumulative Density Function

We use kernel density estimators to approximate the density function from observations on seeding rates. A kernel density estimator assigns a weight between zero and one sums the weighted values. We apply the kernel of Epanechnikov to determines the weights as it is the most efficient in minimizing the mean integrated squared error (Salgado-Ugarte, Shimizu and Taniuchi 1994). We also graph the empirical cumulative distribution of seeding rates. More kernel density estimates and cumulative distribution of seeding rates in different categories are presented below.

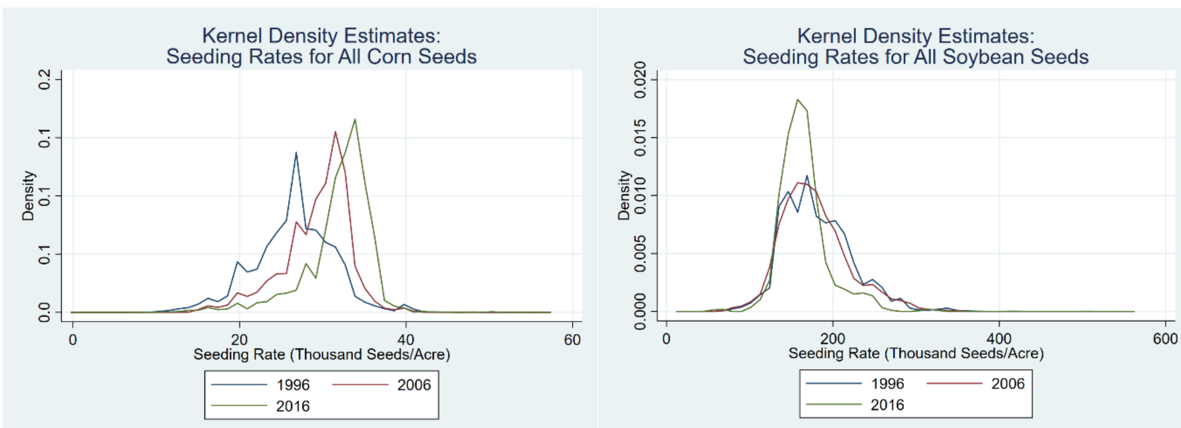


Figure 4A.1 Kernel density estimates for corn and soybean seeding rates

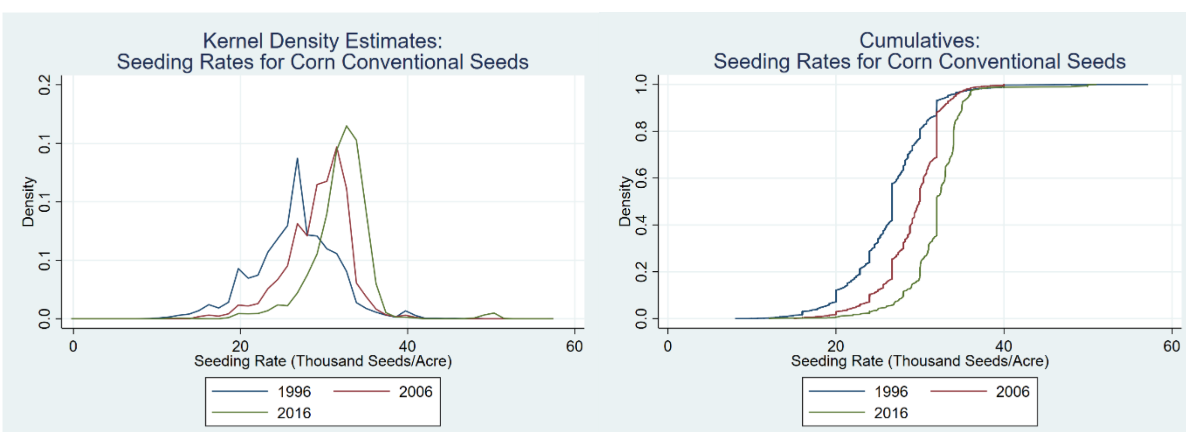


Figure 4A.2 Kernel density estimates and cumulative distribution for corn conventional seeds seeding rates

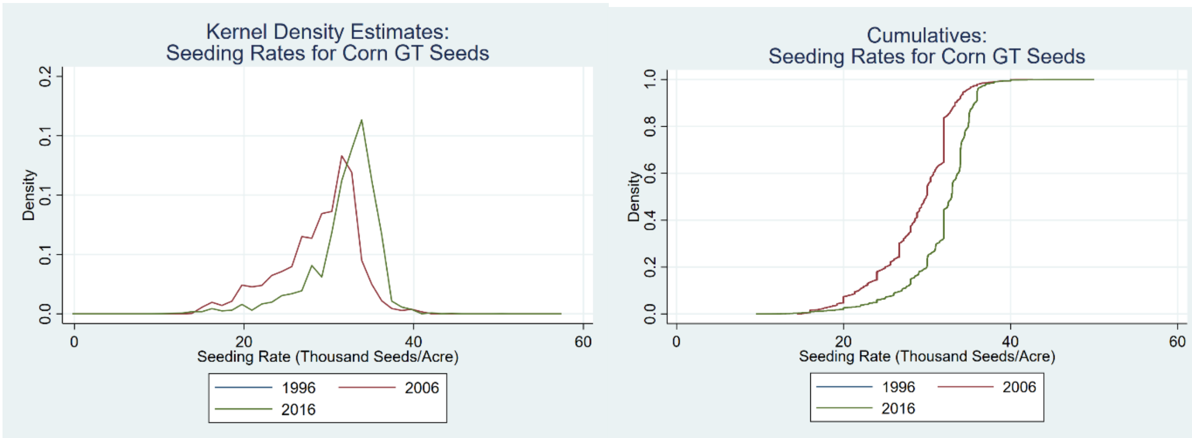


Figure 4A.3 Kernel density estimates and cumulative distribution for corn GT seeds seeding rates

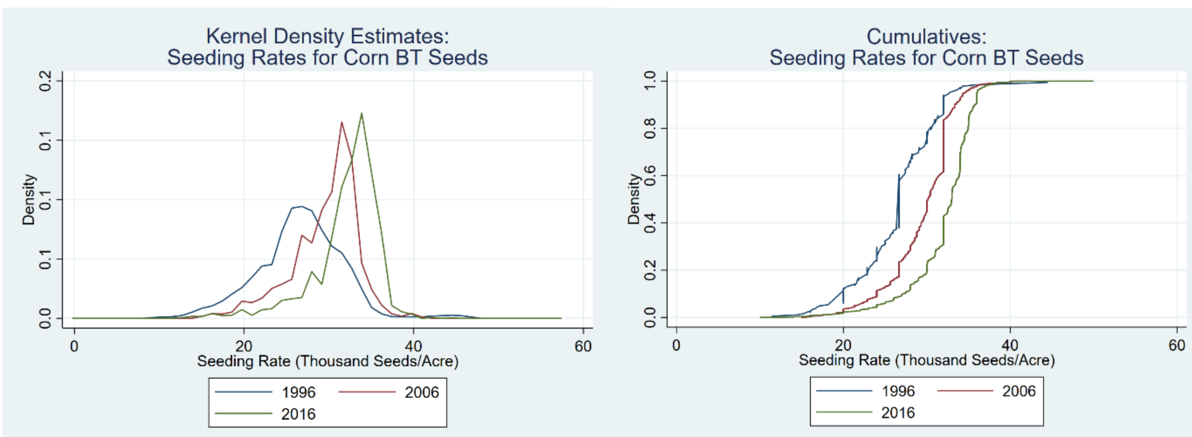


Figure 4A.4 Kernel density estimates and cumulative distribution for corn *Bt* seeds seeding rates

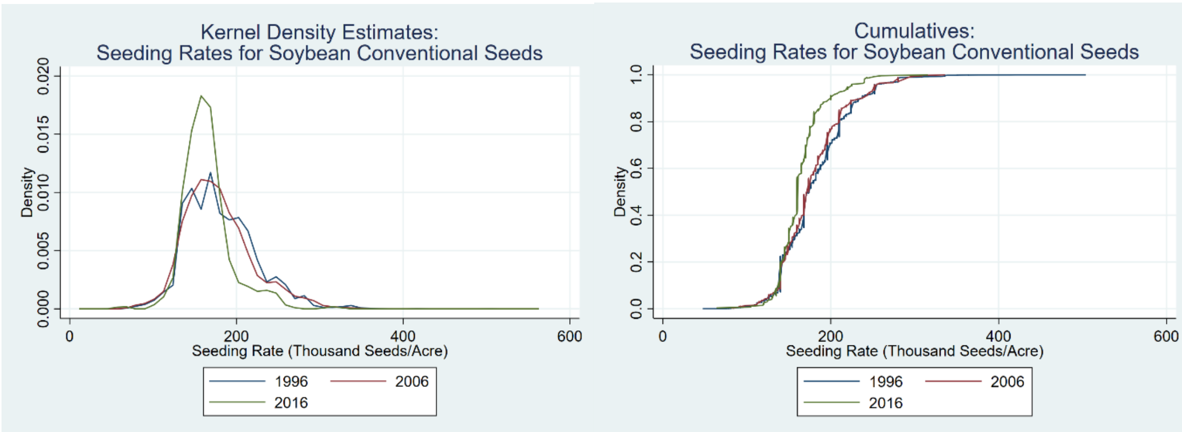


Figure 4A.5 Kernel density estimates and cumulative distribution for soybean conventional seeds seeding rates

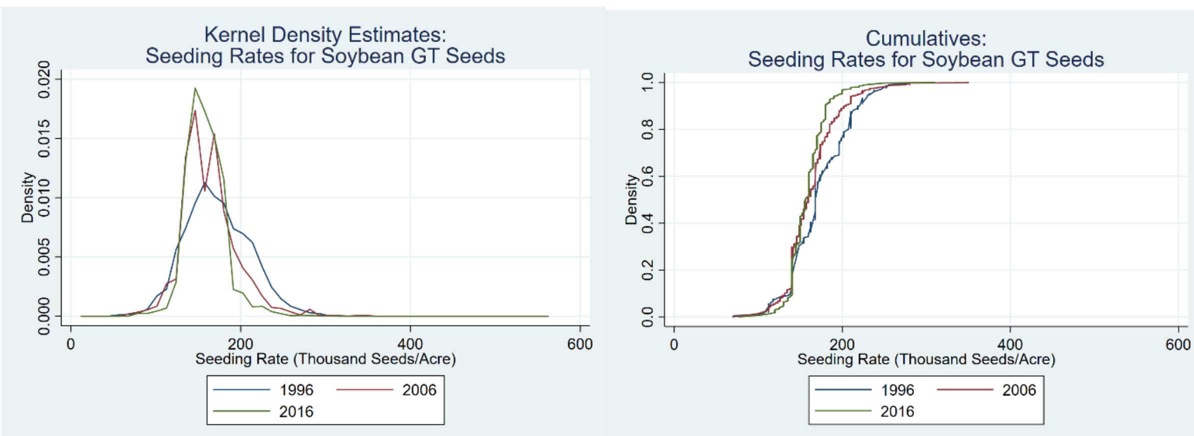


Figure 4A.6 Kernel density estimates and cumulative distribution for soybean GT seeds seeding rates

APPENDIX B: Data Screening

Table 4B.1 Data screening

Summary	Data Screening Details
Original observations	The original dataset reports 442,803 corn seed observations over 1995-2016 and 213,062 soybean seed observations over 1996-2016 across 235 CRDs in 31 states.
Remove observations with zero seeding rate	We remove 66 observations with zero seeding rate for corn. There is no soybean observation with zero seeding rate.
Remove observations with no seed variety identity	Some surveyed farmers did not report the identity of seed variety. We drop these observations because we cannot include variety fixed effects for them. Thus we obtain a reduced sample of 403,262 and 187,776 observations for corn and soybean, respectively.
Limited availability of tillage variable	The AgroTrak® data including tillage information has limited availability over the period 1998-2016, so combining seed and tillage data induces a further reduced sample size of 360,999 for corn and 173,056 for soybean.

APPENDIX C: Detrend Median Planting Date

Let $d_{c,t}$ be median planting date in state *c* and year *t*. A linear trend equation will be estimated as adjusted in Deng, Barnett and Vedenov (2007):

(4C.1) $d_{c,t} = \lambda_0 + \lambda_1(2017 - t) + \phi$,

where $t \in [1995, 2016]$ for corn and $t \in [1996, 2016]$ for soybean. Then the detrend median planting date is calculated as:

(4C.2) $d_{c,t}^{D} = \frac{d_{c,t}}{\hat{d}_{c,t}} \times \hat{d}_{c,2017}$,

where $\hat{d}_{c,t}$ is the predicted median planting date. Thus the dates are adjusted to the year 2017 technological level. We then calculate the deviation of detrended median planting date $d_{c,t}^{D}$ from its mean value across all the study period as an explanatory variable in our seeding rate estimation.

APPENDIX D: T-test Results for Focus Group Responses

Table 4D.1 T-test results of changes in corn seeding rates choices when faced with different environmental changes or agricultural practices

Corn	Environmental changes or agricultural practice changes	All samples		Operators	
		Mean	Pr(T > t)	Mean	Pr(T > t)
Land endowment	Soil quality was better.	0.872	0.000	0.889	0.000
	Soil moisture was higher.	0.128	0.016	0.111	0.052
	Soil moisture was lower.	-0.106	0.971	-0.111	0.978
	Soil varied greater.	-0.192	0.999	-0.194	0.997
	Tillage choice would be changed to be more intensive.	-0.021	0.839	N/A	N/A
	Tillage choice would be changed to be less intensive.	0.149	0.035	0.083	0.162
Seed endowment	Chemical treatment was changed from Yes to No.	0.106	0.067	0.139	0.048
	Chemical treatment was changed from No to Yes.	N/A	N/A	N/A	N/A
	Insect protection above ground trait choice was changed from Yes to No.	-0.081	0.908	-0.077	0.837
	Insect protection above ground trait choice was changed from No to Yes.	0.000	0.500	0.000	0.500
	Insect protection below ground trait choice was changed from Yes to No.	-0.048	0.667	0.000	0.500
	Insect protection below ground trait choice was changed from No to Yes.	0.111	0.297	0.125	0.299
Other agricultural practices	Planting date was earlier.	0.426	0.000	0.361	0.000
	Planting date was later.	-0.128	0.994	-0.111	0.978
	Tile drained was changed from Yes to No.	0.079	0.237	0.069	0.286
	Tile drained was changed from No to Yes.	0.444	0.017	0.571	0.015

Note: To test whether ‘raise’ exceeds ‘lower’, we set ‘lower’ = -1, ‘same’ = 0 and ‘raise’ =1. Then we test whether the mean exceeds 0. The following table shows the value of mean and one-tailed p-value for the difference from zero. “N/A” denotes no responses.

Table 4D.2 T-test results of changes in soybean seeding rates choices when faced with different environmental changes or agricultural practices

Soybean	Environmental changes or agricultural practice changes	All samples		Operators	
		Mean	Pr(T > t)	Mean	Pr(T > t)
Land endowment	Soil quality was better.	-0.604	1.000	-0.622	1.000
	Soil moisture was higher.	0.163	0.016	0.135	0.048
	Soil moisture was lower.	0.082	0.052	0.108	0.022
	Soil varied greater.	0.204	0.001	0.216	0.002
	Tillage choice would be changed to be more intensive.	-0.286	1.000	-0.216	0.995
	Tillage choice would be changed to be less intensive.	0.225	0.000	0.162	0.006
Seed endowment	Chemical treatment was changed from Yes to No.	0.364	0.000	0.406	0.000
	Chemical treatment was changed from No to Yes.	-0.750	0.971	-0.750	0.971
Other agricultural practices	Planting date was earlier.	-0.041	0.656	-0.135	0.872
	Planting date was later.	0.408	0.000	0.460	0.000
	Tile drained was changed from Yes to No.	0.108	0.162	0.185	0.067
	Tile drained was changed from No to Yes.	-0.364	0.981	-0.333	0.960

Note: To test whether ‘raise’ exceeds ‘lower’, we set ‘lower’ = -1, ‘same’ = 0 and ‘raise’ =1. Then we test whether the mean exceeds 0. The following table shows the value of mean and one-tailed p-value for the difference from zero.

REFERENCES

REFERENCES

Afzal, I., T. Javed, M. Amirkhani, and A.G. Taylor. 2020. Modern Seed Technology: Seed Coating Delivery Systems for Enhancing Seed and Crop Performance. *Agriculture* 10(11): 526.

Aglasan, S. 2020. *Three Essays on the Econometric Analysis of Biotic and Abiotic Risk in the Cultivation of Genetically Modified Corn.* Doctoral Dissertation. Raleigh, NC: North Carolina State University.

Andorf, C., W.D. Beavis, M. Hufford, S. Smith, W.P. Suza, K. Wang, M. Woodhouse, J. Yu, and T. Lübberstedt. 2019. Technological Advances in Maize Breeding: Past, Present and Future. *Theoretical and Applied Genetics* 132(3): 817-849.

Assefa, Y., Prasad, P.V., Carter, P., Hinds, M., Bhalla, G., Schon, R., Jeschke, M., Paszkiewicz, S. and Ciampitti, I.A. 2016. Yield Responses to Planting Density for US Modern Corn Hybrids: A Synthesis-Analysis. *Crop Science* 56 (5): 2802–2817.

Assefa, Y., Prasad, P.V., Carter, P., Hinds, M., Bhalla, G., Schon, R., Jeschke, M., Paszkiewicz, S. and Ciampitti, I.A. 2017. A New Insight into Corn Yield: Trends from 1987 through 2015. *Crop Science* 57(5): 2799-2811.

Assefa, Y., P. Carter, M. Hinds, G. Bhalla, R. Schon, M. Jeschke, S. Paszkiewicz, S. Smith, and I.A. Ciampitti. 2018. Analysis of Long Term Study Indicates Both Agronomic Optimal Plant Density and Increase Maize Yield per Plant Contributed to Yield Gain. *Scientific Reports* 8 (1): 4937.

Babcock, B.A. 1992. The Effects of Uncertainty on Optimal Nitrogen Applications. *Applied Economic Perspectives and Policy*, 14(2): 271-280.

Ciampitti, I.A., S.T. Murrell, J.J. Camberato, M. Tuinstra, Y. Xia, P. Friedemann, and T.J. Vyn. 2013. Physiological Dynamics of Maize Nitrogen Uptake and Partitioning in Response to Plant Density and Nitrogen Stress Factors: II. Reproductive Phase. *Crop Science* 53 (6): 2588–2602.

Ciliberto, F., G. Moschini, and E.D. Perry. 2019. Valuing Product Innovation: Genetically Engineered Varieties in US Corn and Soybeans. *The RAND Journal of Economics* 50(3): 615-644.

Corassa, G.M., T.J.C. Amado, M.L. Strieder, R. Schwalbert, J.L.F. Pires, P.R. Carter, and I.A. Ciampitti. 2018. Optimum Soybean Seeding Rates by Yield Environment in Southern Brazil. *Agronomy Journal* 110 (6): 2430–2438.

Davidson, E.A., M.B. David, J.N. Galloway, C.L. Goodale, R. Haeuber, J.A. Harrison, R.W. Howarth, D.B. Jaynes, R.R. Lowrance, B.T. Nolan, and J.L. Peel. 2011. Excess Nitrogen in the US Environment: Trends, Risks, and Solutions. *Issues in Ecology* 15.

DeBruin, J.L., J.R. Schussler, H. Mo, and M. Cooper. 2017. Grain Yield and Nitrogen Accumulation in Maize Hybrids Released during 1934 to 2013 in the US Midwest. *Crop Science* 57(3): 1431-1446.

Deng, X., B. J. Barnett, and D.V Vedenov. 2007. Is There a Viable Market for Area-based Crop Insurance?.*American Journal of Agricultural Economics 89*(2), 508-519.

Du, X., H. Feng, and D.A. Hennessy. 2017. Rationality of Choices in Subsidized Crop Insurance Markets. *American Journal of Agricultural Economics* 99(3): 732-756.

Duvick, D.N. 2005. The Contribution of Breeding to Yield Advances in Maize (Zea mays L.). In *Advances in Agronomy*. Elsevier, pp. 83–145.

Ferreira, A.S., A. Antonio, B. Junior, F. Werner, C. Zucareli, J.C. Franchini, and H. Debiasi. 2016. Plant Density and Mineral Nitrogen Fertilization Influencing Yield, Yield Components and Concentration of Oil and Protein in Soybean Grains. *Bragantia* 75:362–370.

Haarhoff, S.J., and P.A. Swanepoel. 2018. Plant Population and Maize Grain Yield: A Global Systematic Review of Rainfed Trials. *Crop Science* 58 (5): 1819–1829.

Hashemi, A.M., S.J. Herbert, and D.H. Putnam. 2005. Yield Response of Corn to Crowding Stress. *Agronomy Journal* 97 (3): 839–846.

Hennessy, D.A., A.J. Lindsey, Y. Che, L.E. Lindsey, M.P. Singh, H. Feng, E.M. Hawkins, S. Subburayalu, R. Black, E. A. Richer, and D. S. Ochs. 2021. Characterizing the Decision Process in Setting Corn and Soybean Seeding Rates. *The Journal of Extension* forthcoming.

Heim, R. R., Jr. 2002. A Review of Twentieth-century Drought Indices Used in the United States. *Bulletin of the American Meteorological Society* 83: 1149–1165.

Huang, W.Y. and R.M. Lantin. 1993. A Comparison of Farmers' Compliance Costs to Reduce Excess Nitrogen Fertilizer Use under Alternative Policy Options. *Applied Economic Perspectives and Policy* 15(1): 51-62.

Hurley, T., and P. Mitchell. 2017. Value of Neonicotinoid Seed Treatments to US Soybean Farmers. *Pest Management Science* 73 (1): 102–112.

Karl, T. R. 1986. The Sensitivity of the Palmer Drought Sensitivity Index and Palmer’s Z-Index to Their Calibration Coefficients including Potential Evapotranspiration. *Journal of Applied Meteorology and Climatology* 25: 77–86.

Li, Y., R. Miao, and M. Khanna. 2020. Neonicotinoids and Decline in Bird Biodiversity in the United States. *Nature Sustainability* 3 (12): 1027–1035.

Lindsey, A.J. and P.R. Thomson. 2016. Drought-Tolerant Corn Hybrid and Relative Maturity Yield Response to Plant Population and Planting Date. *Agronomy Journal* 108(1): 229-

242.

Lindsey, A. J., P. R. Thomison, and E. D. Nafziger. 2018. Modeling the Effect of Varied and Fixed Seeding Rates at a Small-Plot Scale. *Agronomy Journal* 110(6): 2456-2461.

Hoppe, R.A., J.M. MacDonald, and P. Korb. 2010. *Small Farms in the United States: Persistence Under Pressure*. EIB-63, U.S. Department of Agriculture, Economic Research Service.Moschini, G. 2008.Biotechnology and the Development of Food Markets: Retrospect and Prospects. *European Review of Agricultural Economics* 35: 331–355.

Passeport, E., P. Vidon, K.J. Forshay, L. Harris, S.S. Kaushal, D.Q. Kellogg, J. Lazar, P. Mayer, and E.K. Stander. 2013. Ecological Engineering Practices for the Reduction of Excess Nitrogen in Human-Influenced Landscapes: A Guide for Watershed Managers. *Environmental Management* 51: 392-413.

Perry, E.D., D.A. Hennessy, and G. Moschini. 2018. *Planting Rates in U.S. Maize: Improved Varieties and Learning.* Selected Paper, Agricultural & Applied Economics Association Annual Meeting, Washington D.C., August 5-7, 2018.

Perry, E.D., D.A. Hennessy, and G. Moschini. 2019. Product Concentration and Usage: Behavioral Effects in the Glyphosate Market. *Journal of Economic Behavior and Organization* 158: 543-559.

Perry, E.D., and G. Moschini. 2020. Neonicotinoids in U.S. Maize: Insecticide Substitution Effects and Environmental Risk. *Journal of Environmental Economics and Management* 102: 102320.

Rees, J., L. Thompson, S. Stepanovic, J. Luck, and N. Mueller. 2019. *Soybean Seeding Rates*. Nebraska Institute of Agriculture & Natural Resources.

Ruffo, M.L., L.F. Gentry, A.S. Henninger, J.R. Seebauer, and F.E. Below. 2015. Evaluating Management Factor Contributions to Reduce Corn Yield Gaps. *Agronomy Journal* 107 (2): 495–505.

Rundlöf, M., G.K.S. Andersson, R. Bommarco, I. Fries, V. Hederström, L. Herbertsson, O. Jonsson, B.K. Klatt, T.R. Pedersen, J. Yourstone, and H.G. Smith. 2015. Seed Coating with a Neonicotinoid Insecticide Negatively Affects Wild Bees. *Nature* 521 (7550): 77–80.

Salgado-Ugarte, I. H., M. Shimizu, and T. Taniuchi.1994. Exploring the Shape of Univariate Data Using Kernel Density Estimators. *Stata Technical Bulletin* 3(16).

Schwalbert, R., T.J.C. Amado, T.A.N. Horbe, L.O. Stefanello, Y. Assefa, P.V.V. Prasad, C.W. Rice, and I.A. Ciampitti. 2018. Corn Yield Response to Plant Density and Nitrogen: Spatial Models and Yield Distribution. *Agronomy Journal* 110 (3): 970–982.

Sharma, K.K., U.S. Singh, P. Sharma, A. Kumar, and L. Sharma. 2015. Seed Treatments for

Sustainable Agriculture-A Review. *Journal of Applied and Natural Science* 7(1): 521-539.

Singh, M. 2021. *Soybean Planting Considerations: Planting Date, Seeding Rate and Row Spacing Implications.* Michigan State University Extension. https://www.canr.msu.edu/news/soybean-planting-considerations-planting-date-seeding-rate-and-row-spacing-implications. Accessed June 30, 2021.

Stanger, T.F., and J.G. Lauer. 2006. Optimum Plant Population of Bt and Non-Bt Corn in Wisconsin. *Agronomy Journal* 98 (4): 914–921.

Thompson, N.M., J.A. Larson, D.M. Lambert, R.K. Roberts, A. Mengistu, N. Bellaloui, and E.R. Walker. 2015. Mid-south soybean yield and net return as affected by plant population and row spacing. *Agronomy Journal* 107:979–989.

Tian, F., P.J. Bradbury, P.J. Brown, H. Hung, Q. Sun, S. Flint-Garcia, T.R. Rocheford, M.D. McMullen, J.B. Holland, and E.S. Buckler. 2011. Genome-Wide Association Study of Leaf Architecture in the Maize Nested Association Mapping Population. *Nature Genetics* 43(2): 159-162.

USDA-NASS. 2019. *Publications Highlight 2017 Census-Farms and Farmland.* https://www.nass.usda.gov/Publications/Highlights/2019/2017Census_Farms_Farmland.pdf. Accessed June 24, 2021.

Van Deynze, B. 2020. *To Spray or Not to Spray: The Economics of Weed and Insect Management under Evolving Ecological Conditions*. Doctoral Dissertation. East Lansing, MI: Michigan State University.

Van Roekel, R.J. and J.A. Coulter. 2011. Agronomic Responses of Corn to Planting Date and Plant Density. *Agronomy Journal* 103(5): 1414-1422.

Xu, Z., D.A. Hennessy, K. Sardana, and G. Moschini. 2013. The Realized Yield Effect of Genetically Engineered Crops: U.S. Maize and Soybean. *Crop Science* 53 (3): 735–745.

Zhang, L., and N. Bellaloui. 2014. Effects of Planting and Maturity Dates on Shattering Patterns under Early Soybean Production System. *American Journal of Plant Sciences* 3: 6.