Land tenure, agri-environmental policy, and conservation-practice use in Iowa

by

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

To my mom, Coleen McCracken.

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ABSTRACT

This dissertation broadly looks at farmers' use of agricultural practices that affect water quality in Iowa. Primary themes across these three studies include (1) farmers' willingness to use conservation practices that can improve soil health and water quality, (2) the effects of agri-environmental policy on adoption of conservation practices, and (3) the effects of land tenure on farmers' use of inputs and conservation practices.

Chapter 2 examines whether cost-share programs – which pay farmers to use a specific conservation practice – have had the desired effect of increasing cover-crop use in Iowa. Using a matching estimator, I conclude that cost-share recipients plant cover crops on an additional 15% of their farmland than they would have in absence of payment.

In chapter 3, I study how landowner characteristics affect the use of conservation practices. The chapter focuses on whether leasing versus operating owned farmland decreases the use of conservation practices. I find that cover crops, buffer strips, and ponds/sediment basins are used at lower rates on rented farmland than on owner-operated farmland. However, no-till is used at a higher rate on rented farmland compared to owner-operated farmland. I also find that non-operator landowners have practices on their farmland at lesser rates than do landowners who currently farm.

Chapter 4 uses data envelopment analysis and a panel of farms to estimate an efficient input-output frontier for corn production and calculate farms' efficiency scores. I then evaluate how productivity has changed over time and whether efficiency differs by farm size and land tenure. Technical efficiency increased between the first half of the period (2011-2014) and the second (2015-2018). Additionally, I find that larger farms are more technically efficient than smaller farms, and fully rented farms more technically efficient than fully owner-operated farms.

CHAPTER 1. GENERAL INTRODUCTION

Agricultural pollution has been a leading cause of the water-quality issues of increasing concern throughout the United States. Harmful Algal Blooms and excessive nitrate levels have caused drinking-water treatment crises in municipalities and negatively impacted water recreation throughout the Midwest. On a global scale, nutrient pollution has been a primary contributor to the hypoxic zone in the Gulf of Mexico – an area of low oxygen that has been detrimental to aquatic life. Agriculture in the Upper Mississippi River Basin (Figure 1.1) is estimated to be responsible for 43% of the nitrogen and 27% of the phosphorus delivered to the Gulf of Mexico (Aulenbach et al. 2007). To address these water-quality issues, Iowa developed the Iowa Nutrient Reduction Strategy (INRS) (2017) to provide a science-based framework to evaluate best practices to achieve the goal of reducing nitrogen and phosphorus loss by 41% and 29%, respectively.[1]

One method used to reduce nutrient pollution is nutrient management since fertilizer has been a significant contributor to water-quality issues. However, nutrient management alone may be insufficient to combat the water issues, so the INRS also recommends the use of conservation practices. The INRS finds cover crops, buffer strips, sediment basins, and land retirement to be the practices most effective at reducing nitrogen and includes those practices along with no-till to be most effective at reducing phosphorus loads. However, due to the high costs (both implicit and explicit) of implementing these practices, adoption is low; thus, the U.S. government allocates money to voluntary conservation programs, which pay farmers to use environmentally beneficial practices. There has been a notable shift in conservation policy in recent decades, with

[1] The Mississippi River/Gulf of Mexico Watershed Nutrient Task Force had the twelve states along the Mississippi River develop nutrient reduction strategies.

a transfer in funding from land retirement programs such as the Conservation Reserve Program (CRP) to working lands programs such as the Environmental Quality Incentives Program (EQIP) (Figure 1.2). The research presented in this dissertation focuses on the economics of conservation practices funded primarily through working lands programs.

The overall goal of this dissertation is to evaluate farmers' willingness to use management practices that reduce the negative externalities agriculture has on waterways. I present three separate but related studies in the subsequent chapters. The first study, in Chapter 2, evaluates agri-environmental policy by estimating the effectiveness of cost-share programs at increasing cover-crop use. I then explore the cost-effectiveness of the policy by analyzing program's cost of reducing nitrogen pollution.

Chapter 3 analyzes determinants of conservation-practice use, with a focus on the landowner perspective. In Iowa, distinguishing between landowner and farm operator is essential, since over half of the state's farmland is rented out to a tenant, and owner-operators and tenants' incentives for adoption may differ. The analysis considers four conservation practices: no-till, cover crops, buffer strips, and sediment basins. In particular, I explore how land tenure (whether farmland is owner-operated or rented) and the landowner's farming experience affect the use of conservation practices. The chapter concludes by continuing the analysis of agri-environmental policy, this time focusing on the landowner perspective as opposed to the farm operator perspective, as was studied in chapter 2. I do so by looking at how the adoption of the four studied practices could evolve under three potential agricultural policy regimes.

Lastly, chapter 4 looks at how efficiency of corn production by Iowa farms differs by land tenure and farm size, using two measures of efficiency. The first model calculates the maximum proportional reduction of all inputs a farm could undertake, while still producing the same output level. The second model calculates the extent to which a farm could reduce fertilizer use, holding other inputs constant, while maintaining the same output level. Unlike the other two chapters, which consider conservation practices that reduce nutrient runoff, this study directly addresses one aspect of nutrient management by evaluating the extent to which farmers use fertilizer beyond the technically efficient level.

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Figures

Figure 1.1 Map of the Mississippi River Basin and Gulf of Mexico hypoxic zone. (Source: National Oceanic and Atmospheric Administration)

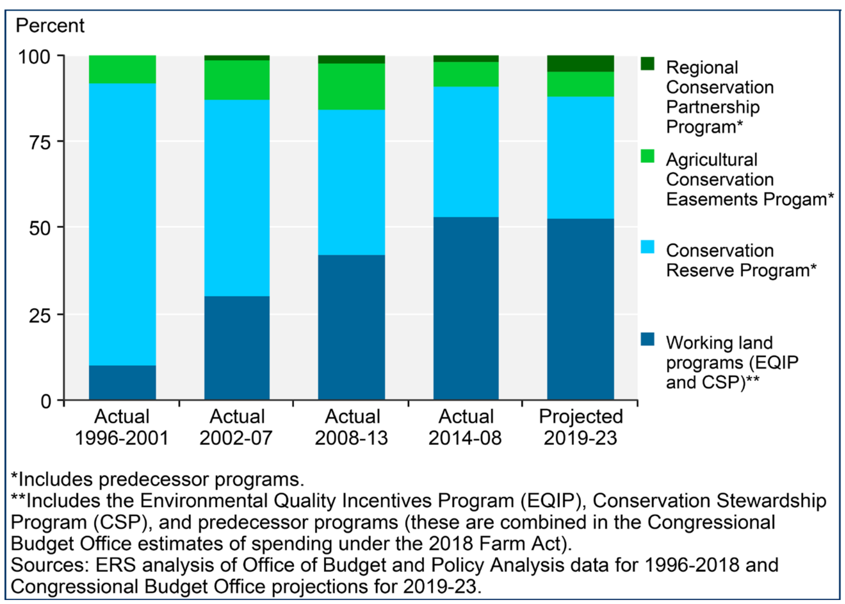

Figure 1.2 Share of federal conservation spending by farm bill. (Source: Economic Research Service

CHAPTER 2. ADDITIONALITY IN COVER CROP COST-SHARE PROGRAMS IN IOWA: A MATCHING ASSESSMENT

Wendiam P.M. Sawadgo[*] and Alejandro Plastina[†]

Abstract

Cover crops can generate both on-farm and water-quality benefits. However, their use in Iowa remains subdued, partly due to implementation costs faced by farmers. We test the hypothesis that monetary incentives through cost-share programs are effective at increasing the area of farmland planted to cover crops in Iowa, using a propensity-score-matching estimator. We find that cost-share payments induced a 15 percentage-point expansion in cover-crop acreage beyond what would have been planted in the absence of payment, among farmers who participated in cost-share programs. In addition, at least half of cost-share expenditures funded acres that would not have been planted without payment.

Introduction

Row-crop farming in the Midwest remains a major non-point source of nutrient pollution to waterways, resulting in mounting pressure on farmers to adopt conservation practices. One promising conservation practice is the use of cover crops,[1] which the Iowa Nutrient Reduction Strategy (2016) lists as one of the practices with the greatest potential for nitrate reduction. Iowa fields with cereal rye saw a nitrate loss reduction of 23% (Martinez-Feria et al. 2016), and nitrate concentration reductions of 48% and 61% (Kaspar et al. 2007 and 2012). The environmental services provided by cover crops in Iowa are not only relevant to manage water quality in the Midwest – but most notably in the hypoxic zone in the Gulf of Mexico – where two-thirds of the

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[1] Winter cover crops are planted in the fall after the cash crop is harvested to provide ground cover during wintertime.

nitrogen that makes up the hypoxic zone is estimated to originate from cultivated agriculture in the Mississippi River Basin (White et al. 2014).[2] From the farmer's perspective, winter cover crops are an attractive option for their in-field benefits, along with the fact that they do not take land out of cash-crop production. The in-field benefits from long-term use of cover crops include reduced soil loss (Kaspar, Radke, and Laflen 2001), increased soil organic matter (Moore et al. 2014, Kaspar and Singer 2011), improved soil health (Snapp et al. 2005), and enhanced water-storage capacity and infiltration (Basche et al. 2016). However, despite their considerable benefits to the cropping system, adoption of cover crops remains subdued in the Midwest. Satellite imagery suggests that cover crops were incorporated into corn and soybean rotations on only 2.65% of Iowa cropland in 2015 (Rundquist and Carlson 2017), while the Census of Agriculture found that the cover crop farmland share increased from 1% to 3%, between 2012 and 2017 (NASS 2012-2017).

A major barrier to cover crop adoption is the uncertainty associated with implementing new practices and their economic returns. Arbuckle and Roesch-McNally (2015) report that some farmers are concerned that cover crops could take water from the soil at the expense of the following cash crop and induce yield drags.[3] Among Iowa farmers, Plastina et al. (2018b) found that the additional costs from planting and terminating cover crops amounted to around $40 per acre, often leading to short-term net losses even among farmers participating in cost-share

[2] Kladivko et al. (2014) look at five Midwest states and estimate the area of land that is suitable for cover crop use. They conclude that if all tile-drained land in continuous corn or corn-soy rotations that is managed with no-till, spring till, or fall till–but could plausibly be converted to spring till used winter rye that was successfully established by overseeding–then there would be a 19% reduction in the nitrate loss transported to the Gulf of Mexico via the Mississippi River.

[3] Experimental results are mixed as to whether cover crops reduce the subsequent cash crop yield. Pantoja et al. (2015), in a study of no-till plots in Iowa, find that cereal rye reduced corn yields by 6%. However, in a meta-analysis of winter cover crop studies in the United States and Canada, Marcillo and Miguez (2017) conclude that cover crops generally do not reduce subsequent corn yields; this is specifically true in the upper Midwest region. In Iowa, Martinez-Feria et al. (2016) do not find consistent corn yield declines following cover crops. Seifert, Azzari, and Lobell (2018), using satellite panel data, find corn yield increases of 0.65% in the Midwest.

programs. Finally, the large percentage of Iowa farmland that is leased (53%) as opposed to owner-operated (37%)[4]–along with the fact that only one-third of those landowners would be willing to help their tenant pay for cover crop planting costs (Zhang, Plastina, and Sawadgo 2018)–are factors that tend to inhibit cover crop adoption.[5]

To promote the use of cover crops, several cost-share programs are available to Iowa farmers.[6] An estimated 317,132 acres of cover crops were planted in Iowa in the fall of 2015 with $8.4 million in financial assistance from government-sponsored cost-share programs (Iowa Nutrient Reduction Strategy 2016). Cost-sharing belongs to the class of Payment for Environmental Services (PES), which can be defined as a contract for a voluntary transaction in which a specific environmental service is provided by a land manager[7] in exchange for a payment, given the fulfillment of the contract (Ferraro 2008). An important concept in the design of cost-share programs is *additionality*: the adoption of a practice that would not have occurred in the absence of the PES program. When additionality is low, farmers who receive cost-share largely do not require it to implement the conservation practice, limiting the program's cost-effectiveness. High additionality can be indicative of an effective program. The goal of this study is to assess the effectiveness of cost-share programs at increasing cover-crop acreage. To estimate the additionality of cover-crop cost-share programs in Iowa, we use a matching

[4] Ten percent of Iowa farmland is in government programs (such as the Conservation Reserve Program) or custom farmed.
[5] Similarly, in other regions, Bergtold et al. (2012) find that tenants in Alabama are 20% less likely to adopt cover crops on rented land, and Singer (2008) finds that only 14% of Corn-Belt farmers would use cover crops on rented land.
[6] These programs include funding from the Iowa Department of Agriculture and Land Stewardship, the Environmental Quality Incentive Program, and the Conservation Stewardship Program. A detailed description of the cost-share programs available to farmers in 2015 is available in Appendix A.
[7] Land manager is defined in this study as the person who makes decisions on farming practices for a particular farm, irrespectively of the land ownership or tenure structure (i.e., irrespectively of whether the land manager is a landowner, tenant, operator, or non-operator).

estimator combining farm-level data from a cover crop survey that was linked to the 2012 Census of Agriculture.

Much of the prior literature regarding cost-share and the adoption of conservation practices examines the effect of cost-share payments as one of many determinants of conservation practice adoption (Prokopy et al. 2008). A handful of studies use stated preference methods to estimate farmers' willingness to adopt conservation practices (Cooper and Keim 1996; Cooper 2003; Ma et al. 2012). A growing branch of the additionality literature makes use of observational micro-data to measure the success of PES programs. Claassen, Duquette, and Smith (2018) find that additionality rates differ among best-management practices such as nutrient management, conservation tillage, and buffer strips across the United States. They also find higher additionality for practices that take land out of crop production or have higher short-term costs. Regarding cover crops specifically, Chabé-Ferret and Subervie (2013) estimate that PES programs in France increase cover crop acreage by 11 hectares per farm.[8] In the United States, studies in Maryland (Lichtenberg and Smith-Ramirez 2011; Fleming 2017; Fleming, Lichtenberg, and Newburn 2018) and Ohio (Mezzatesta, Newburn, and Woodward 2013) find that crop farmers' enrollment in cost-share programs increases the share of acres under cover crops from 8% to 28%. Lastly, results from ongoing work by Gonzalez-Ramirez and Arbuckle (2016) indicate that that cost-share payments increase acreage share of cover crops by 18 percentage points among Iowa farmers, and Lee et al. (2018) find that Iowa farmers who received cost-share or technical assistance were more than twice as likely to plant cover crops than those who did not.

[8] The authors do not report the average area under cover crops, or the average farm size, so we cannot calculate additionality as a relative (percent) measure.

This study makes three primary contributions to the existing literature. First, we use data from a unique cover crop survey that allows for partial-budget analysis to calculate how cover-crop use affects farmers' profit. Second, we provide a back-of-the-envelope calculation of private and public costs of abating nitrate leaching in Iowa through cover crops. While other studies (Fleming 2017; Fleming, Lichtenberg, and Newburn 2018) have looked at the public costs associated with cost-share programs, they do not consider the costs borne by the farmer. Lastly, while cover-crop cost-share additionality estimates exist for the Chesapeake Bay region (Fleming 2017; Fleming, Lichtenberg, and Newburn 2018) and Ohio River Basin (Mezzatesta, Newburn, and Woodward 2013), to our knowledge we provide the first set of final estimates for the Upper Mississippi River Basin. Agriculture in the Upper Mississippi River Basin alone is estimated to be responsible for 43% of nitrogen and 27% of phosphorus loadings delivered to the Gulf hypoxic zone (Aulenbach et al. 2007), thus reducing nutrient loss in this region could have significant global impacts.

We find that cost-share programs do incentivize the use of cover crops in Iowa. Cost-share recipients plant additional cover-crop acreage equivalent to 15% of their farmland that would not have been planted without cost-share payment. The estimated additionality rate is 54%, suggesting that almost half of cost-share dollars subsidize acreage that would have been planted to cover crops even in the absence of the cost-share programs. The combined farmer and public cost of avoiding one pound of nitrogen loss from Iowa fields by using cover crops is estimated at $1.59 to $4.33, and farmers absorb about 70% of those costs as private losses after accounting for cost-share payments that offset the remaining 30%. Furthermore, we estimate the public cost to abate nitrogen loads in Iowa waterways via cover crops beyond what would have occurred in the absence of cost-share programs at $1.72 to $4.70 per pound of nitrogen abated. A comparison of our estimates against similar programs in Maryland suggests that cost-share payments in Iowa are more cost-effective than in Maryland.

Methodology

In an ideal research experiment, we would randomly offer farmers cost-share payments of various amounts to plant cover crops on their land. Our control group would include the farmers who are not offered cost-share. We could then determine the effect of cost-share on cover crop acreage by comparing the average cover crop use of farmers who received each level of cost-share to that of the control group. Due to random assignment, we would not need to worry about selection bias affecting our results. However, such an experiment is not feasible. In reality, selection bias is an issue because each farmer decides whether to plant cover crops and whether to apply for cost-share. To address this issue, we use farmers' observable characteristics and a matching estimator to create a counterfactual for the farmers who received cost-share. We then compare the average cover crop use for cost-share recipients to the group of counterfactuals to estimate the effect of cost-share on cover crop use.

Several methods have been used to correct for selection bias in analyses measuring additionality of PES programs, including endogenous switching regressions (Lichtenberg and Smith-Ramirez 2011; Fleming 2017; Fleming, Lichtenberg, and Newburn 2018), propensity-score matching (Mezzatesta, Newburn, and Woodward 2013; Gonzalez-Ramirez and Arbuckle 2016; Claassen, Duquette, and Smith 2018), and difference-in-difference matching (Chabé-Ferret and Subervie 2013). Advantages of difference-in-difference matching and endogenous switching regressions include that they account for unobservable factors. However, due to data restrictions, difference-in-difference matching is unfeasible in our dataset. We use a matching estimator to exploit the flexibility provided by its semi-parametric approach and use the propensity score to overcome high dimensionality of independent variables.

Econometric Model

Following Rubin (1974), we let the treatment, T_i, be an indicator variable for whether farmer i received a cost-share payment for cover crops during a given year. Our outcome variable of interest, denoted Y_i, is the total proportion of farm acreage under cover crops that year. Let $Y_i(T_i)$ represent the potential outcomes: $Y_i(0)$ is the outcome when the individual does not receive cost-share, and $Y_i(1)$ is the outcome when s/he does. Since we never observe both outcomes for any individual (Rubin 1974), we cannot calculate the treatment effect, $Y_i(1)$ - $Y_i(0)$, and instead must rely on an estimated counterfactual.

It is plausible that farmer *i* who currently receives cost-share payments is intrinsically more willing to plant cover crops than farmer *j* who does not receive cost-share, even in the absence of cost-share programs, such that $Y_j(0)|T_j = 0 < Y_i(0)|T_i = 1$. If we simply attributed the entire difference between the averages across groups of farmers (i.e., $\sum_i^N Y_i(0)/N$ versus $\sum_j^M Y_j(1)/M$) to the effect of cost-share payments, we would be overestimating the effect of cost-share on our outcome variables of interest.

Instead, we use farmer i's observable characteristics, X_i to obtain the counterfactual outcomes we do not observe. However, matching on a large number of observable variables presents the difficulty known as the curse of dimensionality (Rosenbaum and Rubin 1985). One way to reduce the number of dimensions is to use the propensity score, a scalar. In our application, the propensity score, $p(X_i)$, is defined as the probability that a farmer received a cost-share payment, given his/her pre-treatment characteristics:

$$p(X_i) \equiv \Pr(T_i = 1|X_i). \tag{2.1}$$

Rosenbaum and Rubin (1983) show that conditioning on the propensity score is equivalent to conditioning on the set of covariates, under two assumptions. First, the unconfoundedness assumption requires that the potential outcome be independent of whether the individual is treated, conditional on the propensity score. Formally,

$$\{Y_i(0), Y_i(1)\} \perp T_i \mid X_i. \tag{2.2}$$

Second, the overlap assumption ensures common support between the treatment and control groups:

$$0 < p(X_i) < 1 \; \forall \, i. \tag{2.3}$$

If these two assumptions hold, we can use the matching estimator to calculate the average treatment effect on the treated (ATT), which measures the effect that receiving cost-share had on adoption, among those who received cost-share:

$$ATT = E[Y_i(1) - Y_i(0) | T_i = 1]. \tag{2.4}$$

The identifying assumption is that after conditioning on the propensity score, farmers receiving cost-share and farmers not receiving cost-share will have the same willingness to use cover crops. That is, we are able to control for all factors that impact both the farmer receiving cost-share and planting cover crops. Because we use Agricultural Census data, we have a large set of variables relating to many aspects of the farming operation, which makes the identifying assumption plausible. However, unobservable factors that could violate this assumption include farmers' environmental perceptions, network effects, and attitudes towards land stewardship. Although we cannot directly test whether unobservable variables are confounding our results, we conduct a sensitivity analysis to provide evidence that it is highly unlikely that hidden bias is the driver of our results.

Additionally, it is assumed that the treatment does not affect the outcomes among non-treated individuals. That is, an individual receiving cost-share cannot affect the cover crop planting behavior of farmers who did not receive cost-share.[9]

Empirical Analysis

First, we estimate the propensity score as a function of pre-treatment farmer and farm characteristics using a logistic regression:

$$P(T_i = 1) = \frac{1}{1+e^{-X\beta}}, \tag{2.5}$$

where β is a vector of coefficients to be estimated. We use matching with replacement to improve the quality of matches, meaning each control can be a match for more than one treated observation. To ensure sufficient quality of matches, we add a caliper to only consider matches within a specified radius, c, such that $|\, p(X_i) - p(X_j)\,| \le c$. The choice of the caliper value requires consideration of the trade-off between bias and efficiency (Cochran and Rubin 1973; Rosenbaum and Rubin 1985). A smaller caliper reduces bias by requiring better matches, and therefore eliminating treated observations with too few controls, at the expense of efficiency. A larger caliper increases the number of matches and the additional information increases efficiency, but at the expense of lower matching quality and potentially higher bias. The distance between observations is defined as:

$$D_{ij} = \begin{Bmatrix} p(X_i) - p(X_j) & if \left|p(X_i) - p(X_j)\right| \le c \\ \infty & \left|p(X_i) - p(X_j)\right| > c \end{Bmatrix}. \tag{2.6}$$

.

[9] This assumption would not hold if cost-share payments lead to higher cover crop seed costs for all farmers, discouraging adoption among the non-treated; or if the use of cover crops by a community leader who receives cost-share payments incentivizes neighboring farmers to adopt cover crops. Although the assumption might not be completely valid at the township level (among neighboring farms), we argue that this assumption is not violated at the state level when only 3% of Iowa farmland is planted to cover crops. Furthermore, we are not aware of a more flexible matching method that can do away with the assumption.

We match each treated individual to the *m* individuals in the control group with the closest propensity scores, obtaining the counterfactuals:

$$\hat{Y}_i(0) = \frac{1}{m}\sum_{j \in J_m^i} Y_j, \tag{2.7}$$

where J_m^i is the set of controls to treatment observation *i* with the *m*-lowest values of D_{ij}. As noted by Ho et al. (2007), matching on the true propensity score asymptotically balances the covariates between the treatment and control groups. We assess the correctness of our estimated propensity score by evaluating the post-matching balance between the two groups. We conduct a sample balance assessment of the covariates between the treated and control groups, using the standardized mean difference (SMD) (Rosenbaum and Rubin 1985). The SMD is the difference in covariate means across the treated (x_T) and the control group (x_C), divided by the average standard deviation (*s*) across the two groups:

$$SMD = \frac{\bar{x}_T - \bar{x}_C}{\sqrt{\frac{s_T^2 + s_C^2}{2}}}. \tag{2.8}$$

The matched sample is deemed superior to the unmatched sample if the post-matching SMDs are generally smaller in absolute value that the pre-matching SMDs. The evaluation process is repeated after varying the values of *c* and *m* until an adequately balanced sample is obtained. Once matching is complete, we estimate the treatment effect as follows:

$$ATT = \frac{1}{N}\sum_{i \in \{i|T_i = 1\}}\left[Y_i(1) - \hat{Y}_i(0)\right] \tag{2.9}$$

The standard errors are computed following Abadie and Imbens (2006), taking into account that the propensity score is estimated. The estimation and robustness checks are conducted using the *teffects* and *psmatch2* packages in Stata (Leuven and Sianesi 2003; StataCorp 2013).

Sensitivity Analysis

We evaluate the sensitivity of the results to matching specification by comparing the results from the selected model against those from 3 additional matching techniques totaling 30 additional models: (1) 13 nearest-neighbor models with alternative numbers of neighbors (1 through 8) and caliper sizes (0.05 to 0.20), (2) 10 propensity-score kernel-matching models with differing kernel types and bandwidths, and (3) 7 direct-matching models based on covariates with varying numbers of neighbors (1 through 7). Kernel matching, while still using the propensity score, differs from nearest-neighbor matching by matching each treated observation to a weighted average of all available controls, determined using a kernel estimator. We use Epanechnikov and Gaussian kernel types, with bandwidths ranging from 0.01 to 0.2 (Caliendo and Kopeinig 2008).[10] Direct matching is based on the Euclidian distance between covariates instead of on a propensity score.

Next, we evaluate how prone our results are to hidden bias by constructing Rosenbaum bounds, following Diprete and Gangl (2004). The Rosenbaum-bounds method determines whether the estimated ATT would remain significant under the existence of an unobserved factor causing a difference in the odds of cost-share program participation status. Two matched observations with identical observable characteristics but different unobservable characteristics that drive treatment assignment would differ in terms of probability of being treated, presenting a violation of the unconfoundedness assumption. In this study, we are most concerned about positive hidden bias, i.e. unobservable factors associated with higher cover-crop use that increase the likelihood of receiving cost-share and result in an upwardly biased ATT estimate.

[10] Increasing the bandwidth comes with the tradeoff of reducing variance at the expense of larger bias.

To implement the Rosenbaum-bounds procedure, we artificially introduce an unobserved factor that causes a difference in treatment assignment, denoted Γ. Rosenbaum (2002) shows that the odds ratio of two observations with identical observable variables is bounded such that

$$\frac{1}{\Gamma} \leq Odds\ Ratio \leq \Gamma. \tag{2.10}$$

If $\Gamma = 1$, then there is no hidden bias, while values of Γ greater than one imply an unobserved bias. For example, $\Gamma = 2$ implies a hidden bias that could at most double the odds of treatment within matched pairs. The non-parametric Wilcoxon signed-rank test gives the bounds of the test, which tests the null hypothesis that the treatment effect is zero. Again, since we are concerned about positive selection, we focus on the lower bound of the test and compute the test statistic for various values of Γ and the test's p-value (denoted p^+), with higher values of Γ lowering the probability of rejecting the null hypothesis.

Partial Budget Analysis

The goal of the partial-budget analysis is to estimate changes in farmers' profits due to cover crops. We use the partial budget template developed by Plastina et al. (2018a; 2018b) to calculate the net returns to cover crops for each farmer in our sample. Only farms that had a field with cover crops and a field without cover crops, followed by the same subsequent cash crop in 2016 were included in the partial budget analysis. We calculate net returns by comparing each farm's field with cover crops to its field without cover crops, accounting for differences in revenues, cover-crop planting costs, cover-crop termination costs, and other costs:

Net Returns = Differential Revenue – Cover Crop Planting Cost – (2.11)

Cover Crop Termination Cost – Other Differential Costs.

Differences in revenues can be the result of differential (positive or negative) cash crop yields due to cover crops, additional revenue from grazing the cover crop, and the cost-share payment received (if any) for planting the cover crop. Cover crop planting costs include the cost of seeds as well as fixed and variable costs of planting with owned machinery, hired machinery or custom work. Termination costs were null for cover crops terminated with winter kill, and only included the additional costs on top of typical practices applied by each farmer to all of his/her farms if cover crops were terminated with herbicides or mechanically. For example, if a farmer applied a pre-plant burn down to all his/her acres in the spring, only the additional cost (if any) associated with a more concentrated, higher volume, or more expensive herbicide solution, plus the additional machinery cost for any extra spraying passes were counted as termination costs. For farmers who terminated cover crops by mowing or tillage, only machinery and material costs additional to what was typically used on their non-cover cropped acres were counted as termination costs. Lastly, other differential costs include changes in fertilizer application and other input use. We use the median value for the net return in our policy calculations to avoid undue influence of outliers.

Data

The data were collected through a hard-copy survey of Iowa farm operators, which was administered by the Upper Midwest regional office of the National Agricultural Statistics Service (NASS) in 2017. The survey sample of 1,250 operators was determined using randomized cluster sampling by crop reporting district and farm size. Row crop farming rotations in this study were limited to corn, soybeans, and wheat. The survey was first mailed on February 1, 2017, and a second questionnaire was sent to non-respondents in mid-February 2017. Finally, those who did not respond were contacted by telephone. The survey asked detailed questions on agricultural practices relating to the planting and termination of cover crops, farmers' experience with cover crops, and cost-share payments. In total, 674 operators responded (a 54% response rate).

The sample was selected based on prior cover crop acreage, which allows for a larger sample of cover crop users than in most past studies. However, this introduces a sampling bias, which reduces the external validity of our results. For instance, while Iowa was estimated to have cover crops on just 3% of farmland (NASS 2017), the farmers in our sample planted cover crops on 11.7% of their acres, on average. Because relatively few non-adopters were included in the sample, our estimated $\hat{Y}_i(0)$ might be upward biased if the excluded non-adopters were better matches than those included in our sample, which would imply a downward bias in our estimated ATT. Thus, relative to the statewide population of farmers, our ATT estimate should be considered a conservative lower bound. Although our sample is not representative of farmers in the state, it represents cover crop adopters, which are the group of interest in this analysis.[11]

After removing observations for which farmers did not state whether they received cost-share, did not specify how many acres had cover crops, or did not provide information for all 2012 Census variables that we use as covariates, our sample is composed of 407 observations for the matching analysis. Despite dropping 267 observations from the original sample, the sample composition remains similar, with only a small change in the proportion of the sample receiving cost-share and average acreage share in cover crops.[12] Thus, we are not concerned that removing these observations imposes any additional bias on our sample.

The present study focuses on farmers' cover crop decisions for the fall of 2015. Our variables of interest are whether the farmer received a cost-share payment to plant cover crops in 2015, the per-acre payment received,[13] total acreage planted to the most widely used cover crop

[11] The cost of sampling a larger population of farms and securing responses for a high number of cover crop adopters with a 97:3 ratio of non-adopters to adopters was prohibitive.
[12] In the full sample of 674 observations, 21% of farmers received cost-share, and farmers planted cover crops on 12.7% of their land in 2015. Among the 407 observations used in the matching analysis, 22% of farmers received cost-share, and farmers planted cover crops on 12.1% of their land in 2015.
[13] The cost-share source and contract length are not specified. Respondents report different payment rates, presumably due to the various funding sources used.

mix, and farm size. In table 2.1, we report a summary of the make-up of the 407 observations used in the matching analysis. The sample is composed of about the same number of cover crop users and non-users in 2015 (208 vs. 199, respectively). About 40% of cover crop users received cost-share payments. Among this group, the average number of cover crop acres and the proportion of total farmland under cover crops are higher than the corresponding averages among farmers who did not receive cost-share payments.

Survey respondents answered detailed questions about their cover crop planting and termination methods, and how their subsequent cash-crop costs and revenues differed between fields with and without cover crops. We have enough information to calculate net returns to cover crops for 41 farms that received cost-share and 30 farms that did not. This is lower than our total sample size because some respondents did not include adequate information on machinery use or input uses on either their cover-cropped or non-cover-cropped fields. The median net losses per acre from cover crop use among farmers that received cost-share payments and among farmers who did not receive cost-share payments were, respectively, $23 and $40. Furthermore, the average cost-share payment received by farmers in our sample amounted to $26 per acre planted to cover crops.

Each response to our survey was linked by an anonymized identification code to the operator’s data from the 2012 Census of Agriculture, giving us a large set of covariates. The Census variables are all pre-treatment, which is fundamental to our ability to use propensity-score analysis. We include variables regarding farm characteristics, operator characteristics, and operator's experience with conservation, selected based on the existing literature (Chabé-Ferret and Subervie 2013; Mezzatesta, Newburn, and Woodward 2013; Gonzalez-Ramírez and Arbuckle 2016; Claassen, Duquette, and Smith 2018). Each variable is associated with a K-code in the 2012 Census of Agriculture, as detailed in Table 2.2. Variables relating to farm characteristics include total acres operated in 2012 (*Farm Size*), total acres rented or leased from others (*Rented Acres*), gross farm sales (*Farm Sales*), presence of livestock (*Livestock*), presence of poultry (*Poultry*), corn acreage (*Corn*), soybean acreage (*Soy*), acres drained by tile (*Tile Drainage*), and acres drained by ditch (*Ditch Drainage*). Following Imbens (2015), and under the assumption that cover-crop use tends to be correlated over time, we include cover crop acreage in 2012 (*Cover Crops*) as a covariate. For farmer characteristics, we use age of the principal operator (*Age*), years since the operator first operated a farm (*Experience*), number of days the operator worked off the farm (*Off-Farm Labor*), percentage of the farmer's household income that comes from farming (*Farm Income*), and USDA crop-reporting districts as regional indicators. Recipients of cost-share payments in 2015, on average, operated more acres, had higher gross farm sales, had livestock less frequently, harvested more acres of soybeans, and planted more cover crops in 2012 than farmers who did not receive cost-share payments in 2015. Other variables are not statistically significantly different between the treated and non-treated group.

Results

Additionality of Cost-Share Programs

Results of the propensity score equation estimated according to equation (2.5) are reported in Table 2.3. As expected, past cover crop acreage increases the probability of receiving cost-share, since farmers who are more familiar with conservation practices may better understand the nuances of the conservation programs. Farm size also increases the propensity score, suggesting larger farms may have more expertise dealing with government programs and may be more willing to experiment with cover crops than smaller farms. Age increases the probability of receiving cost-share but at a decreasing rate. This finding differs from prior literature (Mezzatesta, Newburn, and Woodward 2013; Gonzalez-Ramírez and Arbuckle 2016), which found that older farmers are less likely to receive cost-share. In addition, having livestock on the farm decreases the propensity score. Other variables are not significantly different from zero at a 95% confidence level.

Given the estimated propensity scores, we create our matched sample. We vary the number of controls matched to each treated observation and the presence and size of the caliper in constructing the sample. The specifications are evaluated based on the balance of the covariates between the cost-share recipients and non-recipients. That is, we choose the specification that performs best at removing bias through the matching procedure (Caliendo and Kopeinig 2008). In our preferred specification, we match each cost-share recipient with seven controls (neighbors) and use a caliper of 0.15. After discarding six observations from the original set of treated farms due to caliper choice, the sample balance across the remaining 400 farms (85 treated and 315 untreated) is analyzed in Table 2.4. After matching, all the SMDs are 11% or less, which is well below the 20% threshold that Rosenbaum and Rubin (1985) deem to be a large bias. This suggests that matching corrected much of the difference in the observable characteristics between cost-share recipients and non-recipients (Figures 2.1 and 2.2).

Applying equation (2.9) to the selected specification (model 1 in Table 2.5a), we find that receiving cost-share payments increases acreage in cover crops, on average, by 15 percentage points, a difference that is significant at a 95% confidence level. We estimate that the 85 farmers who received cost-share payments would have planted cover crops on 12% of their acres in the absence of cost-share, whereas they actually planted cover crops on 27% of their acres. Following Mezzatesta, Newburn, and Woodward (2013) and Fleming, Lichtenberg, and Newburn (2018), we calculate the additionality rate at 54%, which suggests that almost half of cost-share acreage would have been planted to cover crops in the absence of the cost-share programs.

We find that our measure of the impact of cover crop cost-share programs in Iowa is slightly lower than that reported in most previous studies: 15% versus 20% to 30% (Mezzatesta, Newburn, and Woodward 2013; Gonzalez-Ramírez and Arbuckle 2016; Fleming 2017; Fleming, Lichtenberg, and Newburn 2018). Prior studies find additionality rates for cover crop cost-share programs in Maryland (Fleming 2017; Fleming, Lichtenberg, and Newburn 2018) and Ohio (Mezzatesta, Newburn, and Woodward 2013) ranging from 83% to 98%, suggesting that relatively few of those acres would have been planted to cover crops in the absence of cost-share. We postulate that these values are higher than our additionality rate of 54% due to the composition of our sample and differences in payment rates across states. While other studies rely on samples representative of their state's farmers, cover-crop users are over-represented in our sample. If our sample had more non-adopters, some of these observations could be better matches for the cost-share recipients and hence join the control group, decreasing the value of *Y(0)*. This would, in turn, increase the estimated ATT and the additionality rate. Furthermore, while average cost-share payments in Maryland amount to $45 per acre, they amount to $26 per acre in our sample. The higher payment rate may attract more farmers who would be unlikely to use cover crops without payment.

Sensitivity Analysis

Table 2.5b summarizes the results from alternative matching specifications and provides a robustness check to the results from our selected model. Reducing the size of the caliper to ensure higher quality matches and changing the numbers of controls in the propensity-score nearest-neighbor models 2 through 13 do not substantially affect the results. In our selected specification (model 1), we control for past cover crop use. However, if some unobserved factor drives both participation in the cost-share program and past cover crop use, conditioning on past cover crop acreage will confound our results. Model 14 is specified with the same number of neighbors and caliper size as the selected model but omits 2012 cover crop use as an explanatory variable. The ATT estimate for model 14 is 19%, which lies within the 95% confidence interval of model 1.

Overall, the results from the 31 model specifications are similar, with the estimated increase in cover crop acreage share due to cost-share payments ranging from 13 to 19 percentage points. We therefore argue that our results are not sensitive to model specification.

We further evaluate our results by assessing the selection on observables assumption. Although we cannot directly test this assumption on our preferred model because the Rosenbaum bounds procedure (Diprete and Gangl 2004) is only applicable to one-to-one nearest-neighbor matching without replacement, we apply it to model 6 with an ATT of 16%. The p^+ values for various levels of Γ and are reported in table 2.6. Higher values of Γ lower the probability of rejecting the null hypothesis of no treatment effect. We reject the null hypothesis up to $\Gamma = 74$, suggesting that an unobserved factor increasing the odds of being treated by 7300% would not be sufficient to make the estimated ATT result insignificant, at a 95% confidence level. Therefore, we argue that our results are robust to hidden bias.

Cost-effectiveness of Cost-share Programs

To evaluate the cost-effectiveness of cover crop cost-share programs, we focus on nitrate pollution reduction. In reality, cover crops have additional environmental benefits from reduced soil erosion and phosphorous loss, but nitrate commands the most attention. We use literature-derived estimates for the per-acre nitrogen loss reduction due to cover crops, combined with the programs' expenditures to calculate private and public costs of abating nitrate leaching in Iowa through cover crops.

Columns 1 through 3 of Table 2.7 divide Iowa cover crop farmland into (1) cover crop acreage for which the farmer received cost-share, (2) cover crop acreage for which the farmer did not receive cost-share, and (3) all cover crop acreage. In 2015, farmers in Iowa planted an estimated 591,880 acres to cover crops, of which 317,132 acres were funded with cost-share, as is displayed in table 2.7a (Rundquist and Carlson 2017). Our partial-budget analysis suggests that cost-share recipients and non-recipients face per-acre net losses of $23 and $40, respectively, after accounting for cost-share payments (table 2.7b). Applying these figures to the 317,132 cover-crop acres funded with cost-share and the estimated 274,748 acres planted without cost-share, the aggregate estimate of farmers' net losses due to cover crops amounts to $18.28 million (table 2.7c). The Iowa Nutrient Reduction Strategy (2016) reports that $8.4 million were publicly spent on cover crop cost-share.[14] A study in Boone, central Iowa, found that cover crops reduced nitrogen loss by 10.4 to 28.4 pounds per acre per year (Malone et al. 2014). The estimated nitrogen load reduction to Iowa waterways from cover crop use in 2015 amounts to 3,078 to 8,405 tons (table 2.7d), calculated as 10.4 to 28.4 pounds of nitrogen per acre (Malone et al. 2014) divided by 2,000, and multiplied by total estimated acres in cover crops (table 2.7a). Thus, the combined farmer and public cost to abate nitrogen through cover crops is estimated at $1.59 to $4.33 per pound of nitrogen, with farmers undertaking $1.09 to $2.97 per pound in net losses (table 2.7e).

However, since we are mainly interested in the cost-effectiveness of the cost-share programs, we focus on the additionality effects of this program. Applying the 54% additionality rate from model 1 to the estimated cover cropped area with cost-share (column 1 of table 2.7a),

[14] Alternatively, the aggregate cost-share estimate in table 7c could be obtained by multiplying the average cost-share payment in our sample ($26) by the estimated area in cover crops (317,132 acres) to arrive at $8.2 million. The public cost of abating nitrogen through cover crop cost-share programs in Iowa is therefore estimated at $1.69 to $4.61 per pound.

we estimate that 171,927 cover-crop acres were additional in Iowa (column 4 of table 2.7a). The public cost of abating nitrogen through cover crop cost-share programs in Iowa is estimated at \$1.72 to \$4.70 per pound, which is lower than the reported costs in Maryland, ranging from \$5.80 to \$8.87 per pound (Fleming 2017; Fleming, Lichtenberg, and Newburn 2018). Again, the differences in cost effectiveness are likely driven by the higher payment rate in Maryland.[15] Our estimates for Iowa also compare favorably to the nitrogen abatement costs in the Gulf of Mexico from the Lower and Upper Mississippi River Basins reported by Marshall et al. (2018), amounting to \$5.29 and \$23.40 per pound of nitrogen, respectively.[16] The major difference between these estimates and our estimate stems from the fact that Marshall et al. (2018) measure the nitrogen load delivered to Gulf of Mexico, and proximity plays a critical role in their calculation as nitrogen is deposited into river banks en route to the Gulf of Mexico. Thus, using their framework, reducing pollution to the Gulf of Mexico only through cover crops in Iowa would be costly, due to the large distance between the two regions. Finally, our results are in line with the equilibrium price of \$3.13 per pound of nitrogen estimated by Ribaudo, Savage, and Aillery (2014) in an analysis of a water-quality trading scheme among Chesapeake Bay area farmers.

Conclusion

In this study, we analyze the effect of cost-share program participation on cover crop adoption. We first use farms' and farmers' characteristics from the 2012 Census of Agriculture in combination with 2017 survey data from Iowa to calculate the probability a farmer receives cost-share in 2015 (i.e., the propensity score). Second, we match the observations for cost-share

[15] Unfortunately, the nitrogen load reductions are not reported by Fleming (2017) or Fleming, Lichtenberg, and Newburn (2018).
[16] The cost estimates in Marshall et al. (2018) include capital costs, annual implementation costs, and the value of change in inputs and crop yields and exclude financial assistance through federal or state conservation programs.

recipients with similar non-cost-share recipients based on the propensity scores. Then, we estimate the effect of receiving cost-share on the share of farmland in cover crops across the matched observations.

We find that participation in cost-share programs increases the users' share of cover-cropped farmland by an average of 15%, implying an additionality rate of 54%. This suggests that cost-share programs do encourage adoption of cover crops that is additional to that which would occur in their absence, but almost half of the cover-cropped farmland would have had cover crops in the absence of program payments. Despite the relatively low additionality rate, the public cost of abating nitrogen pollution in Iowa waterways through cover crop cost-share is relatively low at $1.72 to $4.70 per pound. This cost is likely lower than in other states because cover crop cost-share payment rates are lower in Iowa (Bowman and Lynch 2019). Furthermore, we estimate that farmers absorb about 70% of total cover crop costs, and public monies finance the remaining 30%.

One limitation of our study is that the sampling strategy does not allow for statistically representative statewide inferences (see footnote 12). Another limitation is that we do not consider slippage, while agricultural payment programs can induce farmers to plant crops on marginal land (Lichtenberg and Smith-Ramirez 2011; Fleming 2017; Fleming, Lichtenberg, and Newburn 2018). However, we are not concerned about slippage in our setting, because even with cost-share, cover crops are still unprofitable for most farmers, short-term. Finally, this study does not venture into farmers' non-economic motives for planting cover crops (Arbuckle and Roesch-McNally 2015; Lee et al. 2018). Since there is evidence that farmers adopt cover crops without government support, even at a short-term profit loss (Plastina et al. 2018a, 2018b), future research should investigate alternative incentive schemes to retain farmers who already plant cover crops, while also encouraging new adoption. Analyses on how cost-share affects those who have never planted cover crops should also be of interest to policymakers.

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Figures and Tables

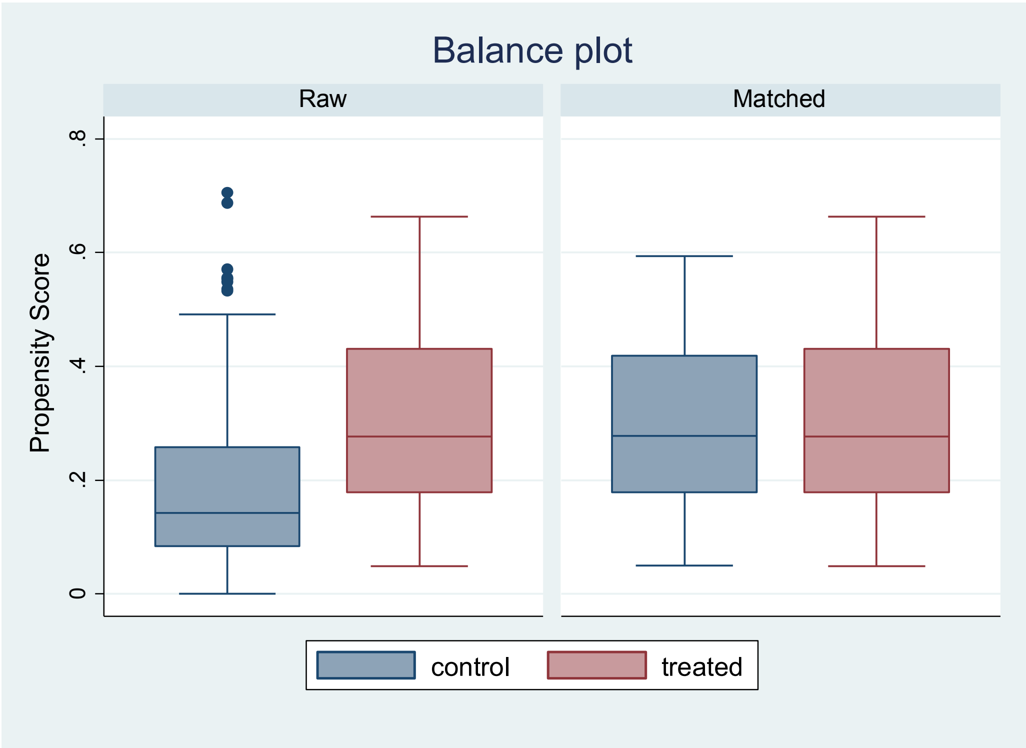

Figure 2.1 Box plot of control and treated observation propensity scores before and after matching.

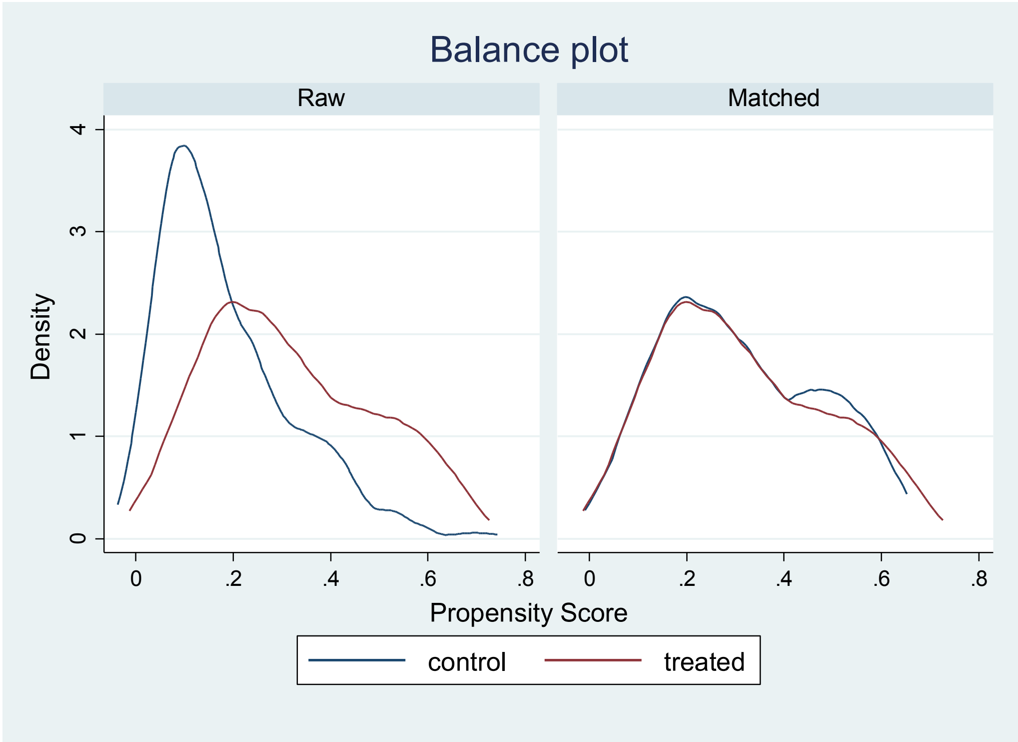

Figure 2.2 Density plot of distribution of treated and control observations before and after matching.

Table 2.1 Sample description.

	Farmers who planted cover crops in 2015			Farmers who did not plant cover crops in 2015
	Frequency	Average cover-crop acreage	Average farmland share in cover crops	Frequency
Received cost-share payment in 2015	91	244	0.276	–
Did not receive cost-share payment in 2015	117	238	0.205	199

Table 2.2 Summary statistics from the 2012 U.S. Census of Agriculture, by participation in cost-share programs in 2015.

Variable Name	**Variable description**	**Census K-Code**	**Mean**		**Significant difference**
			Cost-share (n = 91)	**No cost-share (n = 316)**	
Farm Size	Total acres operated	K46	948.0	766.6	*
Rented Acres	Acres rented or leased from others	K44	562.1	430.4	
Farm Sales	Gross farm sales (in thousands of dollars)	TVP	1046.6	689.7	***
Livestock	Presence of cattle; hogs and pigs; equine; sheep and goats; or other livestock on the operation (1 if present)	K1201, K1211, K1247, K1239	0.63	0.75	**
Poultry	Presence of poultry on the operation (1 if present)	K1217	0.09	0.06	
Corn	Corn acreage harvested for grain	K67	400.1	326.1	
Soy	Soybean acreage harvested for grain	K88	299.7	229.7	*
Cover crops	Acres planted to cover crops	K3456	163.0	73.3	***
Tile Drainage	Acres drained by tile	K3450	424.7	364.0	
Ditch Drainage	Acres drained by ditch	K3451	45.5	37.7	
Age	Age of the principal operator (years)	K925	56.4	57.4	
Experience	Number of years since the principal operator began to operate on any farm	K1834	32.6	32.3	
Off-Farm Labor	Number of days worked off the farm	K929	1.92	2.05	
Farm Income	Percent of the principal operator's total household income from the operation	K1578	67.0	68.5	

*Denotes significance at 0.10 level
**Denotes significance at 0.05 level
***Denotes significance at 0.01 level

Table 2.3 Propensity score regression results.

Variable	Coefficient	
Log Farm Size	0.9104	***
Rented Acres	1.080×10^{-6}	
Farm Sales	3.32×10^{-7}	*
Livestock	-0.8451	***
Poultry	0.4949	
Corn	-0.0015	*
Soy	0.0001	
Cover crops	0.0030	***
Tile Drainage	-0.0005	
Ditch Drainage	-0.0004	
Age	0.3283	**
Age Squared	-0.0031	**
Experience	0.0108	
Experience Squared	2.92×10^{-5}	
Off-Farm Labor	-0.0448	
Farm Income	-0.0109	**
North West	-0.3727	
North Central	-1.1971	
North East	-0.5827	
West Central	-0.0956	
Central	-0.5172	
East Central	-0.2322	
South West	-0.7243	
South Central	-1.7174	**

*Denotes significance at 0.10 level
**Denotes significance at 0.05 level
***Denotes significance at 0.01 level

Note: All variables in table from 2012 Census of Agriculture

Goodness of fit: $\chi^2(24) = 57.17$ (p= 0.0002)

Table 2.4 Sample balance assessment for selected specification, with seven neighbors and c=0.15 (N=400).

Variable	**Standardized mean difference**	
	Before matching	After matching
Log Farm Size	0.406	0.015
Rented Acres	0.172	0.024
Farm Sales	0.249	0.007
Livestock	-0.272	-0.003
Poultry	0.041	0.069
Corn	0.140	0.024
Soy	0.231	0.019
Cover crops	0.466	-0.015
Tile Drainage	0.055	0.030
Ditch Drainage	0.016	0.074
Age	-0.104	0.054
Experience	0.024	0.039
Off-Farm Labor	-0.093	0.013
Farm Income	-0.014	-0.110
North West	0.154	0.009
North Central	-0.143	0.038
North East	-0.108	-0.074
West Central	0.046	0.020
Central	-0.085	0.000
East Central	0.057	0.055
South West	-0.067	0.048
South Central	-0.171	-2.28×10^{-17}

Table 2.5 Average treatment effect on the treated results.

(a) Results from selected specification

	Y(0)	Y(1)	ATT	SE	95% Confidence Interval	Model
Farmland share under cover crops	0.1228	0.2682	0.1454	0.0273	[0.0918, 0.1989]	1

(b) Results from all specifications

Method	Neighbors	Caliper	ATT	SE	Model
Propensity score-nearest neighbor	7	0.2	0.1562	0.0331	2
	7	0.1	0.1582	0.0356	3
	7	0.05	0.1309	0.0298	4
	7	0.02	0.1257	0.0377	5
	1	No	0.1568	0.0409	6
	2	No	0.1245	0.0426	7
	3	No	0.1509	0.0386	8
	4	No	0.1534	0.0379	9
	5	No	0.1549	0.0409	10
	6	No	0.1475	0.0415	11
	7	No	0.1536	0.0412	12
	8	No	0.1506	0.0408	13
	7	0.15	0.1927‡	0.0278	14
	Kernel type	**Bandwidth**	**ATT**	**SE**	**Model**
Propensity score-kernel	Epanechnikov	0.01	0.1574	0.0382	15
	Epanechnikov	0.04	0.1602	0.0357	16
	Epanechnikov	0.1	0.1567	0.0360	17
	Epanechnikov	0.15	0.1599	0.0357	18
	Epanechnikov	0.2	0.1688	0.0355	19
	Gaussian	0.01	0.1626	0.0372	20
	Gaussian	0.04	0.1574	0.0361	21
	Gaussian	0.1	0.1732	0.0354	22
	Gaussian	0.15	0.1873	0.0351	23
	Gaussian	0.2	0.1958	0.0351	24
	Neighbors		**ATT**	**SE**	**Model**
Euclidian distance*	1		0.1396	0.0372	25
	2		0.1647	0.0328	26
	3		0.1491	0.0345	27
	4		0.1466	0.0333	28
	5		0.1475	0.0332	29
	6		0.1516	0.0330	30
	7		0.1419	0.0334	31

*Include bias adjustment and exact matching on livestock

† Use population of 100

‡This specification does not include 2012 cover crop acreage as a covariate in the propensity-score equation

Table 2.6 Rosenbaum sensitivity analysis.

Γ	p^+
1	$<1.0 \times 10^{-16}$
10	3.8×10^{-6}
20	0.0008
30	0.0049
40	0.0126
50	0.0227
60	0.0339
70	0.0454
71	0.0466
72	0.0477
73	0.0489
74	0.0500

Table 2.7 Iowa cover crop acreage, expenditures, and marginal abatement cost of nitrogen (dollars per pound).

	(1) **Farmland cover cropped with cost-share**	**(2)** **Farmland cover cropped without cost-share**	**(3)** **Total cover-cropped farmland**	**(4)** **Additional farmland cover cropped due to cost-share**
		(a) Iowa farmland (acres)		
Estimated acres	317,132	274,748	591,880	171,927
		(b) Average private net loss from cover crop use (dollars per acre)		
Net loss per acre	23	40	31	23
		(c) Total estimated cost (million dollars)		
Cost-share	8.40	0.00	8.40	8.40
Farmer	7.29	10.99	18.28	3.95
Total	15.69	10.99	26.68	12.35
		(d) **Estimated nitrogen load reduction (tons)**		
Estimated N reduction	1,649 – 4,503	1,429 – 3,901	3,078 – 8,405	894 – 2,441
		(e) Marginal abatement cost of nitrogen (dollars per pound)		
Cost-share	0.93 – 2.55	0	0.50 – 1.36	1.72 – 4.70
Farmer	0.81 – 2.21	1.41 – 3.85	1.09 – 2.97	0.81 – 2.21
Total	1.74 – 4.76	1.41 – 3.85	1.59 – 4.33	2.53 – 6.91

CHAPTER 3. WHAT DRIVES LANDOWNERS' CONSERVATION DECISIONS? EVIDENCE FROM IOWA

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Abstract

Conservation practices such as no-till and cover crops have been shown to have on- and off-farm benefits. However, when benefits of a practice do not go to the provider, underinvestment may occur. Farmland rental arrangements where tenants may not reap the benefits of conservation investments are a commonly cited barrier to conservation practice adoption in agriculture and may result in lower adoption rates on rented land than on owner-operated fields. This issue is especially important since more than half of Midwestern farmland is rented. This article examines factors driving adoption of four key conservation practices—no-till, cover crops, buffer strips, and ponds/sediment basins—using a statistically representative survey of Iowa landowners. We find evidence supporting the hypothesis that adoption is lower on rented land for cover crops, buffer strips, and sediment basins, but not for no-till. Our results also show that the large proportion of the state's land owned by non-operating landowners and absentee landowners could present a barrier to increasing adoption of conservation practices. Furthermore, landowners seem open to increasing the use of cover crops in the immediate future and a sizable number are even willing to incentivize tenants by paying for part of the cover crop planting cost. Finally, almost half of landowners would be willing to increase the area of their land under conservation practices if they could receive conservation-related tax credits or deductions, in exchange, suggesting a potential policy strategy to increase adoption.

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Introduction

Nutrient pollution from agriculture remains a major problem in Iowa and across the Midwest. The Iowa Nutrient Reduction Strategy (INRS) calls for vast increases in the use of various conservation practices to address nutrient loss into waterways and aims to reduce nitrogen and phosphorus loads from non-point sources by 41% and 29%, respectively (INRS 2017). Funding for conservation programs has increased in recent decades, exceeding $27 billion from 2014 to 2018 (Pavelis et al. 2011; 113th Congress 2014), and the USDA Environmental Quality Incentives Program (EQIP) allocated almost $30 million to fund conservation practices in Iowa in the 2018 fiscal year alone. However, in 2016, 58% of rivers and streams and 57% of lakes and reservoirs across Iowa had a water quality impairment (IDNR 2017).

A key obstacle is that about half of farmland in the Midwest is rented through short-term leases, which may make tenants less willing to invest in conservation practices with long-term benefits. This is a growing concern−in 2017, just 37% of Iowa farmland was owner-operated, a 13 percentage-point decline from 1982 (Zhang et al. 2018).[1] Additionally, a growing share of farmland belongs to non-operating landowners (NOLs)—landowners who do not currently farm—magnifying the knowledge gap about benefits and the importance of critical conservation practices. From 1982 to 2017, the percentage of Iowa farmland owned by full-time Iowa residents declined from 94% to 80%, which may further hinder conservation practices.

Prior literature looks at a variety of factors affecting farmers' adoption of conservation practices. Prokopy et al. (2008) group variables related to capacity, farm characteristics, farmers' attitudes and environmental awareness, and their impact on adoption, and find that education, income, and total acreage most frequently impact adoption positively. Some studies conclude

[1] These values exclude land enrolled in government programs and custom acres from total farmland. This is why it differs from the number in figure 3.4, which states that 53% of farmland was rented in 2017.

that land tenure insecurity negatively affects the adoption of conservation practices, such as cover crops (Bergtold et al. 2012; Deaton et al. 2018), perennial crops (Fraser 2004), and straw retention (Gao et al. 2018). However, some other studies find that tenants are more likely than owners to use conservation tillage (Varble et al. 2016; Lee and Stewart 1983; Neill and Lee 2001). Soule et al. (2000) suggest that lease type matters—cash renters adopt conservation tillage less than owner-operators and crop-share renters.

Few studies, however, consider the landowner perspective. One exception is Abdulla (2009), who uses a non-representative survey of Iowa landowners and finds that owners operating their own land does not affect conservation tillage adoption but does have an unexpected negative effect on structural conservation practice adoption (e.g., terraces). Other landowner studies largely focus on adoption of conservation practices (Constance et al. 1996; Perry-Hill and Prokopy 2014; Petrzelka and Marquart-Pyatt 2011; Ulrich-Schad et al. 2016) or enrollment in conservation programs (Petrzelka et al. 2012; Perry-Hill and Prokopy 2014) by absentee landowners and/or NOLs. These studies mostly do not compare how adoption rates differ between NOLs and operator landowners; however, a few studies identify barriers for tenants to adopt conservation practices on land owned by NOLs, including the timing and short nature of leasing arrangements, high rental rates, rental market competition, and a lack of communication between landowner and tenant (Carolan 2005; Ranjan et al. 2019).

The purpose of our article is to determine how absentee landownership, land characteristics, and landowner demographics affect current conservation practice use in Iowa. We statistically evaluate three hypotheses: (1) conservation practices are used less on rented land compared to owner-operated land; (2) operator landowners have conservation practices on greater shares of their land than do NOLs; and (3) soil characteristics are major drivers of conservation practice use and their impact varies by practice. To evaluate our hypotheses, we use data from the 2017 Iowa Farmland Ownership and Tenure Survey (IFOTS) (Zhang et al. 2018), which is statistically representative of all farmland and landowners in Iowa as of July 1, 2017. Unlike producer surveys that often overestimate the use of conservation practices, IFOTS provides credible results that closely match adoption rates from the 2017 Census of Agriculture. IFOTS estimates suggest that no-till and cover crops are used on 27% and 4% of the state's farmland, respectively, while census data finds that no-till and cover crops are on 27% and 3% of the state's farmland, respectively (NASS 2017).

We use a descriptive analysis and t-statistics to determine if adoption rates differ by landowner groups for no-till,[2] cover crops, buffer strips, and ponds/sediment basins—four conservation practices highlighted by the INRS for their effectiveness at controlling soil loss and/or nutrient runoff (INRS 2017). We also discuss landowners' stated reasons for not using conservation practices on their land and their plans to use them in the future. Lastly, we look at whether and how alternative conservation policies could spur the use of conservation practices and inquire about landowners' willingness to encourage their tenants to plant cover crops.

Materials and Methods

The data used in this analysis come from the 2017 IFOTS, which is based on a random sample of 16.2 ha (40-ac) tracts of farmland that were chosen in 1988 following a two-stage area sampling design. The first stage assured a geographic dispersal of sample sections in each county in a systematic manner, and the second stage selected a single 16.2 ha (40-ac) unit at random within each sample section within each county. All landowners within this sample unit were then identified and became potential survey respondents.

[2] No-till was defined as a tillage system in which crop residue is left on the soil and the soil is left undisturbed from prior harvest to no-till planting, except for nutrient injection.

Tract landowners were interviewed via telephone by the Iowa State University Center for Survey Statistics and Methodology between October 18, 2017 and February 2, 2018. The target population was owners of land used for agricultural purposes as of July 1, 2017. There were 535 usable responses (68% response rate). An appendix to Zhang et al. (2018) includes the full questionnaire, details about the sampling design, and formulas for the landowner and land weights. These weights allow us to make inferences regarding the percent of owners as well as the percent of the farmland owned at the state and region level.[3] For the purpose of this study, the state's regions are defined by crop reporting districts (CRD) as used by US Department of Agriculture.[4]

The IFOTS questionnaire asks landowners about land parcels they own, the ownership type, and leasing arrangements as of July 1, 2017. Respondents were asked how many acres were in no-till, how many acres had cover crops, and/or buffer strips, and/or a pond/sediment basin (henceforth a pond). Farmers using a specific practice indicated whether the land in question was operated by them, rented out, or both. Farmers not using that practice stated why not and whether they planned to in the future (in most stated preference studies, the magnitude of self-reported future adoption intentions can potentially be inflated).

We aggregate responses to the CRD or state level using the farmland and landowner weights, and, for accuracy, focus on farmland with conservation practices that was entirely operated by the owner or entirely by a tenant.[5] Thus, our estimates for the share of conservation

[3] The expansion to number of owners is only possible when the specific question is based on demographics, not the farmland.
[4] The crop reporting districts and area of cropland in each district are as follows: Northwest (NW) 1,506,099 ha; West Central (WC) 1,549,044 ha; Southwest (SW) 926,673 ha; North Central (NC) 1,401,948 ha; Central (C) 1,440,666 ha; South Central (SC) 699,316; Northeast (NE) 1,255,884 ha; East Central (EC) 1,127,978 ha; and Southeast (SE) 835,170 ha.
[5] Adoption that occurs on land that cannot be easily classified as owner-operated or rented out is limited. Our analysis covers 88% to 94% of all conservation practice adoption, depending on the practice.

practices on rented or owner-operated farmland can be thought of as lower bounds for state totals.

We chose conservation practices based on their effectiveness at reducing nitrogen and phosphorus. Cover crops, buffer strips, ponds, and land retirement through the Conservation Reserve Program (CRP) most effectively reduce nitrogen loads, and the INRS highlights those same practices for reducing phosphorus loads but lists no-till as the best tool for reducing phosphorus loads (INRS 2017).

We use a descriptive analysis to gain a big-picture perspective of Iowa farmland coupled with a statistical analysis to test several hypotheses of interest. We analyze Iowa farmland using various factors to make inferences about the distribution of the farmland and the use of the four conservation practices. We use the R package "Survey" to estimate the proportion of each group of interest that uses each conservation practice (Lumley 2019).

In our statistical analysis, we test whether the proportion of farmland under a specific conservation practice differs across groups of landowners. We have two hypotheses: (1) adoption rates are lower on rented-out farmland than on owner-operated farmland; and (2) operator landowners use conservation practices on a greater share of their land than do NOLs because they are likely to have more current farming knowledge. We also evaluate whether conservation adoption differs across landowner characteristics (i.e., farming experience, residency status, age, and gender). We focus on gender because of evidence that women may be more conservation oriented than men (Eells and Soulis 2013).

We use the two-group t-test to evaluate the null hypothesis that proportions of land with the conservation practice is equal for both groups, with the alternative hypothesis that the proportions differ across groups.[6] We calculate the t-statistic for the difference in the proportions and report the p-values.[7] We then break down these comparisons by various factors to evaluate the robustness of our results.

We use county-level estimates to measure the effects of erosion potential on the adoption of different conservation practices and a simple linear regression to examine whether counties with greater shares of highly erodible land (HEL)[8] have higher rates of conservation practices. We then report the slope coefficient for this relationship, the p-value associated with the t-test of this coefficient, and the R-squared.

Results and Discussion

As table 3.1 shows, no-till is used on 27% of Iowa farmland, making it the most prevalent of the four studied conservation practices. No-till is most concentrated in the Southwest and West Central CRDs—used on 56% and 40% of farmland, respectively—possibly due to erosion common in the loess-hill soils in western Iowa, as evidenced by the high percentages of HEL in that area. We test this idea by examining how conservation practice use differs by soil quality using counties' HEL shares summary data from the Environmental Working Group.[9] We find a positive relationship, suggesting that a 10 percentage-point increase in a county's HEL

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[6] This describes the two-tailed test. When we have a strong reason to believe that the conservation practice rate should be greater for one group than another, we use a one-tailed hypothesis test, instead of the more conservative two-tailed test.

[7] Let θ_f^i be the share of land with conservation practice i in group $f \in \{1,2\}$. For a two-tailed test

H_o: $\widehat{\theta_1^i} = \widehat{\theta_2^i}$

H_a: $\widehat{\theta_1^i} \neq \widehat{\theta_2^i}$

Test statistic: $t = \frac{\widehat{\theta_1^i} - \widehat{\theta_2^i}}{\sqrt{V(\widehat{\theta_1^i} - \widehat{\theta_2^i})}}$, where $V\left(\widehat{\theta_1^i} - \widehat{\theta_2^i}\right)$ is the estimated variance:

$V\left(\widehat{\theta_1^i} - \widehat{\theta_2^i}\right) = V_1^i + V_2^i - 2\left(V_1^i V_2^i\right)^{0.5} \rho$, where V_1^i and V_2^i are the estimated variances for $\widehat{\theta_1^i}$ and $\widehat{\theta_2^i}$, respectively, and $\rho = \frac{cov_{12}}{\sqrt{V_1^i V_2^i}}$ is the correlation coefficient, where cov_{12} is the covariance of groups 1 and 2.

[8] HEL is defined by USDA as having an erodibility index of at least 8.

[9] Obtained via personal communication with Soren Rundquist, Director of Spatial Analysis, Environmental Working Group, based on data from USDA Farm Service Agency - Common Land Unit and the USDA National Agricultural Statistics Service – Cropland Data Layer.

corresponds to a 3.7 percentage-point increase (2.4 to 5.1, 95% confidence interval) in the county's share of no-till (p-value <0.001, $R^2 = 0.248$) (figure 3.1a).

Cover crops are used on 4% of Iowa's farmland. Cover crops are used the most in the Southeast CRD (12% of farmland), followed by the Northeast and South-Central CRDs. All three districts are high in beef or dairy cattle production, possibly due to spillovers across farming enterprises—Plastina et al. (2018) finds that grazing a cover crop or harvesting it for forage adds around $20 per acre in cost savings on animal feed. Figure 3.1b shows on average, a 10 percentage-point increase in a county's HEL share corresponds to a 0.59 percentage-point increase in cover crops (0.02 to 1.2, 95% confidence interval; p-value = 0.043; $R^2 = 0.042$). The presence of HEL appears to be a larger driving factor in the adoption of no-till than for cover crops.

The positive relationship between HEL and the use of these conservation practices can be explained by compliance provisions that require farmers to agree on a conservation plan for HEL with their local NRCS office before participating in most Farm Service Agency or Risk Management Agency Programs or receiving federal government crop insurance subsidies. The dispersion in these regressions could be due to variations in recommendations given and funding provided by the decentralized NRCS offices.

Buffer strips are used on 3% of land statewide and 6% of the land in the North Central and Northeast CRDs. Ponds are used on 2% of land statewide and are most prevalent in the South-Central CRD. Ponds are predominantly used in high livestock production areas, likely because they also provide water for cattle.

In the next two subsections, we analyze conservation practice use across four categories: (1) land tenure (whether the parcel is operated by the landowner or rented out); (2) operator status (whether the landowner farms); (3) farming experience; and, (4) local versus absentee farmer. Figure 3.2 shows the distribution of Iowa farmland by land leasing arrangements and landowner's farming experience and residency status. Operator-landowners include full-time farmer landowners (farm and have no off-farm job) as well as part-time farmer landowners (farm and have off-farm employment). NOLs include owners who have never farmed and those retired from farming. Owner-operated land is farmed by the surveyed landowner or a co-owner, whereas rented-out farmland is farmed by a tenant who is not one of the owners. Absentee landowners do not reside in Iowa and local landowners reside in Iowa at least part of the year. Figure 3.2 shows that 53% of Iowa farmland is rented out by the landowner—only 37% is operated by a landowner. The remaining 10% is custom farmed or in government programs, such as the CRP. Among the rented farmland, 45% belongs to NOLs, and landowners that currently farm own the remaining 8%. Individuals who have never farmed own 25% of the state's farmland. Almost one-third of farmland owned by those who have never farmed belongs to absentee landowners.

Land Tenure

We examine how no-till, cover crop, buffer strip, and pond use differ by land tenure, and test our hypothesis that conservation practices are used on a greater share of owner-operated farmland than rented-out farmland. No-till is a short-term conservation practice and may even be profitable in the short term (Ibendahl 2016); thus, we expect land rental arrangements not to hinder no-till adoption. Figure 3.3 shows the between-group t-test results when comparing the share of owner-operated and rented-out farmland under each conservation practice (1 vs. 2 in figure 3.2). At the state level, buffer strips and ponds are more prevalent on owner-operated land (p-values = 0.071 and 0.083), and there is no statistically significant difference for cover crops (p-value = 0.220), which may be due to the duration and expense of those practices and that tenants are less likely to adopt long-term practices. Thirty-percent of rented-out farmland and

20% of owner-operated farmland uses no-till (p-value=0.006), which is in line with the idea of no-till generating short-term benefits (Ibendahl 2016). We cannot directly infer from figure 3.3 why no-till is more prevalent on rented land than owner-operated land—many factors affect conservation practice use and other variables may confound the effect of land tenure. Thus, we explore the effect of land tenure on conservation practice use by region, landholdings, and farming status.

Land tenure results could be driven by regional specificities, since regional-level soil and land characteristics may affect conservation practice use and the share of rented land varies throughout the state. Figure 3.4 shows the share of no-till and cover crops on owner-operated and rented land by CRD. The statewide relationship between land tenure and no-till is consistent across CRDs—eight of nine CRDs have higher rates of no-till on rented farmland. However, the differences are statistically significantly different from zero only for the Central and South-Central CRDs.

The share of farmland with cover crops is higher on rented land in five CRDs, but only one is statistically significant at a 95% confidence level. Figure 3.4, therefore, confirms that our results are not driven by an anomaly in any one particular district.

We examine whether farming experience affects the share of owner-operated and rented farmland using no-till and cover crops. We use full- versus part-time farming as a proxy for farming operation scale, as full-time farmers operate a greater area of land than part-time farmers, in general.[10] We do not consider retired landowners or those who have never farmed because they do not have owner-operated land. For our robustness checks, we compare the rates

[10] We cannot tell from the survey whether full-time farmers operate more land than do part-time farmers, so we find evidence from the 2017 Census of Agriculture (NASS 2017) that, in Iowa, operators who do not work off farm operate, on average, 519 acres and those who work off farm at least 200 days per year operate 233 acres.

of no-till and cover crops among groups 1.A vs. 2.A and 1.B vs. 2.B from figure 3.2. Landowners who farm full time use no-till on about the same proportion of their operated and rented-out land (29% vs. 31%, p-value = 0.865) (figure 3.5a). However, part-time farmer landowners use no-till on a significantly lower share of their owner-operated land (13%) than on the land they lease out to others (39%) (p-value = 0.002) (figure 3.5a), suggesting that lower no-till adoption on owner-operated land is largely due to low adoption by part-time farmers. We believe this is due to part-time farmers typically operating less land than full-time farmers.[11] Several studies document that conservation-tillage adoption is positively correlated with area of farmland operated (Lee and Stewart 1983; Rahm and Huffman 1984; Epplin and Tice 1986; Gould et al. 1989; Sheikh et al. 2003; Davey and Furtan 2008; Vitale et al. 2011; Wade and Claassen 2017; Canales et al. 2018). Additionally, part-time farmers may not have as much time to engage with other farmers to learn about no-till, and may be less likely to adopt due to the learning curve associated with using no-till. Full- and part-time owner-operators have cover crops on a greater proportion of their owner-operated than rented-out land (7% vs. 3% and 3% vs. 1%, respectively), but the difference is only statistically significant for landowners who farm full time (p-values = 0.005 and 0.101, respectively) (figure 3.5b)[12].

Operator Status, Farming Experience, and Iowa Residency

We analyze how operator status, farming experience, and residency affect conservation practice use (see table 3.2 for results), and find that operator-landowners have all four conservation practices on higher proportions of their farmland than do NOLs, which is significant because NOLs own 57% of the state's farmland (Zhang et al. 2018). We expect

[11] See footnote 8.
[12] We did not breakdown the results for cover crops because the relationship between land tenure and cover crop use is robust when further comparing across gender, age, and farming experience.

landowners with farming experience to be more likely to use conservation practices because they likely possess more knowledge of them. We observe this expectation across all four conservation practices when we compare full-time farmer landowners with those who have never farmed, but not for part-time or retired farmers. This is especially concerning because landowners who have never farmed own 34% of the state's farmland (Zhang et al. 2018).

All four conservation practices are implemented on a lower share of absentee landowner acres when compared to local landowners (table 3.2c). Novel approaches may be needed to increase the effectiveness of outreach to NOLs, especially absentee NOLs, per Petrzelka and Armstrong (2015).

Financial Characteristics

Table 3.3 shows how conservation use differs by owner's landholdings, percent of agriculture-based income, and percent of land that has been paid for. On average, landowners with more land tend to use no-till at a higher rate. Landowners with more than 809 ha (2000 ac) use no-till on 36% of their land compared to just 20% for those who own 0–40 ha (0 to 99 ac). There was no obvious pattern for cover crops, buffer strips, or ponds.

Landowners with higher percentages of agriculture-based income have higher farmland shares of no-till and cover crops, with the exception of landowners with entirely agriculture-based income. Among landowners with entirely agriculture-based income, 80% are operator landowners and 60% state that current income is the most important reason for owning farmland. There is not a clear relationship between percentage of land that is paid for and conservation practice use.

Landowner Demographics

Tables 3.4a, 3.4b, and 3.4c show Iowa's conservation practice use by landowners' age, gender, and education, respectively. Table 3.4a shows there is no consistent relationship between landowner age and use of conservation practices. No-till is least prevalent on land owned by someone less than 55 years old, which contrasts with prior literature that suggests older farmers are less likely to adopt conservation practices because they may have less time to obtain the benefits (Prokopy et al. 2008). Landowners younger than 55 use cover crops and ponds at the highest rates.

Gender does not have an effect on conservation practice adoption. Each practice is used on about the same proportion of farmland owned by males and females, which fails to support women landowners being more likely to adopt the conservation practices studied, despite findings that female landowners may be more conservation oriented than male landowners (Eells and Soulis 2013; Druschke and Secchi 2014). Druschke and Secchi (2014) find that although women are favorable toward conservation, they have lower knowledge levels about conservation practices, and Carolan (2005) finds female landowners may feel alienated and less comfortable making recommendations to male tenants. Women own 47% of Iowa farmland (Zhang et al. 2018); thus, increasing outreach efforts to female landowners could have a sizable impact on conservation use.

The relationship between education and conservation practice prevalence is unclear. There is a direct relationship for ponds—landowners with higher levels of education have ponds on a greater share of their land. However, the opposite is observed for no-till—high-school educated landowners have no-till on 34% of their land, compared to 21% for landowners with a graduate degree.[13] This contrasts with past studies that find a positive relationship between education and conservation practice adoption (Prokopy et al. 2008).

[13] This might be in part because less educated landowners tend to be operators. For instance, 45% of non-operators' farmland belongs to someone with a college degree or higher, while only 36% of land owned by operators belongs to those with a college degree or higher.

Landowner Perspectives and Future Intentions

We look at how conservation practice use is expected to evolve in the near future. Tables 3.5a and 3.5b show that landowners are open to having more cover crops on their land—in the next five years, 18% are likely to use them and an additional 34% might use them. These two groups of landowners own 19% and 38% of Iowa farmland, respectively. It is unlikely that these farmers will adopt cover crops on all of their land; however, it would be a substantial increase from the 4% of farmland that is currently cover cropped. Only 10% of landowners state that they are likely to use no-till, 4% are likely to use buffer strips, and 2% are likely to use ponds over the next five years.

Table 3.5c shows which policies could be effective at inducing landowners to adopt conservation practices. Tax credits or deductions in exchange for implementation of conservation practices would be most effective—45% of landowners state that they would be likely or very likely to adopt more conservation practices under such a policy. Thirty-six percent of landowners are likely or very likely to adopt more conservation practices if tax-free cost sharing is available, and 22% if land enrolled in conservation programs is excluded from the value of the estate for tax purposes. Enthusiasm among landowners is understandable; however, their future adoption will be contingent on whether and how these new policies are delineated.

We also investigate landowners' willingness to encourage their tenants to use cover crops. Barriers to conservation practices on rented land exist on both the landowner and tenant side (Carolan 2005); thus, we disentangle these factors by examining whether and in what ways landowners are willing to encourage their tenants to use more cover crops. As table 3.5d shows, about one-third of landowners would pay for a portion of cover crop planting costs, or increase the length of a tenant's lease if they adopted or increased the area under cover crops, which is important because prior literature cites high costs (Roesch-McNally et al. 2018) and short leases (Ranjan 2019; Carolan 2005) as barriers to tenants adopting conservation practices.

Table 3.5d shows landowners' willingness to help tenants use cover crops based on whether the landowner has any no-till farmland, which helps us determine if having a conservation practice on their land makes them more willing to help tenants adopt a different conservation practice on rented land. We find landowners' willingness to help tenants is higher for no-till users than for those who don't use no-till—42% (41%) of landowners using no-till are willing to give tenants a longer lease (pay for a portion of planting costs) in exchange for planting more cover crops, compared to just 12% (30%) of those without any no-till acres. This suggests there may be links between the adoption of no-till and cover crops.

Table 3.6 shows landowners' responses to an open-ended question about their main reasons for not using each conservation practice. For NOLs, the primary reason for not using no-till is that they deem it not suitable for the land (46%), while the primary reason for not using cover crops is that the decision is up to the tenant (36%).

For operator landowners, the primary reasons for not using no-till is that it hurts crop yield (17%), it is the tenant's decision (15%), and that they tried it but did not like it (13%); and, the main reasons for not using cover crops are that it is the tenant's decision (19%), the cost of terminating the cover crop is too high (19%), and they do not have time to plant them in the fall (16%). A relatively low proportion of NOLs indicate that no-till and cover crop use are decisions made solely by the tenant (6% and 36%, respectively), which suggests that landowners and tenants typically make joint conservation decisions on rented land. This confirms Arbuckle's (2019) survey in which 38% of farmers stated that the tenant should solely be responsible for conservation decisions.

The overwhelming reason for not using buffer strips (84%) or ponds (88%) is that the landowner deems they are not needed on the land. These values are similar across owner-operated and rented-out land. We also note that previous research such as Zhang et al. (2016) and Arbuckle and Roesch-McNally (2015) show that farmers' conservationist identity and perceived efficacy of a conservation practice in reducing erosion or runoff is critical for higher adoption.

Perceptions related to economics and factors of production drive many landowners' reasons for not using cover crops; whereas land attributes are the main reason for not using buffer strips and ponds (and somewhat no-till). As research results emerge to address preconceived ideas, perceptions may evolve. For instance, while some landowners' reasons for not using cover crops fall in line with previous literature, others' are inconsistent with what has been observed. Roesch-McNally et al. (2018) find that barriers to adopting cover crops include costs and lack of time to plant them in the fall, which is similar to what the landowners stated. However, the sources of costs differ from what the landowners mentioned. Plastina et al. (2018) find cover crops' greatest expense is planting costs—costs of terminating the cover crop are minor, as on average, farmers do not use additional inputs or machinery passes (e.g., extra tillage) than they use in absence of cover crops. NOLs cite termination costs as a reason for not using cover crops at a greater rate than operator landowners, suggesting a gap in perceptions between landowner types.

Summary and Conclusions

This study provides three main contributions to the literature. First, we conduct a statistically representative examination of conservation practice use on Iowa farmland owned by operator landowners and NOLs. Our results demonstrate the importance of landowners' farming experience, knowledge, value systems, and residency in driving conservation decisions, which is increasingly important as the proportion of rented farmland in the United States grows. Second, we provide statistical evidence that conservation practice adoption is lower on rented land for three practices (cover crops, buffer strips, and ponds/sediment basins), but not for no-till. Third, we shed light on landowners' reasons for non-adoption and their views regarding current and alternative conservation policies and find that landowners would consider increasing conservation practice acreage if they could receive tax credits or deductions for doing so.

Landowners seem open to having more cover crops on their land (INRS 2017), which would help meet INRS goals. The majority of landowners do not expect to increase adoption of no-till, buffer strips, or sediment basins, but over half of landowners, who own 57% of the state's farmland, indicate they are open to increasing cover crop acreage on their land in the next five years. This does not imply that farmers will plant cover crops on all of this land, but it could represent a large increase from the 4% of farmland on which cover crops are currently used. Our results also show landowners' reasons for not having cover crops on their land differs between operator landowners and NOLs, which suggests it is important for land-grant universities to provide more research-based extension services targeting NOLs to reduce the perception gap.

Our work has several policy implications that complement the current state of conservation programs. The 2018 Farm Bill allocated an estimated $60 billion for conservation practices over ten years (Stubbs 2019), and it continues funding programs like EQIP, which promote conservation practices. Current conservation programs use a cost-share strategy; however, almost half of landowners indicate they would be somewhat or very likely to use more conservation practices on their land under a tax-credit policy. Meeting the goals of the INRS will require novel policies targeting absentee landowners, given the state's landownership dynamics (INRS 2017).

One shortfall of our approach is that many of the analyzed variables are likely to be confounded. We disentangle some of these effects, but our sample size limits the number of factors by which we can break down the results. Moreover, we do not have information on landowners' rented-in farmland and cannot explore the tenants' conservation preferences or decisions. While this research does not causally identify the effects that important factors such as land tenure have on adoption of conservation practices, it provides a big-picture understanding of conservation practice use in Iowa. Future work will investigate potential landowner effects in adopting conservation practices, for example whether using one practice increases likelihood of using others, or whether using a practice on operated land increases likelihood of using the same practice on rented land.

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Figures and Tables

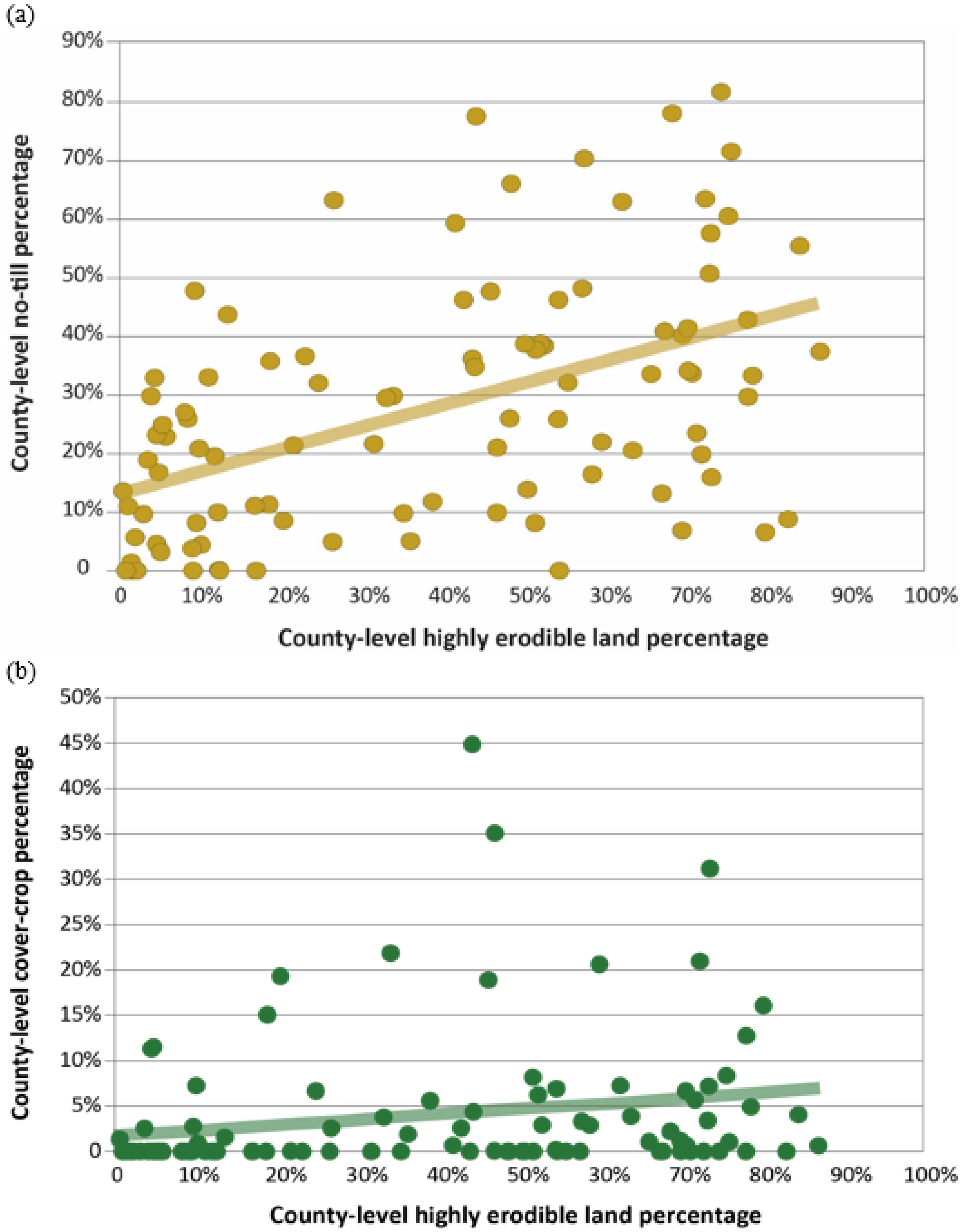

Figure 3.1 County shares of highly erodible land vs. share of (a) no-till and (b) cover crops.

Note: (a) p-value <0.001, $R^2 = 0.248$
Note: (b) p-value = 0.043; $R^2 = 0.042$

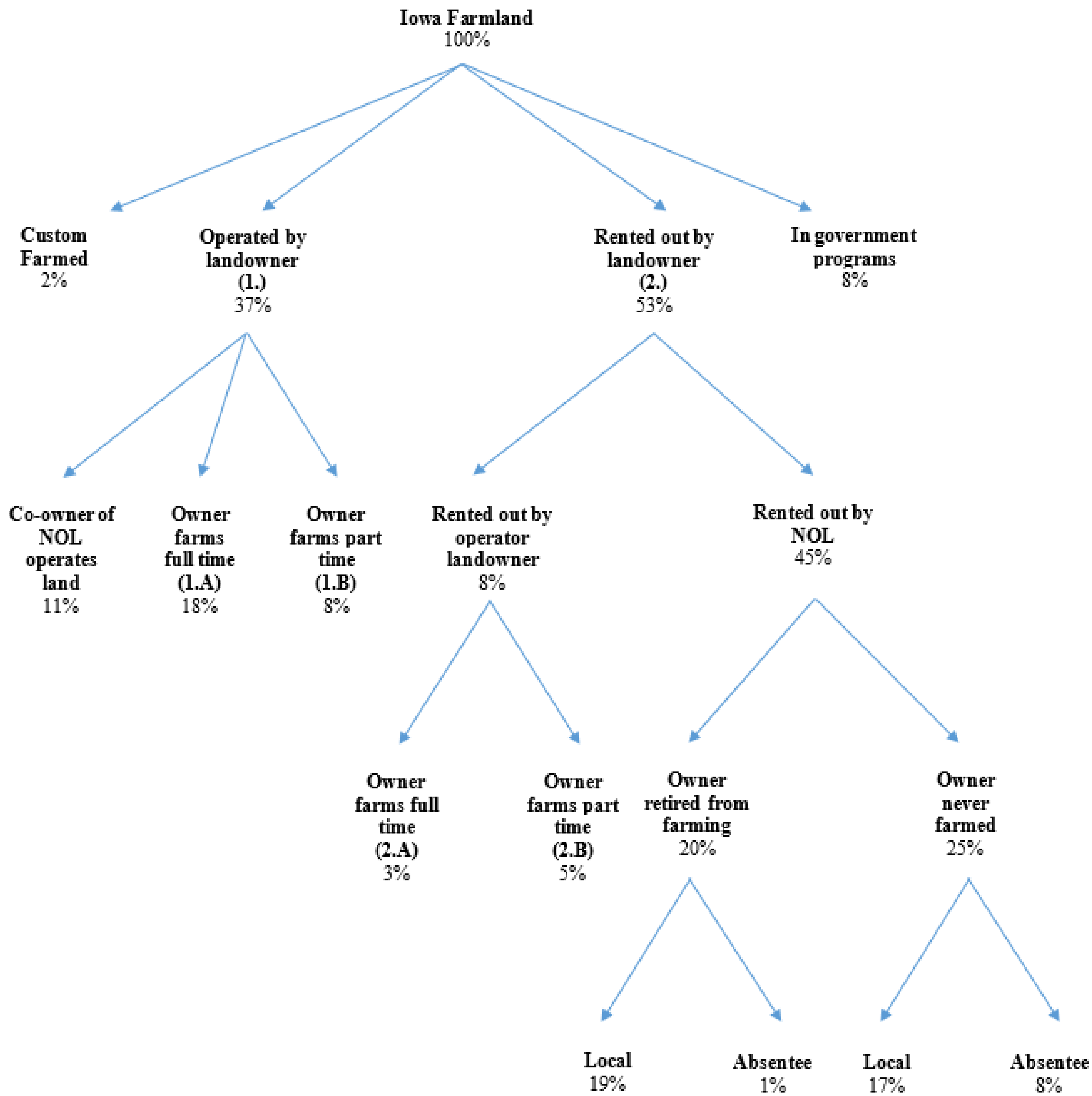

Figure 3.2 Breakdown of Iowa farmland by landowner type.

Note: "Co-owner of NOL operates land" represents land for which the surveyed landowner did not farm the land, but the respondent indicated that another owner did.

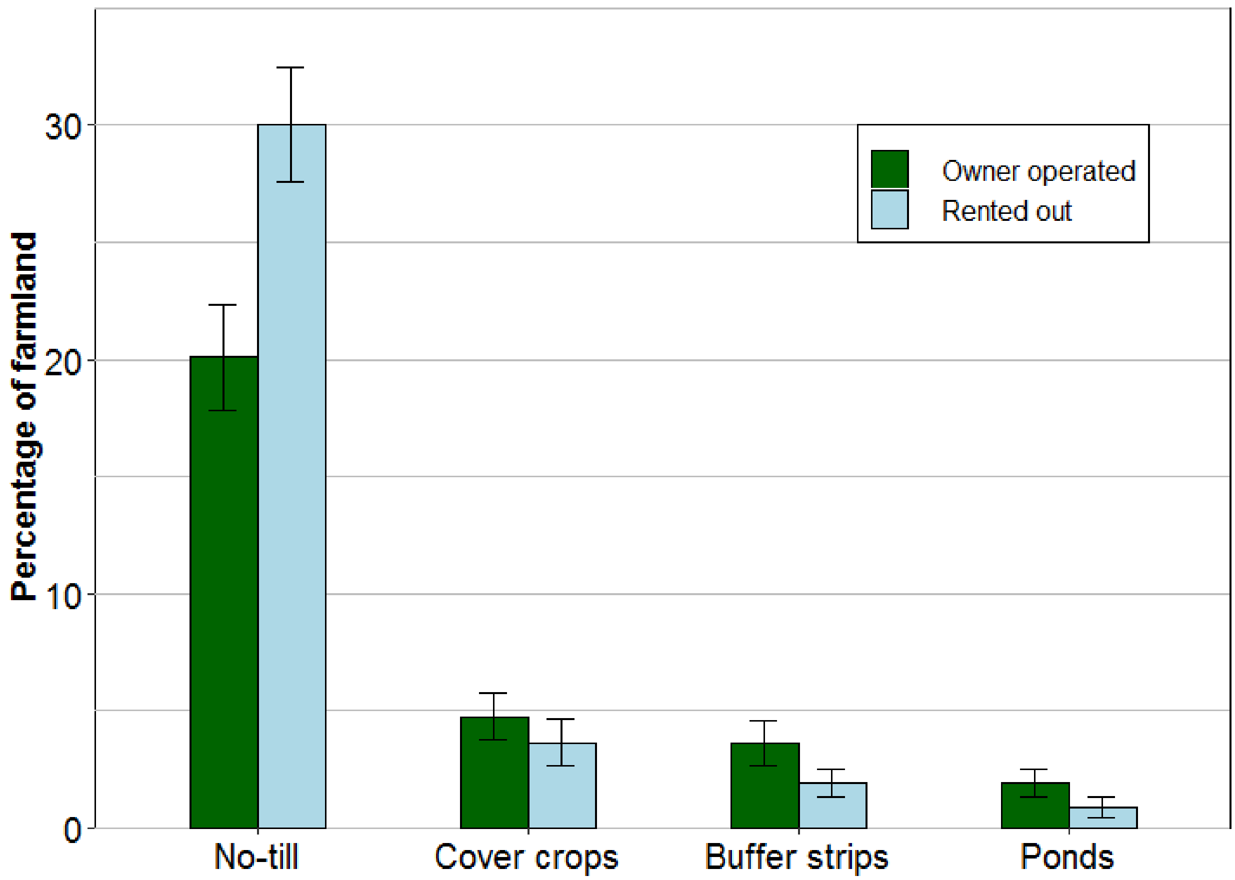

Figure 3.3 Iowa conservation practice farmland shares by land tenure and practice type.

Note: Bars reflect standard error of the mean.

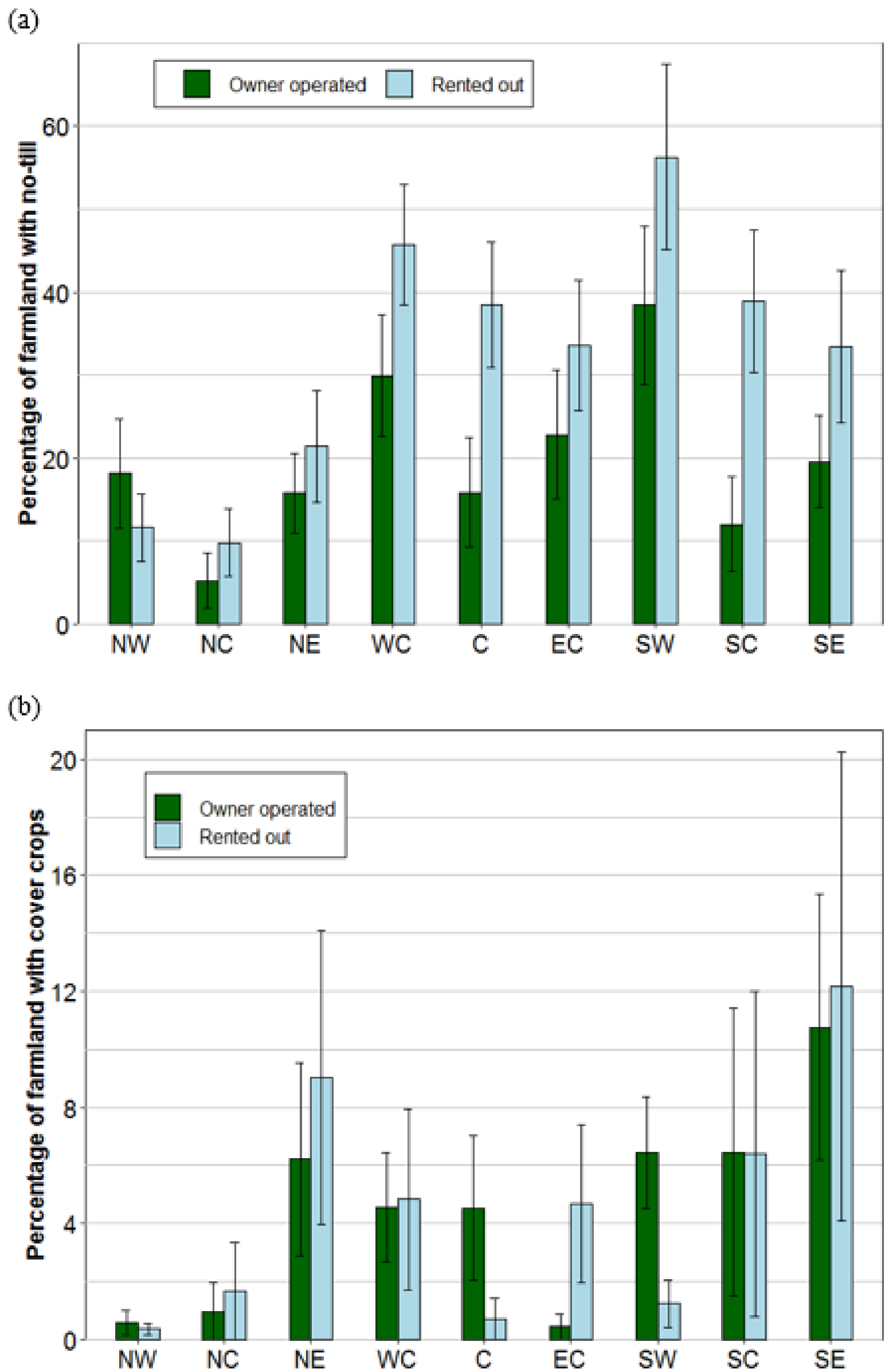

Figure 3.4 Iowa share of farmland with (a) no-till and (b) cover crops by land tenure, and crop-reporting district.

Note: Bars reflect standard error of the mean.

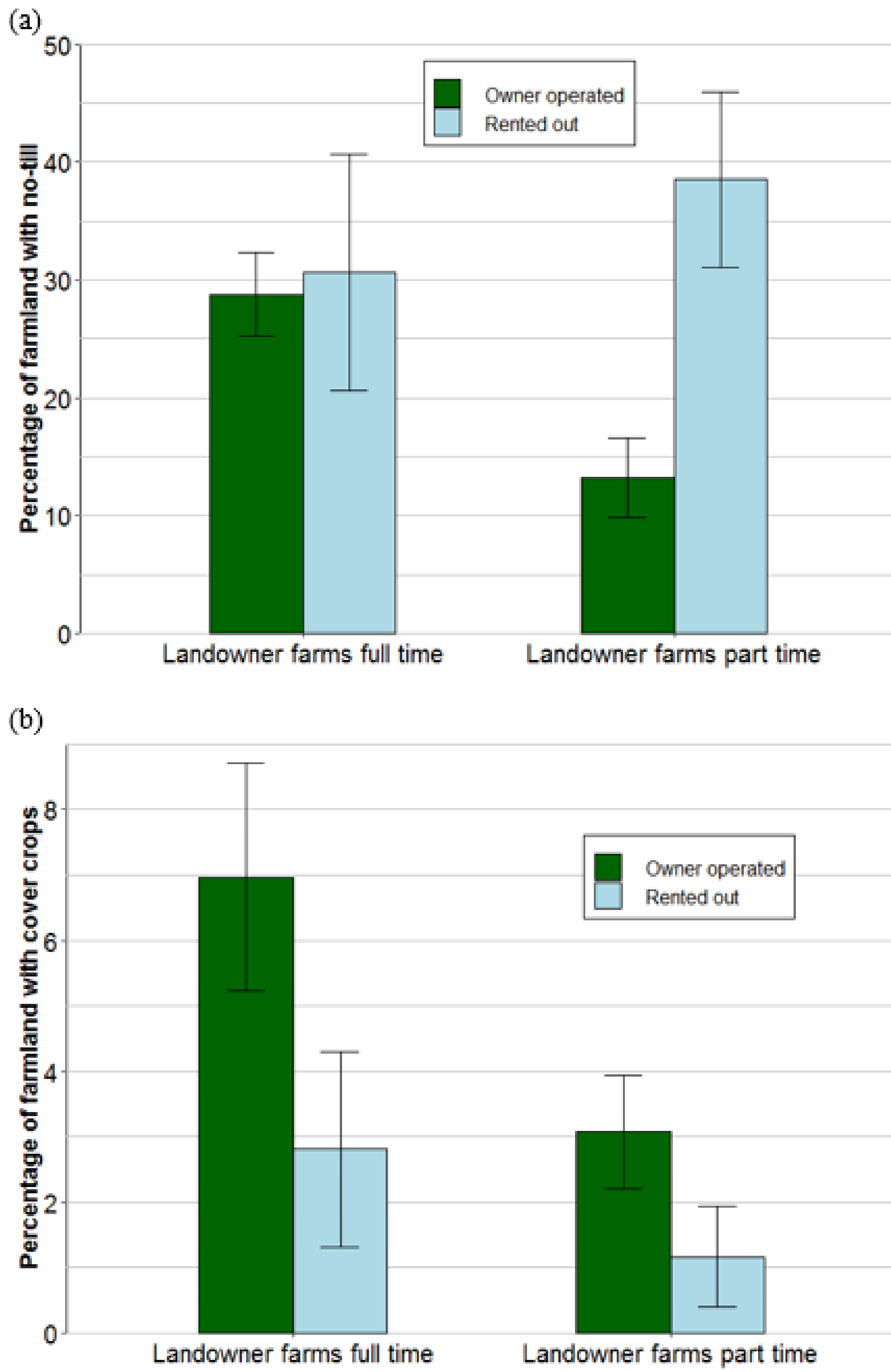

Figure 3.5 Share of owner-operated vs. rented out Iowa farmland that has (a) no-till and (b) cover crops by landowner farming status.

Note: Bars reflect standard error of the mean.

Table 3.1 Distribution of Iowa farmland using conservation practices by crop-reporting district.

	State wide	North west	North central	North east	West central	Central	East central	South west	South central	South east
No-till	**27%**	16%	8%	19%	40%	29%	33%	56%	26%	26%
Cover crops	**4%**	< 1%	1%	8%	5%	2%	2%	4%	7%	12%
Buffer strips	**3%**	2%	6%	6%	1%	4%	4%	3%	3%	3%
Ponds	**2%**	< 1%	< 1%	2%	1%	< 1%	2%	1%	5%	3%

A description and map of which counties are included in each region is available at Zhang et al. (2018) on pages 8 and 9.

Table 3.2 Distribution of Iowa farmland under conservation practices by (a) landowner operator status, (b) farming experience, and (c) Iowa residency.

(a) Operator landowner vs. NOL				
	No-till	Cover crops	Buffer strips	Ponds
Operator	29%	5%	4%	2%
NOL	26%	4%	2%	1%
(b) Landowners' farming experience				
	No-till	Cover crops	Buffer strips	Ponds
Farms full time	33%	6%	4%	2%
Farms part time	24%	3%	4%	2%
Retired from farming	31%	4%	1%	1%
Never farmed	23%	4%	2%	1%
(c) Iowa residency				
	No-till	Cover crops	Buffer strips	Ponds
Year-around	28%	5%	3%	1%
Part of year	32%	5%	3%	4%
Not at all in Iowa	23%	3%	2%	<1%

Table 3.3 Iowa farmland shares of conservation practices by landowner financial characteristics.

(a) Landholdings (acres)					
	No-till	Cover crops	Buffer strips	Ponds	Number of responses
0 to 49	20%	8%	3%	0%	59
50 to 99	20%	0%	1%	0%	58
100 to 249	26%	3%	4%	3%	190
250 to 499	28%	4%	1%	1%	187
500 to 999	32%	7%	3%	1%	158
1000 to 1999	27%	8%	7%	3%	64
2000 or more	36%	1%	1%	0%	19
(b) Landowner's percentage of income from agriculture					
	No-till	Cover crops	Buffer strips	Ponds	Number of responses
Less than 10	24%	2%	3%	1%	50
11 to 40	27%	3%	2%	1%	57
41 to 75	28%	4%	4%	2%	83
76 to 99	46%	5%	1%	0%	55
100	23%	2%	5%	3%	54
(c) Landowner's percentage of land paid for					
	No-till	Cover crops	Buffer strips	Ponds	Number of responses
0 to 33	29%	5%	2%	2%	146
34 to 66	28%	7%	3%	2%	48
67 to 99	32%	4%	4%	2%	59
100	26%	4%	3%	1%	482

Table 3.4 Shares of Iowa farmland under conservation practices by landowner (a) age, (b) gender, and (c) education.

(a) Landowner's percentage of land acquired by purchase				
	No-till	Cover crops	Buffer strips	Ponds
0 to 25	22%	2%	1%	1%
25 to 50	17%	<1%	1%	<1%
50 to 75	24%	7%	2%	<1%
75 to 100	31%	5%	4%	2%
(b) Landowner's percentage of land acquired by inheritance				
	No-till	Cover crops	Buffer strips	Ponds
0 to 25	30%	5%	4%	2%
25 to 50	26%	9%	1%	1%
50 to 75	18%	<1%	2%	<1%
75 to 100	22%	2%	1%	1%
(c) Landowner's primary reason for owning the land				
	No-till	Cover crops	Buffer strips	Ponds
Income	29%	6%	3%	1%
Investment	26%	2%	5%	1%
Family/Sentimental	27%	4%	2%	2%
Live On	21%	<1%	1%	<1%
Fun	15%	<1%	5%	1%

Table 3.5 Shares of Iowa farmland under conservation practices by landowner's future intentions regarding conservation practices.

(a) Distribution of landowners by expected prevalence of each practice in next five years

	No-till	Cover crops	Buffer strips	Ponds
Yes	10%	18%	4%	2%
No	64%	49%	84%	94%
Maybe	26%	34%	12%	4%

(b) Distribution of farmland by owner's expected prevalence of each practice in next five years

	No-till	Cover crops	Buffer strips	Ponds
Yes	14%	19%	5%	2%
No	56%	43%	82%	93%
Maybe	30%	38%	13%	6%

(c) Distribution of landowners by likelihood of adopting conservation practices under various policy scenarios

	Estate tax*	Cost share*	Tax credits*
1 = Not at all likely	27%	24%	16%
2	10%	5%	6%
3	25%	20%	21%
4	11%	15%	21%
5 = Very likely	11%	21%	24%
Unsure	15%	16%	13%

(d) Distribution of farmland by owner's willingness to help tenant with cover crops and method by no-till prevalence

	Have no-till on land		Do not have no-till on land	
	Longer lease	Pay for portion of planting cost	Longer lease	Pay for portion of planting cost
Yes	42%	41%	12%	30%
No	48%	35%	63%	43%
Maybe	10%	24%	25%	26%

*These policy scenarios would involve the value of land enrolled in conservation programs being excluded from the value of the estate for estate tax purposes, tax-free cost sharing being available for conservation practices, or landowners being able to receive tax credits or deductions for implementation of conservation practices.

Table 3.6 Distribution of Iowa farmland by landowner operator status and reason for not using no-till or cover crops.

	No-till			Cover crops		
	Operator	NOL	All	Operator	NOL	All
Not suitable for the land	12%	46%	21%	–	–	–
Hurts crop yield	17%	22%	18%	7%	3%	6%
It's the tenant's decision	15%	6%	13%	19%	36%	25%
Not applicable in my situation, all in pasture, all in CRP, hay ground	9%	14%	10%	9%	<1%	6%
Tried it, didn't like it	13%	3%	10%	5%	<1%	3%
Cost of terminating them in the spring is too high	–	–	–	19%	27%	22%
No time to get them planted in the fall, season is too short, too cold for cover crops, not enough manpower, workload too high	–	–	–	16%	9%	14%
Just don't want to, haven't gotten around to it yet, don't believe in it	10%	0%	8%	8%	7%	8%
Uses minimum till, vertical tillage, strip till	10%	5%	9%	–	–	–
Don't need it, flat land, no erosion problem, don't have HEL	3%	3%	3%	5%	8%	6%
Used for manure disposal	6%	2%	5%	–	–	–
Doesn't fit with my operation or erosion is controlled with my no-till and tiling already	–	–	–	6%	3%	5%
Doesn't know enough, need to do some more research, no one around here does them	–	–	–	3%	5%	3%
Don't have the right equipment	5%	0%	4%	1%	<1%	1%
Soil is too heavy, clayey, takes moisture out of soil	–	–	–	2%	1%	2%
Land is terraced, not set up to no-till, land not tiled well enough	<1%	<1%	<1%	–	–	–

Note: Dashes mean that no landowner listed the response as a reason for not using the specified practice.
Note: Buffer strips–Not needed on the land was primary reason for 83% of operator landowners' farmland, 79% of NOLs' farmland, and 84% of all farmland
Note: Ponds–Not needed on the land was primary reason for 89% of operator landowners' farmland, 85% of NOLs' farmland, and 88% of all farmland

CHAPTER 4. EFFICIENCY, FARM SIZE, AND LAND TENURE: THE EVOLUTION OF IOWA FARMS

Wendiam P.M. Sawadgo

Abstract

In recent decades, agriculture has shifted to larger farms with increasing shares of rented farmland and older operators. In this paper, we use data envelopment analysis and a panel of Iowa farms to analyze the evolution of productive efficiency in corn production and how efficiency interacts with farm size, land tenure, and age of the operator. Two approaches are used to measure productive inefficiency with respect to the efficient farms. We measure both proportional overuse of all inputs and overuse of fertilizer. We find that farms have, on average, overall technical efficiency scores of 52% and fertilizer efficiency scores of 20%, with efficiency increasing with farm size and percentage of farmland rented. Older operators are less technically efficient than younger operators. Technical efficiency improved from 2011 to 2018. Scale efficiency is very high in Iowa corn production, averaging 93%.

Introduction

This chapter looks at how farm efficiency has evolved in Iowa during the 2010s, a period during which farm incomes began to decline in 2013. We focus on how agricultural production efficiency differs by land tenure, farm size, and operator age — three factors that have changed significantly over the past several decades. First, there has been a decline in the presence of small and medium farms (less than 1,000 acres): the share of farmland in large farms has increased from 30% to 50% between 1997 and 2017 in Iowa (United States Department of Agriculture, 1997-2017). Therefore, it is increasingly critical to understand the impact of farm size on efficiency and assess the viability of small- and medium-sized farms. Second, the share of land that farmers rent has increased from to 45% to 59% between 1982 and 2017 (Zhang, Plastina, and Sawadgo, 2018). Third, the average operator age has increased from 47.6 to 57.4 years over the same period (United States Department of Agriculture, 1997-2017). We analyze how these shifts have affected efficiency in agricultural production.

When considering agricultural production efficiency, fertilizer is a critical input with effects beyond the farm. It has been suggested that farmers largely do not use best-management practices in applying fertilizer, as Ribaudo et al. (2011) estimate that in 2006 only 35% of US fields applied correct rates of nitrogen, accounting for relevant factors such as nitrogen available from the previous crop, applied nitrogen close to planting the crop, and used methods to reduce nutrient loss. Moreover, prior work has shown that farmers tend to apply fertilizer beyond levels the crop can uptake (Sheriff, 2005). Uncertainty regarding effects of nutrient application and risk-aversion may also affect the amount of applied fertilizer and the timing of application (Feinerman, Choi, and Johnson, 1990). Federal crop insurance programs are another factor that may affect farmers' fertilizer use: while Horowitz and Lichtenberg (1993) find crop insurance tends to increase fertilizer use, Babcock and Hennessy (1996) and Smith and Goodwin (1996) see a decrease in fertilizer use when farmers purchase crop insurance. Moreover, Mieno, Walters, and Fulginiti (2018) suggest that accounting for actual production history — a factor in determining the level of guaranteed revenue in revenue protection insurance — increases optimal input use, since higher yields are also rewarded in future years.

In this paper, we use data envelopment analysis and 3,416 observations from 2011 to 2018 to calculate input-oriented technical efficiency scores for a sample of Iowa farms. We use both a radial measure that evaluates farms' potential to proportionally reduce all inputs and a directional distance measure that estimates the potential to reduce fertilizer while holding other inputs constant. The radial measure can be thought to describe the long-term potential to reduce overall inefficiency in corn production, and the directional distance measure to determine the short-term potential to reduce fertilizer overuse, while leaving output unchanged. We then analyze how efficiency has changed over time in Iowa and break down efficiency by farm size, land tenure, and operator age.

This research makes several contributions to the literature. First, we examine how efficiency differs by land tenure, which to our knowledge has not been analyzed in prior studies. Second, we provide evidence confirming prior findings of increased efficiency among larger farms, suggesting that farm consolidation may increase overall efficiency of the agricultural sector. Third, we add to the limited literature on farm productivity by examining efficiency in corn production in Iowa, the highest corn producing state.

We find that farms had a technical efficiency of 56.6%, on average, with a sizable increase between the first and second half of the period studied. Larger farms are more efficient, when considering both the model that allows proportional reduction of all inputs and the model allowing reduction in fertilizer, suggesting the increase in farm size may have efficiency benefits. Next, efficiency tends to increase as the share of farmland rented increases, and efficiency decreases as the operators' ages increase. These results suggest that land tenure, farm size, and operator age affect overall farm efficiency, in both the short- and long-term measures. We conclude that tenants may underuse some inputs compared to owner-operators as a way to contain short-term costs. Lastly, scale efficiency of our sample is 96.6%, with little variation by farm size.

Methodology

Theoretical Framework

Data envelopment analysis is a non-parametric method based on mathematical programming that uses input and output data of decision-making units to measure efficiency. In this paper, the decision-making units are farms. In data envelopment analysis, the input and output combinations for each farm are used to determine a frontier of efficient farms, by taking the convex hull. The convex hull contains the set of efficient farms and acts as a set of reference points for the farms within the frontier. In essence, each inefficient farm is assigned a linear combination of two efficient farms to represent its theoretically efficient input-output combination, or benchmark. Finally, efficiency values are calculated by comparing each farm's actual input-output combination to its benchmark.

We assume that all farms produce corn using a similar set of inputs. Let y_{it} be the corn production and x_{it} an m-dimensional vector of inputs used in corn production for farm i in year t. Let T represent the production set describing attainable combinations of corn production and inputs:

$$T_{it} = \{(x_{it}, y_{it}) | x_{it} \in \mathbb{R}_{+}^{m}, y_{it} \in \mathbb{R}_{+}, (x_{it}, y_{it}) \ is \ feasible\}, \quad (4.1)$$

which can be rewritten as an input set:

$$L(y_{it}) = \{x_{it} \in \mathbb{R}_{+}^{m} | (x_{it}, y_{it}) \in T_{it}\}. \quad (4.2)$$

We calculate several measures of farms' input-oriented technical efficiency. The first, TE_{it}^{F}, is a radial measure that gives the maximum proportional contraction of inputs, θ, each farm could achieve to efficiently produce the same level of output (Farrell, 1957).

$$TE_{it}^{F} = min\{\theta | \theta x_{it} \in L(y_{it})\} \quad (4.3)$$

The following linear programming model is solved to calculate technical efficiency values under constant returns to scale (CRS), following (Farrell, 1957):

$$\begin{aligned}
&\min_{\theta,\lambda} \quad \theta \\
&\text{s.t.} \\
&y_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}\lambda_{it} \geq 0, \\
&\theta x_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}\lambda_{it} \geq 0, \\
&\lambda_{it} \geq 0, \forall i, t
\end{aligned} \tag{4.4}$$

where the λs are farm weights. The constant returns to scale assumption imposes that $L(\alpha y_{it}) = \alpha L(y_{it})$, which may be unrealistic in many settings since it assumes a constant average product.

To relax this assumption, we calculate technical efficiency scores under variable returns to scale (VRS) by adding the additional constraint:

$$\sum_{i=1}^{N}\sum_{t=1}^{T} \lambda_{it} = 1 \tag{4.5}$$

to equation 4.4.

In reality, there may be some inputs that we could reduce at a rate higher than θ. Thus, in addition to the radial measures, we calculate technical efficiency using the directional input distance function introduced by (Chambers, Chung, and Färe, 1996). Instead of assuming a proportional reduction of all inputs, the directional distance allows for reduction of some inputs, while holding other inputs quasi-fixed. The directional distance function, D_i is:

$$D_{it}(x_{it}, y_{it}, g_x) = sup\{\beta | (x_{it} - \beta g_x) \in L(y_{it})\}, \tag{4.6}$$

where g_x is the reference feasible input bundle that could produce the same output.

The linear programming problem for calculating the directional input distance function efficiency is as follows, (Silva, Lansink, and Stefanou, 2015):

$$
\begin{aligned}
&\max_{\beta,\lambda} \quad \beta \\
&\text{s.t.} \\
&y_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} y_{it}\lambda_{it} \geq 0, \\
&\beta x_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}\lambda_{it} \geq 0, \\
&\lambda_{it} \geq 0, \forall i, t
\end{aligned}
\tag{4.7}
$$

Lastly, we calculate how close farms are to the optimal scale determined by the input-output combination that maximizes average product. Scale efficiency is calculated as the ratio of technical efficiency under constant returns to scale and technical efficiency under variable returns to scale:

$$SE_{it} = TE_{it}^{CRS}/TE_{it}^{VRS} \leq 1 \tag{4.8}$$

The efficiency scores are calculated for each farm using the DEA 'Benchmarking' package in R (Bogetoft, Otto, and Otto, 2019).

Data

We use data assembled by the Iowa Farm Business Association. The dataset includes accrued income statements and balance sheets for 601 farm enterprises from 2011-2018, providing information on operated acreage, outputs, revenues, and input expenditures. For the purpose of this study, we focus on corn and inputs used in its production. Output and input quantities are expressed on a per acre basis, to avoid skewing the distribution of efficiency scores towards the smallest farms that, by definition, have the smallest farmland areas in production. Furthermore, since land has the slowest adjustment rate to changing market or production conditions (Yang and Shumway, 2016), treating land as another variable input would impose a strong inertia in the radial efficiency scores through time, underestimating the true change in the efficiency of use of the mix of variable inputs.

We use input price data from the 2011-2018 Estimated Costs of Crop Production in Iowa published by Iowa State University Extension and Outreach (Ag Decision Maker File A1-20, various issues) to deflate expenditures and calculate input quantities for each operation. Prices for hired labor, seed, and fertilizer are obtained directly from Ag Decision Maker File A1-20, while price indices for machinery, fuel, herbicide, and insecticide are calculated using annual per acre values from the same publications. The fertilizer price index is calculated as a weighted average of nitrogen, phosphate, and potash prices, using 180 lb. nitrogen, 82 lb. phosphate, and 66 lb. potash per acre as weights. The machinery price index is calculated as the sum of the fixed costs for pre-harvest machinery, combine, and grain cart. The price for operator labor is obtained from the Ag Decision Maker C1-10 File.

Quantities for inputs are calculated by dividing the total expense on each input by its price in the given year. Labor is measured as the sum of operator and hired labor, and we assume that operators work 173 hours per month. Summary statistics for the input and output quantities can be found in table 4.1. We include five inputs in the data envelopment analysis: labor, machinery, fertilizer, and materials, an intermediate good, composed of seeds, herbicide, insecticide, and fuel. Land is accounted for implicitly by expressing all quantities on a per-acre basis.

Because data envelopment analysis is sensitive to the presence of outliers, we use scatter plots and box plots to check for input and output values that were likely incorrectly entered into the financial software.[1] After removing 728 observations containing outliers, 3,416 observations remain.[2]

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[1] Observations were removed if the annual per-acre value was outside of 150-300 bushel corn yield, 0.001-0.1 months of labor, 0.4-6 machinery index, 0-30 gallons of fuel, 40-700 pounds of fertilizer, 10,000-70,000 seeds, 0-3 insecticide index, or 0-6 herbicide index. Only farms that had 100-3,000 acres in corn production were included.

[2] Our data are not representative of the population of Iowa farmers. Compared to the 2017 Census of Agriculture,

Results

Radial

Efficiency scores were estimated in a model calculating a proportional reduction of all inputs. We first evaluate results of the model of five inputs. Technical efficiency scores under both variable returns to scale and constant returns to scale, as well as the calculated scale efficiency scores are presented in table 4.2. We find that farms are 96.6% scale efficient, on average. However, due to the importance of farmland in corn production, and the difficulty in reducing or acquiring farmland, we prefer a model of four inputs normalized by land, or expressed per acre.[3] Thus all subsequent results (except for scale efficiency) are from a model where inputs and output are measured per acre and technical efficiency is measured under variable returns to scale, to allow for flexibility.

The average technical efficiency scores for each year are reported (table 4.3). Over the entire sample, farms could have used just 56.6% of their inputs to achieve the same production level, on average. As expected, these values for the per-acre model are lower than those from the model using total output, because it is much more difficult for farmers to reduce land than to reduce all non-land inputs, while holding output constant.

There is an increase in technical efficiency between the first and second half of the period (52.4% vs. 60.5%). However, our finding of an increase in technical efficiency over time differs from the result of Mugera and Langemeier (2011), who find a decrease in technical efficiency from 1993 to 2007. Agricultural financial conditions represent a potential reason for this

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farmers in our dataset, on average, are slightly younger (56.7 vs. 57.4 years), have lower yields (195 vs. 199 bushels/acre), grow more corn (461 vs. 295 acres), and rent a greater share of their farmland (57% vs. 51%). However, this data is meant to largely represent mid-sized farms, and the farms included in the analysis are limited to between 100 and 3,000 acres of corn production.

[3] This is evidenced by the smaller slack values in the model of four inputs. The slacks expressed as a percentage of the mean value for labor, machinery, fertilizer, and materials were 20%, 10%, 9%, and 3% in the model of five inputs, compared to 6%, 3%, 4%, and 0% in the model of four inputs.

difference. During the period in our sample, net farm income increased until 2013 and decreased thereafter, whereas net farm income was relatively stable throughout the period analyzed by Mugera and Langemeier (2011). Scale efficiency exhibits a similar but less drastic pattern over time than technical efficiency (tables 4.2 and 4.3).

Directional Distance

To allow for flexibility, the remaining results are presented under the assumption of variable returns to scale. In this section, we analyze the potential reduction in fertilizer to produce the same output, holding other inputs constant. Over the entire sample, the average farm could have used just 20.1% of its fertilizer to produce its level of output (table 4.4). This finding supports the idea that a non-trivial segment of mid-sized commercial farms overuse inputs in production, especially fertilizer. Similar to the results in the radial model, there is an increase in technical efficiency between the first and second halves of our sample.

Land Tenure

We divide farms into three land tenure groups: full-owners own all the land they operate, full-renters rent all the land they operate, and part-owners farm both owned and rented land. We further break down part-owners into farmers who rent half of their farmland or less and those who rent more than half of their farmland. Table 4.5 presents results of technical efficiency by land tenure. We find that full-renters and part-owners who rent most of their land are most technically efficient (58.8%), followed by part-owners who rent less than half of their land (55.5%), and full-owners (51.9%). A similar pattern is observed regarding the efficiency of fertilizer use, but with a greater distinction between groups. Full-owners could have the greatest reduction of fertilizer and full-renters the least. Scale efficiency scores are approximately equal across all groups.

While the shift to rented land (as described in chapter 3) could be a result of farmers' pursuit of higher productivity, it could simply reflect dynamics and incentives of ownership. Following findings from chapter 3, owners may be more willing to make investments in farmland than tenants, which is reflected by higher use of inputs that have a carryover to future years. For instance, owners may have more incentives than tenants to over apply nitrogen, and may do so to ensure they have fertile fields and a higher actual production history for crop insurance purposes in the future. Given that an increasing share of Iowa farmland is rented (Zhang, Plastina, and Sawadgo, 2018), our findings that corn producers who rent more of their farmland are relatively more technically efficient in fertilizer application seems to suggest that the environmental footprint of corn production has been declining through time.

Looking at the summary statistics broken down by land tenure (table 4.6), there is a notable difference in per acre fertilizer use, with full-owners using 365 lb. and full-renters using 312 lb., compared to the 328-lb. benchmark used in determining the fertilizer index in this study. Yield and other inputs do not follow a discernible pattern across land tenure groups.

Farm Size

We use corn acreage as the measure of farm size, and classify farms into three categories: small (less than 300 acres), medium (300 to 600 acres), and large (at least 600 acres). Technical efficiency scores by operated corn acreage are presented in table 4.7. Large farms have the highest technical efficiency when considering reduction of all inputs (60.7%), followed by medium farms (57.7%), and small farms (52.8%). A similar pattern is observed when considering the efficiency in fertilizer use. The finding of higher technical efficiency for larger farms is consistent with prior work (Mugera and Langemeier, 2011; Weersink, Turvey, and Godah, 1990; Paul et al., 2004) and supports a positive aspect of concentration in the agricultural sector.

Scale efficiency scores by farm size are presented in table 4.8. Over the entire sample, medium farms are the most scale efficient, but the average hides the fact that small farms were the most scale-efficient group in the period of increasing farm income, and large farms the most scale-efficient group in periods of declining farm income. This result differs from the findings of Mugera and Langemeier (2011), who found small farms to be the most scale efficient and large farms the least scale efficient.

Operator Age

We divide farmers into three age groups: younger than 50 years of age, 50 to 65 years of age, and 65 years of age or older. We find that younger farmers are, on average, the most technically efficient (table 4.9). Farmers younger than 50 years of age have the highest technical efficiency (60.5%), followed by those 50 to 65 years of age (56.3%), and farmers 65 or older (53.5%) in the model allowing for a proportional reduction of all inputs. The results for fertilizer efficiency follow a similar pattern, but there is no meaningful relationship between operator age and scale efficiency.

Our results follow prior findings of declines in farm productivity as age increases. In a nationwide analysis of eight editions of the Census of Agriculture (1978 to 2012), Tauer (2017) finds a concave relationship, with operators between 25 and 34 years of age to be most productive, and declines thereafter. However, due to increases in the age distribution of farmers, we do not have an adequate number of farmers younger than 25 in our sample to make any meaningful comparisons. The observed relationship is troubling, given the aging population of farmers.

Conclusion

In this study, we analyze how technical efficiency in Iowa corn production has evolved from 2011 to 2018. We use data envelopment analysis to identify the frontier of corn production and calculate technical efficiency for 3,416 farm-year observations, using two methods. First, we use a radial distance measure, which calculates the maximum proportional reduction in inputs possible to maintain the level of output. Second, we use a directional input distance measure to determine the amount of fertilizer a farm could reduce, holding other inputs fixed, to produce the same level of output. We consider the radial measure to represent the long-term potential to reduce overall inefficiency in corn production, and the directional distance measure the short-term potential to reduce fertilizer overuse. We evaluate how technical efficiency varies by land tenure, farm size, and operator age.

We find that the average farm's technical efficiency is 56.6%. There is a notable jump between 2011 to 2014 (52.4%) and 2015 to 2018 (60.5%), which coincides with the decline in farm incomes that began in 2013. We find that smaller farms are less efficient than large farms, in both the short- and long-term measures. Over the past several decades, there has been an increase in the prevalence of large farms at the expense of mid-sized farms. The results of this study are consistent with the idea that farm consolidation in recent decades may have been driven by higher efficiency of larger farms. Technical efficiency increases with share of farmland rented, both in reduction of all inputs and reduction of fertilizer. Lastly, technical efficiency decreases with farm operator age.

One shortcoming of this research is that land tenure, farm size, and operator age are correlated. Younger farmers operate a greater number of corn acres, but a greater proportion of their farmland is rented, compared to older farmers. Thus, it is difficult to determine the drivers in differences in technical efficiency. Future work could look to disentangle the effects of size of the operation from attitudes relating to land rental on efficiency. Another extension of this study would determine how technical efficiency translates into economic efficiency after accounting for prices.

With increased pressure to encourage agriculture to reduce its environmental externalities, policymakers should be aware of factors that affect fertilizer use. Prior work has found input tax policies to be more effective at reducing fertilizer than a tax on the crop produced (Sun, Delgado, and Sesmero, 2016). Our results suggest that such a fertilizer tax may have differential impacts across farmer age, size, and land-tenure groups. The present analysis is intended to help design farm and environmental policy to promote efficiency and environmental stewardship in corn production.

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Tables

Table 4.1 Data summary statistics (per acre per year).

	Mean	Standard Deviation	Minimum	Maximum
Corn (bushels)	195.01	23.55	150.00	289.30
Labor (hours)	3.87	2.13	0.19	17.22
Machinery (index)	2.30	0.93	0.41	5.98
Fertilizer (pounds)	328.07	122.64	41.26	696.49
Materials (index)	0.91	0.19	0.34	1.98
Seed (thousand kernels)	30.17	6.69	10.11	68.78
Herbicide (index)	1.33	0.67	0.00	5.82
Insecticide (index)	0.30	0.52	0.00	2.82
Fuel (gallons)	8.17	4.29	0.01	30.00

Table 4.2 Efficiency scores (five inputs).

	VRS	CRS	Scale
2011	0.738	0.709	0.963
2012	0.706	0.668	0.953
2013	0.727	0.696	0.961
2014	0.740	0.712	0.965
2015	0.818	0.791	0.969
2016	0.841	0.816	0.972
2017	0.843	0.820	0.973
2018	0.804	0.776	0.967
Mean 2011-2014	0.730	0.699	0.961
Mean 2015-2018	0.827	0.801	0.970
Overall Mean	0.780	0.752	0.966

Table 4.3 Radial technical efficiency scores (four inputs).

2011	0.522
2012	0.495
2013	0.532
2014	0.539
2015	0.602
2016	0.612
2017	0.615
2018	0.590
Mean 2011-2014	0.524
Mean 2015-2018	0.605
Overall Mean	0.566

Table 4.4 Technical efficiency scores for use of fertilizer (four inputs).

2011	0.199
2012	0.190
2013	0.179
2014	0.163
2015	0.214
2016	0.216
2017	0.226
2018	0.220
Mean 2011-2014	0.182
Mean 2015-2018	0.219
Overall Mean	0.201

Table 4.5 Technical efficiency scores by percent of farmland rented

	Radial	Directional	Scale	Count
0%	0.519	0.162	0.957	825
1% to 50%	0.555	0.190	0.969	534
51% to 99%	0.588	0.216	0.975	1155
100%	0.588	0.225	0.961	902
All farms	0.566	0.201	0.966	3416

* Radial and directional technical efficiency scores are from the four input model under VRS. Scale efficiency is measured from the five input model.

Table 4.6 Average corn production and input use by land tenure (per acre per year)

	Full-owner	Part-owner		Full-renter
	0%	1-50%	51-99%	100%
Corn (bushels)	195.062	195.164	194.631	195.356
Labor (hours)	4.324	4.035	3.532	3.772
Machinery (index)	2.476	2.356	2.241	2.197
Fertilizer (pounds)	365.360	326.649	314.536	312.133
Materials (index)	0.945	0.927	0.893	0.904
Seed (thousand kernels)	30.968	30.900	29.755	29.532
Herbicide (index)	1.419	1.356	1.261	1.322
Insecticide (index)	0.274	0.310	0.312	0.303
Fuel (gallons)	8.637	7.821	7.842	8.370

Table 4.7 Technical efficiency scores by farm size.

	Radial	Directional	N
Small	0.528	0.189	1236
Medium	0.577	0.200	1374
Large	0.607	0.222	806
All farms	0.566	0.201	3416

* Radial and directional technical efficiency scores are from the four input model under VRS.

Table 4.8 Scale efficiency by farm size.

	All	Small	Medium	Large
2011	0.963	0.915	0.990	0.984
2012	0.953	0.896	0.990	0.984
2013	0.961	0.913	0.988	0.988
2014	0.965	0.921	0.987	0.987
2015	0.969	0.936	0.993	0.982
2016	0.972	0.943	0.994	0.981
2017	0.973	0.946	0.995	0.981
2018	0.967	0.933	0.990	0.975
Mean	0.966	0.927	0.991	0.983

* Radial distance measure

Table 4.9 Efficiency scores by farm operator age.

	Radial	Directional	Scale	N
Less than 50	0.605	0.241	0.966	748
50 to 65	0.563	0.194	0.970	1936
65 or older	0.535	0.179	0.956	732
All farms	0.566	0.201	0.966	3416

* Radial and directional technical efficiency scores are from the four input model under VRS. Scale efficiency is measured from the five input model.

CHAPTER 5. GENERAL CONCLUSION

Agricultural pollution continues to intensify water-quality issues in Iowa, magnifying the importance of limiting nutrient loss to waterways. However, there is evidence that farmers over-apply some nutrients, and the use of conservation practices such as cover crops remains low, even though these practices have on-farm benefits in addition to their public benefits. Thus, the three studies presented in this dissertation examine factors that affect the rate at which farmers use agricultural practices that can mitigate nutrient pollution. The preceding three chapters highlight the crucial role that agri-environmental policy and land tenure play in affecting conservation-practice use.

Agri-environmental policy has been at the center of the effort to increase conservation practice adoption. Cost-share programs give farmers payments in exchange for implementing conservation practices, and have been shown to be effective at increasing cover crop use in Iowa. In chapter 2, we estimate that cost-share recipients planted cover crops to 15% more of their farmland than they would have in absence of payment. Moreover, these programs have been a relatively low-cost method to reduce nitrogen pollution. Additional agri-environmental policies could aim to target landowners – especially NOLs – as opposed to farm operators. Results from chapter 3 suggest that landowners would most like to see a program in which they could receive tax credits or deductions for using conservation practices, with 45% of the state’s farmland belonging to landowners who state that they would be likely to increase their acreage in conservation practices under such a policy.

Conventional wisdom suggests that the large share of rented farmland could contribute to the low adoption of conservation practices, as tenants may not be willing to take on the short-term costs of using conservation practices without the guarantee of obtaining the benefits.

Furthermore, the high rate of ownership by NOLs – who may lack knowledge about farming techniques and the benefits of conservation practices – can exacerbate this issue. Chapter 3 adds some evidence in support of these two hypotheses, finding (1) lower use of cover crops, buffer strips, and sediment basins on rented land compared to owner-operated land, and (2) lower rates of no-till, cover crops, buffer strips, and sediment basins on farmland owned by NOLs compared to the farmland owned by current farm operators. However, we find that no-till is used at a higher rate on rented land than it is used on owner-operated land.

The importance of land tenure is not limited to conservation practice use. In chapter 4, I examine how land tenure affects input use in general, with a focus on fertilizer. I find that full-renters are more technically efficient at using fertilizer in corn production and use about 30 fewer pounds of fertilizer per acre than do full-owners, on average.

Moving forward, there is room for researchers to continue to identify factors that affect farmers' use of conservation practices, to help meet INRS goals. Future research could look at whether the effectiveness of cost-share programs differs with respect to the per-acre payment rate. In 2017, IDALS implemented the Cover Crop - Crop Insurance Demonstration Pilot – a program in which enrolled farmers receive a five-dollar discount on their crop insurance premium for cover-cropped acres. Additional analysis is needed to determine whether such a small payment (relative to the average $26 payment we observed in the data used in chapter 2) is enough to encourage adoption that would not have occurred without payment.

APPENDIX. COST-SHARE PROGRAM INFORMATION

Cost-share programs differ in their payments, requirements, and maximum length of participation. The payment amount for most programs depends on the cover crop mixture used, and farmers are required to follow seeding guidelines set by the National Resources Conservation Service (NRCS). Moreover, programs typically have annual sign-up periods, as opposed to longer contracts. The Iowa Department of Agriculture and Land Stewardship (IDALS) is the main source of cost-share for farmers in the present analysis. Through IDALS, first-time cover crop users are eligible for $25 per acre and experienced cover crop users are eligible for $15 per acre. Federal funding is also available through the Environmental Quality Incentives Program, Conservation Stewardship Program, and Regional Conservation Partnership Program.

The main sources of cost-share funding for farmers came from the Iowa Department of Agriculture and Land Stewardship (IDALS), Environmental Quality Incentives Program (EQIP), and Conservation Stewardship Program (CSP). While IDALS and EQIP funding are suitable for both new and experienced farmers, CSP is tailored for farmers already using conservation practices but looking to increase their conservation use.

Iowa Department of Agriculture and Land Stewardship

First-time cover crop users are eligible for $25 per acre and continuing users are eligible for $15 per acre, on up to 160 acres subject to maintenance agreements through the Iowa Water Quality Initiative.

Environmental Quality Incentive Program

The farmer is paid up to three annual payments, with the payment amount differing by seed type. NRCS seeding requirements must be met. The farmer fills out an application for the adopted practice, and applications during the signup period are chosen using a ranking tool in which points are assigned for different environmental benefits.

Chemical or Mechanical Kill Species

A grass/legume/brassica cover crop or cover crop mix is planted within 30 days of the cash crop harvest. The cover crop is allowed to reach early to mid bloom before the cover crop is terminated prior to planting of the next crop. Termination is done with approved chemical or mechanical methods.

Payment: $41.13/acre

Winterkill Species

Small grain or small grain/brassica mix is planted within 30 days of the cash crop harvest. Seed is planted with no-till drill. The cover crop species winterkills.

Payment: $30.15/acre

Conservation Stewardship Program (CSP)

The CSP gives farmers an annual payment in exchange for producing environmental benefits. Farmers work with their local NRCS agronomist to augment their conservation efforts in their crop rotation. The farmer fills out documentation of their ongoing practices and the application for the adopted practice. The NRCS reviews the application, and given the proposed changes estimates the environmental benefits using the Conservation Measurement Tool to assign conservation points. These points are used for ranking applications and determining payments. The CSP has enhancement activities that address various environmental aspects. The specific enhancements for cover crops on cropland and their purposes are discussed below:

ENR12

Cover crops are used to reduce or replace synthetic nitrogen application. Legume cover crops are selected to credit at least 40 pounds of nitrogen per acre. The enhancement is considered to be adopted when the cover crop has been planted to achieve the credit.

Documentation required:

1. Map of field where enhancement was applied
2. Type of cover crop planted
3. Calculations to estimate available nitrogen
4. Additional nitrogen application rate
5. Realistic yield goals

PLT20

Cover crops are used to suppress weed seed germination and add carbon to the carbon pool. The farmer seeds a high-residue cover crop between each crop in the rotation, excluding double-cropped acreage. The cover crop must be planted within date range determined by NRCS agronomist, following a seeding rate. Cereal grain cover crops must be top-dressed with nitrogen as determined by the NRCS. The cover crop must reach maturity level (growth stage) to ensure full soil coverage for 3 months. The cover crop can be terminated using chemical or non-chemical methods. The crop rotation must maintain a Soil Tillage Intensity Rating (STIR) less than 10 as determined with RUSTL2.

Documentation required:

1. Cover crop or cover crop mix, seeding rate, and date planted
2. Nitrogen top-dress rate and date
3. Cover crop termination stage and termination method

SQL04

Use of multiple cover crop species or cultivars with different maturity dates, selected from the NRCS state-specific list.

Documentation required:

1. Cover crop species, date planted, and termination method and date
2. Date and quantity of N fertilizer
3. Crop planted after cover crop and method
4. Grazing plan (if applicable)
5. Map of field
6. Photos showing cover crop mixes

SQL12

Use of cover crops during all non-crop production times for annual crops. The cover crops is planted as soon as feasible after harvest using seeding rates that achieve uniform stand and rapid ground coverage. Alternatively, it may be seeded into a standing crop if adequate to achieve an adequate crop stand. The cover crop cannot be harvested or grazed and each cover crop in the rotation must meet one of the following and two over the course of the rotation:

1. High biomass cover crop for erosion control and improved soil organic matter
2. Legume cover crop for N fixation
3. Non-legume with deep root system to capture or recycle residual nitrogen
4. Weed suppression
5. Biodiversity improvement to attract beneficial or trap damaging insects

Documentation:

1. Crop rotation records
2. Sequence and description of operations for each crop

3. Photos of cover crop showing timing and method of establishment and extent of growth before termination
4. Seed and legume inoculant tags and receipts

WQL10

Plant cover crops such as cereal rye, barley, forage radish, or sorghum sudan that scavenge residual nitrogen in the soil after harvest and supply nutrients to the subsequent crop.

Documentation:

1. Map of field
2. Cover crop species, planting date, and seeding rate
3. Annual crop planted
4. N application rate for annual crop and justification for increase or decrease of N rate
5. Treatment acres

WQL33

Terminate cover crop with non-chemical methods to reduce detrimental water quality impact from herbicides. Crop is killed by mowing, roller-crimping, undercutting, or weather kill

Documentation:

1. Cover crop, planting date, and termination date
2. Annual crop planted
3. N application rate and date
4. Cash crop and planting method
5. Map of field
6. Photos of fields showing roller-crimping (if applicable)