Additionality in Cover Crop Cost-Share Programs in Iowa: A Matching Assessment*

Wendiam P.M. Sawadgo, Alejandro Plastina, and Fang-ge Liu

Department of Economics, Iowa State University

Abstract

Cover crops have been shown to have both on-farm and water quality benefits. However, the use of cover crops in Iowa remains subdued, in part due to the implementation costs faced by farmers. In this paper, we test the hypothesis that monetary incentives through cost-share programs are effective at increasing the amount of farmland planted to cover crops in Iowa, using a propensity-score matching estimator. Combining data from a unique cover crop survey of 674 farm-operator respondents and the 2012 Census of Agriculture, we find that cost-share payments induced an 18 percentage-point expansion of the cover crop area beyond what would have been planted in absence of the programs, for the farmers who participated in cost-share programs. In addition, at least two-thirds of the payments funded acres that would not have been planted without cost share. We also calculate farmers' net returns to using cover crops with a partial budget analysis and estimate that the combined public and farmer cost of avoiding one pound of nitrogen pollution through cover crops is between \$1.72 and \$4.69 per pound, with farmers undertaking 70% of this cost through net losses. Overall, cost share for cover crops has been a relatively low-cost method to reduce nitrogen pollution to waterways in Iowa.

JEL Codes: Q12, Q15, Q18, Q53

Keywords: conservation agriculture, winter cover crops, payment for environmental services (PES), additionality, matching estimator, nitrogen, abatement cost

*This research is part of a project funded by NCR-SARE and the Iowa State University Center of Agricultural and Rural Development.

1. Introduction

Row-crop farming in the Midwest remains a major non-point source of nitrate 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 (2014) lists as one of the practices with the greatest potential for nitrate-N 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 nitrogen contributed to the 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).

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

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 some concern among farmers that cover crops take water at the expense of and induce yield drags in the following cash crop.[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, oftentimes leading to short-term net losses even among farmers participating in cost-share 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 have been implemented in Iowa.[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

[3] Experimental results are mixed as to whether cover crops actually 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.
[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 I.

which a defined environmental service is provided by a land manager[7] in exchange for a payment, given the fulfilment 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 payments largely do not require it to implement the conservation practice, limiting the program's cost-effectiveness. As such, a high additionality is indicative of an effective program. The goal of this study is to assess the effectiveness of cost-share programs at increasing cover crop acreage in the state of Iowa. To estimate the additionality rate of cost-share programs for cover crops in Iowa, we combine responses from a statewide survey of 674 farm-operator responses with data from the 2012 Census of Agriculture and use propensity-score matching to address selection bias.

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 2003; Cooper and Keim 1996; Ma et al. 2012). A growing branch of the additionality literature makes use of observational micro-data to measure 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 find higher additionality for practices that take land out of crop production and/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. In the United States, studies in Maryland (Fleming, Lichtenberg,

[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 land owner, tenant, operator, or non-operator).

and Newburn 2018; Fleming 2017; Lichtenberg and Smith-Ramirez 2011) and Ohio (Mezzatesta, Newburn, and Woodward 2013) find that crop farmers' enrollment in cost-share programs increase 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.

This study makes three major contributions to the existing literature. First, while cover-crop cost-share additionality estimates exist for the Chesapeake Bay region (Fleming, Lichtenberg, and Newburn 2018; Fleming 2017) 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 hypoxic zone (Aulenbach et al. 2007), and reducing agricultural pollution in this region could have significant global impacts. Second, our study uses data from a unique survey with which we use partial-budget analysis to calculate how cover-crop use affects farmers' profit. Although the sample composition is not representative of agriculture in Iowa as a whole, our results show how cost share affects cover-crop adopters in the state. Lastly, 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, Lichtenberg, and Newburn 2018; Fleming 2017) have looked at the public costs associated with cost share programs, they do not consider the costs borne by the farmer.

We find that cost-share programs do incentivize the use of cover crops in Iowa. Cost-share recipients plant an additional area to cover crops equivalent to 18% of their fields that would not be planted to cover crops without cost-share payments. The additionality rate is estimated at 67%, suggesting that roughly one in three cost-share dollars subsidizes acreage that would have been planted to cover crops even in the absence of the cost-share programs. Furthermore, our back-of-the-envelope calculations indicate that the combined farmer and public cost of avoiding one pound of nitrogen loss from Iowa fields by using cover crops ranges from $1.72 to $4.69, and farmers absorb about 70% of those costs as private losses after accounting for cost-share payments that offset the remaining 30%. A comparison of cost-share payments per pound of nitrate reduction in Iowa via cover crops against similar programs in Maryland suggests that cost-share payments in Iowa are more cost-effective than in Maryland. This is mostly due to differences in the sample compositions between the studies and because the average per-acre cost-share payment in our sample is about 40% lower than the corresponding payment in Maryland (Fleming, Lichtenberg, and Newburn 2018; Fleming 2017).

This paper proceeds with an explanation of the methodology, followed by a description of the data used in the analysis. The empirical results are then presented along with policy implications of our findings, and final remarks are discussed in the concluding section.

2. 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 and did not have any access to funding. 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 due to both costs, ethical considerations, and the actual prevalence of cost-share programs for cover crops. In reality, selection bias is an issue because each farmer decides whether to plant cover crops and whether to apply for cost-share. Thus to address this issue, we use farmers' observable characteristics and a matching estimator to create a control group for the farmers who received cost share. We then compare the average cover crop use for cost-share recipients and our constructed control group 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. The methods used include endogenous switching regressions (Fleming 2017; Fleming, Lichtenberg, and Newburn 2018; Lichtenberg and Smith-Ramirez 2011), propensity-score matching (Claassen, Duquette, and Smith 2018; Gonzalez-Ramirez and Arbuckle 2016; Mezzatesta, Newburn, and Woodward 2013), and difference-in-difference matching (Chabé-Ferret and Subervie 2013). Among matching estimators, propensity score is often used to overcome high dimensionality of independent variables.

2.1 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.

The problem the econometrician faces is that s/he never observes both outcomes for any individual (Rubin 1974). Thus, s/he is never able to observe the treatment effect, $Y_i(1) - Y_i(0)$, and instead must rely on estimating the 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, which is a scalar. The propensity score, $p(X_i)$, is defined in our application as the probability that a farmer received a cost-share payment, given his/her pre-treatment characteristics:

(1) $$p(X_i) \equiv \Pr(T_i = 1|X_i).$$

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,

(2) $$Y_i(0) \perp T_i \mid X_i \quad .$$

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

(3) $$p(X_i) < 1 \; \forall \, i \quad .$$

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.

(4) $$ATT = E[Y_i(1) - Y_i(0)|T_i = 1]$$

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, and by controlling for these pretreatment variables, we reduce bias. 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. 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.[8]

2.2 Empirical Analysis

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

$$P(T_i = 1) = \frac{1}{1+e^{-X\beta}}. \tag{5}$$

Next, we define our measure of distance. 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 such that we 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 at the expense of efficiency. The same goes for the number of matches to each treated observation. Increasing the

[8] This is a restrictive assumption that 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.

number of matches lowers their quality, but the additional information increases efficiency. Thus, the distance between observations is defined as:

(6)
$$D_{ij} = \begin{Bmatrix} p(X_i) - p(X_j) & if\ |p(X_i) - p(X_j)| \le c \\ \infty & |p(X_i) - p(X_j)| > c \end{Bmatrix}.$$

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

(7)
$$\hat{Y}_i(0) = \frac{1}{m}\sum_{j\in J_m^i} Y_j.$$

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:

(8)
$$SMD = \frac{\bar{x}_T - \bar{x}_C}{\sqrt{\frac{s_T^2 + s_C^2}{2}}}.$$

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:

(9)
$$ATT = \frac{1}{N}\sum_{i\in\{i|T_i = 1\}}\left[Y_i(1) - \hat{Y}_i(0)\right]$$

The standard errors are computed following Abadie and Imbens (2006), taking into account that the propensity score is estimated.

2.3 Sensitivity Analysis

Next, we evaluate our results by assessing the selection on observables assumption. Although there is no way to directly test this assumption, we provide evidence of how prone our results are to bias by constructing Rosembaum bounds, following Diprete and Gangl (2004). The Rosembaum-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. That is, 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 selection–unobservable factors associated with higher cover-crop use increase the likelihood of receiving cost share, thus resulting in an upward biased ATT.

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

(10) $$\frac{1}{\Gamma} \leq Odds\ Ratio \leq \Gamma.$$

If $\Gamma = 1$, then there is no hidden bias, while values of Γ above 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.

3. 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 among farmers who reported using cover crops on at least 10 acres and operating at least 50 acres of row crops in the 2012 Census of Agriculture. 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 farm 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 percent 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, this would result in an upward bias in our estimate of $Y(0)$ 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 is a 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.

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 proportion of the sample receiving cost share and average acreage share in cover crops[9]. Thus, we are not concerned that removing these observations imposes any additional bias to our sample.

The present study focuses on farmers' cover crop decisions for the fall of 2015–holding constant cost-share program rules, macro-economic conditions, and time passed since the 2012 Agricultural Census. Our variables of interest are whether the farmer received a cost-share payment to plant cover crops in 2015, the per-acre payment received,[10] total acreage planted to the most widely used cover crop mix, and farm size. In table 1, we report a summary of the make-up of the 403 respondents[11] used in our chosen specification of the matching analysis. The specifications are evaluated based on the balance of the covariates between the treatment and control group. That is, we choose the specification that has performed best at removing bias after the matching procedure (Caliendo and Kopeinig 2008). The sample is composed of about the same number of cover crop users and non-users in 2015 (204 vs. 199, respectively). About 40% of cover crop users received cost-share payments. Among this group, the average number of cover crop

[9] 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.

[10] The cost-share source and contract length are not specified. Respondents report different payment rates, presumably due to the various funding sources used.

[11] Note that four observations are removed due to the inclusion of the caliper.

acres and the proportion of total farmland under cover crops is larger than the corresponding averages among farmers who did not receive cost-share payments. Again, it is important to note that our sample's average acreage share in cover crops of 11.7% is greater than the state average, suggesting this sample may not be representative of Iowa farmers in general.

Table 1. Matched sample description

	Farmers who planted cover crops in 2015			Farmers who did not plant cover crops in 2015
	Frequency	Average Cover Crop Acreage	Average Share of Acreage in Cover Crops	Frequency
Received cost-share payment in 2015	87	224	0.26	–
Did not receive cost-share payment in 2015	117	238	0.21	199

Survey respondents also 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 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.

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 key to our ability to use propensity-score analysis. We include variables regarding farm characteristics, operator characteristics, and operators experience with conservation, selected based on the existing literature (Gonzalez-Ramírez and Arbuckle 2016; Chabé-Ferret and Subervie 2013; Mezzatesta, Newburn, and Woodward 2013; Claassen, Duquette, and Smith 2018). Each variable is associated with a K-code in the 2012 Census of Agriculture, as detailed in Table 2. Variables relating to farm characteristics include total acres operated in 2012

(*Acres*), 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*). We use cover crop acreage in 2012 (*Cover Crops*) as a measure of past conservation efforts. Imbens (2015) suggests including lagged dependent variables as a covariate, which we do since we expect cover-crop use to be correlated over time. 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 farmers 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 livestock less frequently, had higher gross farm sales, 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 treatment and control groups.

4. Results

4.1 Additionality of Cost-Share Programs

Results of the propensity score equation estimated according to equation (5) are reported in Table 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

Table 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 Cost-share (n = 87)	Mean No cost-share (n = 316)	Difference t-statistic
Acres	Total acres operated	K46	716.6	514.8	3.2313***
Rented Acres	Acres rented or leased from others	K44	540.5	430.4	1.3189
Farm Sales	Gross farm sales (in thousands of dollars)	TVP	971188.9	689742.4	2.0949**
Livestock	Presence of cattle; hogs and pigs; equine; sheep and goats; or other livestock on the operation (1 if present)	K1201, K1211, K1247, K1239	0.6207	0.7468	2.3293**
Poultry	Presence of poultry on the operation (1 if present)	K1217	0.0805	0.061	0.6823
Corn	Corn acreage harvested for grain	K67	394.8	326.1	1.0609
Soy	Soybean acreage harvested for grain	K88	295.8	229.7	1.8106*
Cover crops	Acres planted to cover crops	K3456	144.6	102.3	2.3037**
Tile Drainage	Acres drained by tile	K3450	404.1	364.0	0.4537
Ditch Drainage	Acres drained by ditch	K3451	42.1	37.7	0.2953
Age	Age of the principal operator (years)	K925	56.5	57.4	0.7051
Experience	Number of years since the principal operator began to operate on any farm	K1834	32.7	32.3	0.2739
Off-Farm Labor	Number of days worked off the farm	K929	1.97	2.05	0.4671
Farm Income	Percent of the principal operator's total household income from the operation	K1578	67.98	68.50	0.1432

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

Table 3. Propensity score regression results

Variable	Coefficient		Standard Error
Log Acres	0.9493	***	0.3124
Rented Acres	-0.0001		0.0004
Farm Sales	3.16E-07	*	1.81E-07
Livestock	-0.8581	***	0.2998
Poultry	0.5599		0.4836
Corn	-0.0014	*	0.0008
Soy	0.0003		0.0010
Cover crops	0.0016	**	0.0008
Tile Drainage	-0.0004		0.0004
Ditch Drainage	-0.0005		0.0010
Age	0.3122	**	0.1575
Age Squared	-0.0030	**	0.0015
Experience	0.0006		0.0632
Experience Squared	0.0002		0.0011
Off-Farm Labor	-0.0537		0.1019
Farm Income	-0.0090	*	0.0049
North West	-0.3424		0.5055
North Central	-0.8072		0.6852
North East	-0.4704		0.4950
West Central	-0.0296		0.5037
Central	-0.3572		0.5280
East Central	-0.3232		0.4679
South West	-0.7709		0.5921
South Central	-1.6145	*	0.8589
Intercept	-13.6025	***	4.1901

*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)

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 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 in the farm decreases the propensity score. Other variables are not significantly different from zero at a 95% confidence level.

Table 4. Sample balance assessment

Variable	**Standardized mean difference**	
	Before matching	After matching
Log Acres	0.4100	0.0474
Rented Acres	0.1722	0.0502
Farm Sales	0.2627	0.0808
Livestock	-0.2727	0.0414
Poultry	0.0793	0.1053
Corn	0.1429	0.0777
Soy	0.2343	0.0388
Cover crops	0.2835	0.0501
Tile Drainage	0.0634	0.0738
Ditch Drainage	0.0348	0.0602
Age	-0.0919	0.0188
Age Squared	-0.1409	0.0177
Experience	0.0349	-0.0405
Experience Squared	-0.0342	-0.0463
Off-Farm Labor	-0.0581	0.0324
Farm Income	-0.0170	-0.0105
North West	0.1452	0.0712
North Central	-0.1460	-0.0088
North East	-0.1158	-0.0502
West Central	0.0383	-0.0194
Central	-0.0531	0.0852
East Central	0.0383	0.0276
South West	-0.0727	0.0130
South Central	-0.1736	-0.0772

Given the estimated propensity scores, we create our matched sample. The sample is constructed after varying the number of controls matched to each treated observation and the presence and size of the caliper. In our selected specification, we match to the seven nearest neighbors and use a caliper of 0.2. An examination of the sample's balance is displayed in Table 4. After matching, the SMDs are all less than 11%, 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 1 and 2 in Appendix II).

Table 5 presents the ATT results for the matched samples, calculated using equation (9). In our chosen specification (shown in table 5a), we find that receiving cost-share payments increases acreage in cover crops, on average, by 17.7 percentage points, a difference that is significant at a 95% confidence level. We estimate that farmers who received cost-share payments would have planted cover crops on 8.8% of their acres in the absence of cost-share, whereas they actually planted cover crops on 26.5% of their acres. Following Mezzatesta, Newburn, and Woodward (2013) and Fleming, Lichtenberg, and Newburn (2018), we calculate the additionality rate, which measures the additional cover crop acres as a share of total cover crop acreage due to cost-share payments. Our estimated additionality rate is 67%, which suggests that one-third of cost-share acreage would have been planted to cover crops even in the absence of the cost-share programs.

Table 5b summarizes the results from alternative matching specifications and provides a robustness check to the results of our selected model. In our chosen model, 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. Thus, we include a specification omitting 2012 cover crop use as a variable. The ATT estimate for the specification without past cover crop usage is 19%, which is similar to that of our chosen specification. Furthermore, reducing the size of the caliper to ensure higher quality matches and changing the numbers of controls to which each treated observation is matched do not substantially affect the results.

Table 5. Average treatment effect on the treated results

(a) Results from chosen specification

	Y(0)	Y(1)	ATT	SE	95% Confidence Interval
Farmland share under cover crops	0.0882	0.2649	0.1767	0.0137	[0.1498 , 0.2035]

(b) Results from all specifications

Method	Neighbors	Caliper	ATT	SE
Propensity score-nearest neighbor	7	0.2	0.1767	0.0137
	7	0.1	0.1857	0.0087
	7	0.05	0.1580	0.0328
	7	0.02	0.1902	0.0268
	7	0.2	0.1942‡	0.0266
	1	No	0.1325	0.0516
	2	No	0.1449	0.0346
	3	No	0.1560	0.0245
	4	No	0.1631	0.0212
	5	No	0.1735	0.0179
	6	No	0.1746	0.0170
	7	No	0.1767	0.0137
	8	No	0.1766	0.0126
	Kernel type	**Bandwidth**	**ATT**	**SE**
Propensity score-kernel	Epanechnikov	0.01	0.1140	0.0368
	Epanechnikov	0.04	0.1104	0.0369
	Epanechnikov	0.1	0.1676	0.0335
	Epanechnikov	0.15	0.1754	0.0330
	Epanechnikov	0.2	0.1805	0.0326
	Gaussian	0.01	0.1153	0.0368
	Gaussian	0.04	0.1595	0.0337
	Gaussian	0.1	0.1807	0.0240
	Gaussian	0.15	0.1864	0.0316
	Gaussian	0.2	0.1908	0.0314
	Neighbors		**ATT**	**SE**
Euclidian distance*	7		0.1620	0.0337
	2		0.1833	0.0334
	Neighbors	**Replications**	**ATT**	**SE**
Genetic†	1	500	0.1738	0.0372
	5	1000	0.1917	0.0314
	1	1000	0.1738	0.0372

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

*Includes bias adjustment and exact matching on livestock

† Uses population of 100

In addition, we try three other matching techniques: kernel matching, covariate matching, and genetic matching. 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. In the kernel matching analysis, bandwidths are varied from 0.01 to 0.2.[12] Next, we match directly on covariates instead of on the propensity score, using the Euclidian distance as the measure. In this covariate method, we vary the number of neighbors chosen. Lastly, genetic matching uses a genetic search algorithm to optimize a combination of matching on covariates and the propensity score (Diamond and Sekhon 2013). Overall, the results from the 28 alternative specifications are similar, with the increase in cover crop acreage share due to cost-share payments ranging from 11.0 to 19.4 percentage points. This suggests that our results are not dependent on the chosen specification.

We find that our measure of additionality for cover crop cost-share programs in Iowa falls in line with most previous studies, which found increased acreage shares between 20 and 30 percentage points (Fleming, Lichtenberg, and Newburn 2018; Fleming 2017; Gonzalez-Ramírez and Arbuckle 2016; Mezzatesta, Newburn, and Woodward 2013). Prior studies find additionality rates for cover crop cost-share programs in Maryland (Fleming, Lichtenberg, and Newburn 2018; Fleming 2017) 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 67% due to the composition of our sample. While the other studies have samples representative of their state's farmers, our study more heavily samples cover-crop users. If our sample had more non-adopters, it is possible that these observations would be better matches for the cost-share recipients and

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

hence join the control group, decreasing the value of *Y(0)*. This would in turn increase the estimated ATT and the additionality rate.

The lower additionality rate in our study may also reflect differences in cost-share payment rates: payments in Maryland are $45 per acre, while payments in our sample average $25.87 per acre. The higher payment rate may attract more farmers who would be unlikely to use cover crops without payment.

4.2 Sensitivity Analysis

We further evaluate our results by assessing the selection on observables assumption. Although we cannot directly test this assumption, we provide evidence of how prone our results are to bias by constructing Rosembaum bounds, following the method of Diprete and Gangl (2004). While we cannot conduct this test on our chosen model, we do so on an alternative model that also uses nearest-neighbor matching on the propensity score[13]. Note that the estimated ATT for this specification is 18.7%.

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. We report results of the test in Table 6. We reject the null hypothesis until $\Gamma = 74$. That is, an unobserved factor increasing the odds of being treated by 7300% would not be sufficient to make our ATT result insignificant, at a 95% confidence level. Therefore, we conclude that our results are robust to hidden bias.

[13] The Rosembaum bounds procedure (Diprete and Gangl 2004) is only applicable to one-to-one nearest-neighbor matching, without replacement.

Table 6. Rosembaum sensitivity analysis

Γ	p^{+}
1	0
2	0
3	1.10E-16
4	7.50E-13
5	1.20E-10
10	3.80E-06
20	0.000779
30	0.004896
40	0.012642
50	0.022704
60	0.033886
70	0.045416
71	0.046568
72	0.04772
73	0.048869
74	0.050017

4.3 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 public 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 obtain a back-of-the-envelope (not statistically representative) calculation of private and public costs of abating nitrate leaching in Iowa through cover crops. A study in Boone, Iowa found a reduction in nitrogen loss of 10.4 to 28.4 pounds per acre annually due to cover crops (Malone et al. 2014). We use this range of values to calculate a rough aggregate estimate of the private and public costs of nitrogen reduction with cover crops in Iowa.

Columns 1 through 3 of Table 7 divide Iowa cover crop farmland by (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

Table 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 totals			
Acres	317,132	274,748	591,880	211,541
	(b) Expenditures (million dollars)			
Cost Share	8.40	0.00	8.40	8.40
Farmer	8.52	11.92	20.44	5.68
Total	16.92	11.92	28.84	14.08
	(c) Marginal abatement cost of nitrogen (dollars per pound)			
Cost Share	0.93 – 2.55	0	0.50 – 1.36	1.40 – 3.82*
Farmer	0.95 – 2.58	1.53 – 4.17	1.22 – 3.32	0.95 – 2.58*
Total	1.88 – 5.13	1.53 – 4.17	1.72 – 4.69	2.34 – 6.40*

*Includes benefits on the additional acres, total cover crop cost share expenditures, and farmer net losses on the additional farmland.

591,880 acres to cover crops, of which 317,132 acres were funded with cost share, as is displayed in table 7a (Rundquist and Carlson 2017). Our partial-budget analysis suggests that cost-share recipients and non-recipients face per-acre net losses of $27 after accounting for cost-share payments, and $43, respectively. Applying these figures to the 317,132 cover-crop acres funded with cost share and the estimated 274,748 acres planted without cost share, this amounts to $20.44 million in farmer expenses for cover crops (table 7b). Recall that this is compared to the $8.4 million publically spent on cover crop cost share (Iowa Nutrient Reduction Strategy 2016). Thus, the combined farmer and public cost to abate nitrogen through cover crops is estimated at $1.72 to $4.69 per pound nitrogen, with farmers undertaking $1.22 to $3.32 per pound in net losses (table 7c).

However, we are also interested in the cost effectiveness of the cost share programs, while taking into account additionality. From our empirical results, we estimate that 211,541 cover-crop acres were additional in Iowa, as is shown in column 4 of Table 7a.

Considering the benefits on the additional acres, we evaluate the cost-share programs' cost effectiveness. We find that the public cost of abating nitrogen through cover crop cost share programs is \$1.40 to \$3.82 per pound (table 7c). This is less than that of the cost share program in Maryland, where studies have found nitrogen abatement costs 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. We also compare our results to those of Marshall et al. (2018), who look at reduction of nitrogen delivery to the Gulf of Mexico. They find that in the Lower Mississippi River Basin, nitrogen abatement by cover crop would cost \$5.29 per pound, while in the Upper Mississippi River Basin, where Iowa is located, the cost would be \$23.40 per pound of nitrogen. These differences are because Marshall et al. (2018) only consider nitrogen loss to the Gulf of Mexico, and proximity plays a great factor. Thus, using their framework, reducing pollution to the Gulf of Mexico through cover crops in Iowa would be costly, due to the large distance between the two regions. Furthermore, in an analysis of a water-quality trading scheme among Chesapeake Bay area farmers, Ribaudo, Savage, and Aillery (2014) find an equilibrium price of \$3.13 per pound of nitrogen.

5. Conclusion

In this paper, 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 to calculate the propensity score, which is the probability a farmer receives cost-share in 2015, using data from a unique survey of Iowa cover crop users conducted in 2017. Second, we match the observations for cost-share recipients with similar non-cost-share recipients based on the propensity score. 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 18%, from an average of 9% to a farmland share of 26%, implying an additionality rate of 67%. This suggests that cost-share programs do encourage adoption of cover crops that is additional to that which would occur in their absence, but as many as one-third of acres would have used cover crops without the payment. Despite the relatively low additionality rate, the public cost of abating nitrogen pollution through cover crop cost-share is relatively low in Iowa at $1.40 to $3.82 per pound. This cost is likely lower than what we would find in other states because cover crop cost share payment rates are lower in Iowa than in other states (Bowman and Lynch 2019).

Although the sampling strategy applied to collect our survey data does not allow for statistically representative statewide inferences, we report some rudimentary calculations. These results suggests that abating nitrogen pollution through cover crops costs around $1.72 to $4.69 per pound of nitrogen, with 71% of the cost absorbed by farmers and the remaining 29% financed with public monies. Further research is needed to confirm or disprove these non-representative estimates.

One limitation of our study is that it only considers farmers who have used cover crops in the past. This prevents us from being able to make inferences on how cost-share affects those who have never planted cover crops. Furthermore, when evaluating the policy, we do not consider slippage, even though prior literature sees that agricultural payment programs can induce farmers to plant row crops on marginal land (Fleming 2017; Fleming, Lichtenberg, and Newburn 2018; Lichtenberg and Smith-Ramirez 2011). This paper also does not venture into farmers noneconomic motives for planting cover crops. The established findings that farmers face negative short-term returns from cover crops indicates that many cover-crop adopters may have motives other than profit. These could include land-value impacts, environmental stewardship, and farmers' perceptions of cover crops (Arbuckle and Roesch-McNally 2015; Lee et al. 2018), which have been understudied in the literature. Moreover, 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 would look to better address whether payment schemes are the best way to retain farmers who already plant cover crops, while also encouraging new adoption.

References

Abadie, A., and G.W. Imbens. 2006. "Large Sample Properties of Matching Estimators for Average Treatment Effects." *Econometrica* 74 (1): 235–267.

Arbuckle, J.G., and G.E. Roesch-McNally. 2015. "The Role of Perceived Practice Characteristics." *Journal of Soil and Water Conservation* 70 (6): 418–29.

Basche, A.D., T.C. Kaspar, S.V. Archontoulis, D.B. Jaynes, T.J. Sauer, T.B. Parkin, and F.E. Miguez. 2016. "Soil Water Improvements with the Long-Term Use of a Winter Rye Cover Crop." *Agricultural Water Management* 172: 40-50.

Bergtold, J.S., P.A. Duffy, D. Hite, and R.L. Raper. 2012. "Demographic and Management Factors Affecting the Adoption and Perceived Yield Benefit of Winter Cover Crops in the Southeast." *Journal of Agricultural and Applied Economics* 44 (1): 99-116.

Bowman, M. and L. Lynch. 2019. "Government Programs that Support Farmer Adoption of Soil Health Practices: A Focus on Maryland's Agricultural Water Quality Cost-Share Program." *Choices* 34 (2).

Caliendo, M., and S. Kopeinig. 2008. "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys* 22 (1): 31-72.

Chabé-Ferret, S., and J. Subervie. 2013. "How Much Green for the Buck? Estimating Additional and Windfall Effects of French Agro-Environmental Schemes by DID-Matching." *Journal of Environmental Economics and Management* 65 (1): 12–27.

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

Cochran, W.G., and D.B. Rubin. 1973. "Controlling Bias in Observational Studies: A Review." Sankhyā: *The Indian Journal of Statistics*, Series A: 417-446.

Cooper, J.C. 2003. “A Joint Framework for Analysis of Agri-Environmental Payment Programs.” *American Journal of Agricultural Economics* 85 (4): 976–987.

Cooper, J.C., and R.W. Keim. 1996. “Incentive Payments to Encourage Farmer Adoption of Water Quality Protection Practices.” *American Journal of Agricultural Economics* 78 (1): 54–64.

Diamond, A., and J.S. Sekhon. 2013. "Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies." *Review of Economics and Statistics* 95 (3): 932-945.

DiPrete, T.A., and M. Gangl. 2004. "Assessing Bias in the Estimation of Causal Effects: Rosenbaum Bounds on Matching Estimators and Instrumental Variables Estimation with Imperfect Instruments." *Sociological Methodology* 34(1): 271-310.

Ferraro, P.J. 2008. “Asymmetric Information and Contract Design for Payments for Environmental Services.” *Ecological Economics* 65 (4): 810–821.

Fleming, P. 2017. "Agricultural Cost Sharing and Water Quality in the Chesapeake Bay: Estimating Indirect Effects of Environmental Payments." *American Journal of Agricultural Economics* 99 (5): 1208-1227.

Fleming, P., E. Lichtenberg, and D.A. Newburn. 2018. "Evaluating Impacts of Agricultural Cost Sharing on Water Quality: Additionality, Crowding in, and Slippage." *Journal of Environmental Economics and Management* 92: 1-19.

Gonzalez-Ramírez, M. J., and J.G. Arbuckle Jr. 2016. “Cost-Share Effectiveness in the Diffusion of a New Pollution Abatement Technology in Agriculture: The Case of Cover Crops in Iowa.” Working Paper.

Ho, D.E., K. Imai, G. King, and E.A. Stuart. 2007. "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis* 15 (3): 199-236.

Imbens, G.W. 2015. "Matching methods in practice: Three examples." *Journal of Human Resources* 50 (2): 373-419.

Iowa Nutrient Reduction Strategy. 2014. “A Science and Technology-Based Framework to Assess and Reduce Nutrients to Iowa Waters and the Gulf of Mexico.” Iowa Department of Agriculture and Land Stewardship, Iowa Department of Natural Resources, and Iowa State University College of Agriculture and Life Sciences, Ames, IA.

Iowa Nutrient Reduction Strategy. 2016. “A Science and Technology-Based Framework to Assess and Reduce Nutrients to Iowa Waters and the Gulf of Mexico.” Iowa Department of Agriculture and Land Stewardship, Iowa Department of Natural Resources, and Iowa State University College of Agriculture and Life Sciences, Ames, IA.

Kaspar, T.C., D.B. Jaynes, T.B. Parkin, and T.B. Moorman. 2007. "Rye Cover Crop and Gamagrass Strip Effects on NO 3 Concentration and Load in Tile Drainage." *Journal of Environmental Quality* 36 (5): 1503-1511.

Kaspar, T.C., D.B. Jaynes, T.B. Parkin, T.B. Moorman, and J.W. Singer. 2012. "Effectiveness of Oat and Rye Cover Crops in Reducing Nitrate Losses in Drainage Water." *Agricultural Water Management* 110: 25-33.

Kaspar, T.C., J.K. Radke, and J.M. Laflen. 2001. "Small Grain Cover Crops and Wheel Traffic Effects on Infiltration, Runoff, and Erosion." *Journal of Soil and Water Conservation* 56 (2): 160-164.

Kaspar, T.C., and J.W. Singer. 2011. “The Use of Cover Crops to Manage Soil.” In Soil Management: Building a Stable Base for Agriculture. Ed. J.L. Hatfield and T.J. Sauer. Madison: American Society of Agronomy and Soil Science Society of America.

Kladivko, E.J., T.C. Kaspar, D.B. Jaynes, R.W. Malone, J. Singer, X.K. Morin, and T. Searchinger. 2014. "Cover Crops in the Upper Midwestern United States: Potential Adoption and Reduction of Nitrate Leaching in the Mississippi River Basin." *Journal of Soil and Water Conservation* 69 (4): 279-291.

Lee, D., J.G. Arbuckle, Z. Zhu, and L.W. Nowatzke. 2018. “Conditional Causal Mediation Analysis of Factors Associated with Cover Crop Adoption in Iowa, USA.” *Water Resources Research* 54: 1-19. https://doi.org/10.1029/2017WR022385

Lichtenberg, E., and R. Smith-Ramirez. 2011. "Slippage in Conservation Cost Sharing." *American Journal of Agricultural Economics* 93 (1): 113-129.

Ma, S., S.M. Swinton, F. Lupi, and C. Jolejole-Foreman. 2012. “Farmers’ Willingness to Participate in Payment-for-Environmental-Services Programmes.” *Journal of Agricultural Economics* 63 (3): 604–626.

Malone, R.W., D.B. Jaynes, T.C. Kaspar, K.R. Thorp, E. Kladivko, L. Ma, D.E. James, J. Singer, X.K. Morin, and T. Searchinger. 2014. "Cover Crops in the Upper Midwestern United States: Simulated Effect on Nitrate Leaching with Artificial Drainage." *Journal of Soil and Water Conservation* 69 (4): 292-305.

Marcillo, G.S., and F.E. Miguez. 2017. "Corn Yield Response to Winter Cover Crops: An Updated Meta-Analysis." *Journal of Soil and Water Conservation* 72 (3): 226-239.

Marshall, E., M. Aillery, M. Ribaudo, N. Key, S. Sneeringer, L. Hansen, S. Malcolm, and A. Riddle. 2018. “Reducing Nutrient Losses from Cropland in the Mississippi/Atchafalaya

River Basin: Cost Efficiency and Regional Distribution." No. 277567. United States Department of Agriculture, Economic Research Service.

Martinez-Feria, R.A., R. Dietzel, M. Liebman, M.J. Helmers, and S.V. Archontoulis. 2016. "Rye Cover Crop Effects on Maize: A System-Level Analysis." *Field Crops Research* 196: 145-159.

Mezzatesta, M., D.A. Newburn, and R.T. Woodward. 2013. "Additionality and the Adoption of Farm Conservation Practices." *Land Economics* 89 (4): 722–742.

Moore, E.B., M.H. Wiedenhoeft, T.C. Kaspar, and C.A. Cambardella. 2014. "Rye Cover Crop Effects on Soil Quality in No-Till Corn Silage–Soybean Cropping Systems." *Soil Science Society of America Journal* 78 (3): 968-976.

National Agricultural Statistical Service (NASS). 2012-2017. Census of agriculture. Washington, DC: U.S. Department of Agriculture.

Pantoja, J.L., K.P. Woli, J.E. Sawyer, and D.W. Barker. 2015. "Corn Nitrogen Fertilization Requirement and Corn–Soybean Productivity with a Rye Cover Crop." *Soil Science Society of America Journal* 79 (5): 1482-1495.

Plastina, A., F. Liu, F. Miguez, and S. Carlson. 2018a. "Cover Crops Use in Midwestern U.S. Agriculture: Perceived Benefits and Net Returns." *Renewable Agriculture and Food Systems*: 1-11. DOI:10.1017/S1742170518000194

Plastina, A., F. Liu, W. Sawadgo, F.E. Miguez, S. Carlson, and G. Marcillo. 2018b. "Annual Net Returns to Cover Crops in Iowa." *Journal of Applied Farm Management* 2 (2): 19-36.

Prokopy, L.S., K. Floress, D. Klotthor-Weinkauf, and A. Baumgart-Getz. 2008. "Determinants of Agricultural Best Management Practice Adoption: Evidence from the Literature." *Journal of Soil and Water Conservation* 63 (5): 300–311.

Ribaudo, M., J. Savage, and M. Aillery. 2014. "An economic assessment of policy options to reduce agricultural pollutants in the Chesapeake Bay." ERR-166. United States Department of Agriculture, Economic Research Service.

Rosenbaum, P.R. 2002. *Observational Studies*. Springer, New York, NY.

Rosenbaum, P. R., and D.B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70 (1): 41–55.

Rosenbaum, P.R., and D.B. Rubin. 1985. "Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score." *The American Statistician* 39 (1): 33-38.

Rubin, D.B. 1974. "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies." *Journal of Educational Psychology* 66 (5): 688.

Rundquist, S., and S. Carlson. 2017. "Mapping Cover Crops on Corn and Soybeans in Illinois, Indiana and Iowa, 2015-2016." Environmental Working Group & Practical Farmers of Iowa, Washington, DC.

Seifert, C.A., G. Azzari, and D.B. Lobell. 2018. "Satellite Detection of Cover Crops and their Effects on Crop Yield in the Midwestern United States." *Environmental Research Letters* 13 (6): 064033.

Singer, J.W. 2008. "Corn Belt Assessment of Cover Crop Management and Preferences." *Agronomy Journal* 100 (6): 1670-1672.

Snapp, S.S., S.M. Swinton, R. Labarta, D. Mutch, J.R. Black, R. Leep, J. Nyiraneza, and K. O'Neil. 2005. "Evaluating Cover Crops for Benefits, Costs and Performance within Cropping System Niches." *Agronomy Journal* 97 (1): 322–332.

White, M.J., C. Santhi, N. Kannan, J.G. Arnold, D. Harmel, L. Norfleet, P. Allen et al. 2014. "Nutrient Delivery from the Mississippi River to the Gulf of Mexico and Effects of Cropland Conservation." *Journal of Soil and Water Conservation* 69 (1): 26-40.

Zhang, W., A. Plastina, and W. Sawadgo. 2018. "Iowa Farmland Ownership and Tenure Survey 1982-2017: A Thirty-five Year Perspective." Iowa State University Extension and Outreach PM 1983. Available at: https://www.card.iastate.edu/farmland/ownership/FM1893.pdf.

Appendix I. Cost-Share Program Descriptions

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 Incentives 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 a 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 by the Revised Universal Soil Loss Equation Version 2.

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)

Appendix II.

Figure 1. Balance Plot of Control and Treated Observation Propensity Scores Before and After Matching

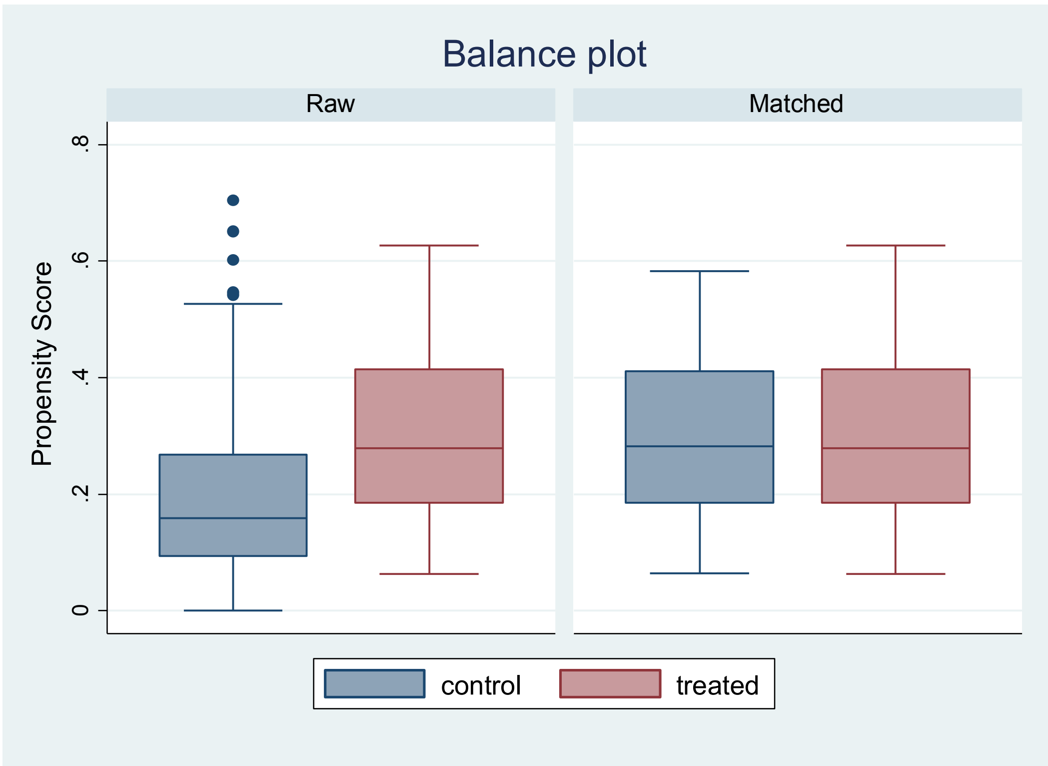

Figure 2. Density Plot of Distribution of Treated and Control Observations Before and After Matching