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Do cost-share programs increase cover crop use? Empirical evidence from Iowa

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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 tested the hypothesis that monetary incentives through cost-share programs are effective at increasing the area of farmland planted to cover crops in Iowa, as opposed to the alternative in which the participants of cost-share programs would have planted the same cover-crop acreage in the absence of payment. We found 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. The estimated additionality rate was 54%, suggesting at least half of cost-share expenditures funded cover-crop acreage that would not have been planted without payment. Furthermore, we estimated the public cost to reduce nitrogen loads to Iowa waterways via cover crop, beyond what would have occurred in the absence of cost-share programs, to be \$1.72–\$4.70 lb^{-1} N (\$3.79–\$10.36 kg^{-1} N). Farmers absorbed about 70% of those costs as private losses, and cost-share payments offset the remaining 30%. Although the additionality rate estimated in this study is less than what has been found in other states, the cost-share programs in Iowa have been relatively cost-effective, due to their lower payment rate.

Row-crop farming in the Midwestern USA remains a major non-point source of nutrient pollution to waterways. A promising conservation practice is the use of winter cover crops, which the Iowa Nutrient Reduction Strategy (2016) lists as one of the practices with the greatest potential for nitrate reduction. Iowa fields with winter cereal rye (*Secale cereale*) saw a nitrate leaching reduction of 20% (Martinez-Feria *et al.*, 2016), and subsurface drainage water nitrate concentration reductions of 48 and 61% (Kaspar *et al.*, 2007, 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 that makes up the hypoxic zone is estimated to originate from cultivated agriculture in the Mississippi River Basin (White *et al.*, 2014). From the farmer's perspective, cover crops are appealing due to 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 *et al.*, 2001), increased soil organic matter (Kaspar and Singer, 2011; Moore *et al.*, 2014), improved soil health (Snapp *et al.*, 2005) and enhanced water-storage capacity and water 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 (*Zea mays*) and soybean (*Glycine max*) 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) reported that some farmers were concerned that cover crops could take water from the soil at the expense of the following cash crop and induce yield drags. 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, found that cereal rye reduced corn yields by 6%. However, in a meta-analysis of winter cover-crop studies in the USA and Canada, Marcillo and Miguez (2017) concluded 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) did not find consistent corn yield declines following cover crops. Seifert *et al.* (2018), using satellite panel data, found corn yield increases of 0.65% in the Midwest.

Among Iowa farmers, Plastina *et al.* (2018b) found that the additional costs from planting and terminating cover crops amounted to around \$40 ac^{-1} (\$99 ha^{-1}), often leading to short-term net losses even for farmers participating in cost-share programs. In addition, the large percentage of Iowa farmland that was leased as of 2017 (53%)—along with the fact that only one-third of landowners would have been willing to help their tenant pay for cover-crop planting costs (Zhang *et al.*, 2018)—tends to inhibit cover-crop adoption. In other regions, Bergtold *et al.* (2012) found that tenants in Alabama were 20% less likely to adopt cover crops on rented land, and Singer (2008) found that only 14% of Corn-Belt farmers would use cover crops on rented land.

To promote the use of cover crops, several cost-share programs are available to Iowa farmers. Details of cost-share programs available to farmers are included in Appendix I. An estimated 317,132 ac (128,339 ha) 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 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 implies that farmers would not implement the practices without cost-share and can be indicative of an effective program. The goal of this study was to assess the effectiveness of cost-share programs at increasing cover-crop acreage among cover-crop users. To estimate the additionality of cover-crop cost-share programs in Iowa, we used a matching estimator combining farm-level data from a cover-crop survey that had been 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 used 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 *et al.* (2018) found that additionality rates differed among best-management practices such as nutrient management, conservation tillage and buffer strips across the USA. They also found greater additionality for practices that take land out of crop production or have greater short-term costs. Regarding cover crops specifically, Chabé-Ferret and Subervie (2013) estimated that PES programs in France increase cover-crop acreage by 27 ac (11 ha) per farm. In the USA, studies in Maryland (Lichtenberg and Smith-Ramirez, 2011; Fleming, 2017; Fleming *et al.*, 2018) and Ohio (Mezzatesta *et al.*, 2013) found that crop farmers' enrollment in cost-share programs increased the share of acres under cover crops from 8 to 28%. Lastly, results from ongoing work by Gonzalez-Ramírez 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) found 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 primary contributions to the existing literature. First, we used data from a unique cover-crop survey in Iowa linked to the 2012 Census of Agriculture to calculate the additionality of cover-crop cost-share programs among adopters. Secondly, we provided a calculation of private and public costs of abating nitrate loads via cover crops. While other studies (Fleming, 2017; Fleming *et al.*, 2018) have looked at the public costs associated with cost-share programs, they have not considered the costs borne by farmers. Lastly, while cover-crop cost-share additionality estimates existed for the Chesapeake Bay region (Fleming, 2017; Fleming *et al.*, 2018) and Ohio River Basin (Mezzatesta *et al.*, 2013), to our knowledge, we provided 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.

Methodology

Matching estimators offer a semi-parametric method to correct for observable selection in observational studies. In the setting of this research, selection bias is present because each farmer decides whether to plant cover crops and whether to apply for cost-share. To address this issue, we used farmers' observable characteristics and a propensity-score matching estimator to create a counterfactual for the farmers who received cost-share. That is, for each farm that received cost-share, we found a group of similar farms who did not receive cost-share and used this group of farms' cover-crop planting behavior as our estimate of what the cost-share recipient would have done in the absence of payment.

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 can 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., $\sum_i^N Y_i(0)/N$ *vs* $\sum_j^M Y_j(1)/M$] to the effect of cost-share payments, we would have overestimated the effect of cost-share on our outcome variables of interest.

Instead, we used farmer i's observable characteristics, X_i to obtain the counterfactual outcomes we cannot 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 this application, the propensity score, $p(X_i)$, is the probability that a farmer receives a cost-share payment, given his/her pre-treatment characteristics:

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

Rosenbaum and Rubin (1983) showed that conditioning on the propensity score is equivalent to conditioning on the set of

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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,

$$\{Y_i(0), Y_i(1)\} \perp T_i \mid X_i. \tag{2}$$

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

$$0 < p(X_i) < 1 \ \forall\ i. \tag{3}$$

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, which is one measure of additionality.

$$\text{ATT} = E[Y_i(1) - Y_i(0) | T_i = 1]. \tag{4}$$

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 were able to control for all factors that impact both the farmer receiving cost-share and planting cover crops. Because we used Agricultural Census data, we had a large set of variables relating to many aspects of the farming operation, which made the identifying assumption plausible. However, unobservable factors that could have violated this assumption include farmers' environmental perceptions, network effects and attitudes toward land stewardship. Although we could not directly test whether unobservable variables were confounding our results, we conducted a sensitivity analysis to provide evidence that it is highly unlikely that bias due to unobservable factors was the driver of our results.

Empirical analysis

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

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

where β is a vector of coefficients to be estimated. We used 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 added a caliper to only consider matches within a specified radius, c, such that $|p(X_i) - p(X_j)| \leq c$. 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:

$$D_{ij} = \left\{ \begin{array}{ll} p(X_i) - p(X_j) & \text{if } |p(X_i) - p(X_j)| \leq c \\ \infty & \text{if } |p(X_i) - p(X_j)| > c \end{array} \right\}. \tag{6}$$

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

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

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 assessed the correctness of our estimated propensity score by evaluating the post-matching balance between the two groups. We conducted 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:

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

The matched sample was deemed superior to the unmatched sample if the post-matching SMDs were generally smaller in absolute value than the pre-matching SMDs. The evaluation process was repeated after varying the values of c and m until an adequately balanced sample was obtained. Once matching was completed, we estimated the treatment effect as follows:

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

The standard errors were computed following Abadie and Imbens (2006), to take into account that the propensity score was estimated. The estimation was conducted using the *teffects* and *psmatch2* packages in Stata (Leuven and Sianesi, 2003; StataCorp, 2013).

Calculating private net returns

We used 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 calculated 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. Differences in revenues could be the result of differential cash-crop yields due to cover crops, additional revenue from grazing the cover crop and any cost-share payment received for planting the cover crop. Cover-crop planting costs included 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 burndown to

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all his/her acres in the spring, only the additional cost (if any) associated with a more concentrated, greater volume or more expensive herbicide solution, plus the additional machinery cost for any extra spraying passes were counted as termination costs. Other differential costs included changes in fertilizer application and other input use.

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 1250 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 (*Triticum aestivum*). 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 allowed for a larger sample of cover-crop users than in most past studies. However, this introduced a sampling bias. 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.

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 was composed of 407 observations for the matching analysis. Despite dropping 267 observations from the original sample, the sample composition remained similar, with only a small change in the proportion of the sample receiving cost-share (12.7 *vs* 12.1%) and average acreage share in cover crops (21 *vs* 22%). Thus, we are not concerned that removing these observations imposed any additional bias on our sample.

The present study focused on farmers' cover-crop decisions for the fall of 2015. Our variables of interest were whether the farmer received a cost-share payment to plant cover crops in 2015, the per-acre payment received (the source is not disclosed), total acreage planted to their most widely used cover-crop mix and farm size. In Table 1, we report a summary of the make-up of the 407 observations used in the matching analysis. The sample was 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 were greater 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 had enough information to calculate net returns to cover crops for 41 farms that received cost-share and 30 farms that did not. This is less than our total sample size because some respondents did not include adequate information on machinery use or input uses on their cover-cropped or non-cover-cropped fields. The median net losses from cover-crop use among farmers that received cost-share payments and among farmers who did not receive cost-share payments were \$23 and \$40 ac^{-1} (\$57 and \$99 ha^{-1}), respectively. Furthermore, the average cost-share payment received by farmers in our sample amounted to \$26 ac^{-1} (\$64 ha^{-1}) 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 were all pre-treatment, which is fundamental to our ability to use propensity-score analysis. We included variables regarding farm characteristics, operator characteristics and operator's experience with conservation, selected based on the existing literature (Chabé-Ferret and Subervie, 2013; Mezzatesta *et al*., 2013; Gonzalez-Ramírez and Arbuckle, 2016; Claassen *et al*., 2018). A description of the variables included is presented in Table 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 included cover-crop acreage in 2012 (*Cover crops*) as a covariate. For farmer characteristics, we used 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 greater 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 were not statistically significantly different between the treated and non-treated group.

Results

Results of the propensity-score equation estimated according to Equation (5) are reported in Table 3. As expected, past cover-crop acreage increased 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 increased 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 increased the probability of receiving cost-share but at a decreasing rate. In addition, having livestock on the farm decreased the propensity score. Other variables were not significantly different from zero at a 95% confidence level.

Given the estimated propensity scores, we created our matched sample. We varied the number of controls matched to each

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Table 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. Summary statistics from the 2012 US census of agriculture, by participation in cost-share programs in 2015

			Mean		
Variable Name	Variable description	Census *K*-code	Cost-share ($n = 91$)	No cost-share ($n = 316$)	Statistical Difference (*t*-statistic)
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.

treated observation and the presence and size of the caliper in constructing the sample. The specifications were evaluated based on the balance of the covariates between the cost-share recipients and non-recipients. That is, we chose the specification that performed best at removing bias through the matching procedure (Caliendo and Kopeinig, 2008). In our preferred specification, we matched each cost-share recipient with seven controls (neighbors) and used 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 displayed in Table 4. After matching, all the SMDs were 11% or less, which is well below the 20% threshold that Rosenbaum and Rubin (1985) deemed 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 (Figs. 1 and 2 in Appendix II). We present 30 additional models in Appendix III with similar findings, suggesting our results are robust to model choice.

Lastly, we evaluate how prone our results are to hidden bias by constructing Rosenbaum bounds, following Diprete and Gangl (2004). Details are provided in Appendix IV. We found that only an unobserved factor increasing the odds of being treated by over 7300% would 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.

Applying Equation (9) to our matched sample, we found that receiving cost-share payments increases acreage in cover crops by 15 percentage points, on average, a difference that is significant at a 95% confidence level (Table 5). We estimated 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 *et al.* (2013) and Fleming *et al.* (2018), we calculated 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 found that our measure of the impact of cover-crop cost-share programs in Iowa is slightly less than what is reported in most previous studies: 15 *vs* 20–30% (Mezzatesta *et al.*, 2013; Gonzalez-Ramírez and Arbuckle, 2016; Fleming, 2017; Fleming

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Table 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	**

Note: All variables in the table from the 2012 Census of Agriculture.
Goodness of fit: $\chi^2(24) = 65.96$ ($P < 0.0001$).
*Denotes significance at 0.10 level.
**Denotes significance at 0.05 level.
***Denotes significance at 0.01 level.

Table 4. Sample balance assessment ($N = 400$)

	Standardized mean difference	
Variable	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}

et al., 2018). Prior studies found additionality rates for cover-crop cost-share programs in Maryland (Fleming, 2017; Fleming *et al.*, 2018) and Ohio (Mezzatesta *et al.*, 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 greater than our additionality rate of 54% due to the composition of our sample and differences in payment rates across states. While other studies relied 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 ac^{-1} (\$111 ha^{-1}), they amounted to \$26 ac^{-1} (\$64 ha^{-1}) in our sample. The greater payment rate may attract more farmers who would be unlikely to use cover crops without payment.

To evaluate the cost-effectiveness of cover-crop cost-share programs, we focused on nitrate pollution reduction, even though cover crops have additional environmental benefits such as reduced soil erosion and phosphorous loss. We used 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 6 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) total cover-crop acreage. In 2015, farmers in Iowa planted an estimated 591,880 ac (239,525 ha) to cover crops, of which 317,132 ac (128,339 ha) were funded with cost-share, as displayed in Table 6a (Rundquist and Carlson, 2017). Our partial-budget analysis suggests that cost-share recipients and non-recipients face net losses of \$23 and \$40 ac^{-1} (\$57 and \$99 ha^{-1}), respectively, after accounting for cost-share payments (Table 6b). Applying these figures to the 317,132 ac (128,339 ha) of cover crops funded with cost-share and the estimated 274,748 ac (111,187 ha) planted without cost-share, the aggregate estimate of farmers' net losses due to cover crops amounts to \$18.28 million (Table 6c). The Iowa Nutrient Reduction Strategy (2016) reports that \$8.4 million were publicly spent on cover-crop cost-share. A study in Boone, Iowa found that cover crops reduced nitrogen loss by 10.4–28.4 lb N ac^{-1} (11.7–31.8 kg N ha^{-1}) annually (Malone *et al.*, 2014). The estimated load reduction to Iowa waterways from cover-crop use in 2015 amounts to 3078–8405 tons N (2.792–7.625 Mt N) (Table 6d). Thus, the

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Table 5. Average treatment effect on the treated results

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

Table 6. Iowa cover-crop acreage, private net losses from cover crops, total estimated expenditures, nitrogen load reduction and marginal abatement cost

	(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	1649–4503	1429–3901	3078–8405	894–2441
(e) Marginal abatement cost of nitrogen (dollars per pound)				
Cost-share	0.93–2.55	0	0.50–1.36	1.72–4.70[a]
Farmer	0.81–2.21	1.41–3.85	1.09–2.97	0.81–2.21[a]
Total	1.74–4.76	1.41–3.85	1.59–4.33	2.53–6.91[a]

[a]Includes benefits on the additional acres, total cover-crop cost-share expenditures and farmer net losses on the additional farmland.

combined farmer and public cost to abate nitrogen through cover crops is estimated at \$1.59–\$4.33 lb^{-1} N (\$3.51–\$9.55 kg^{-1} N), with farmers undertaking \$1.09–\$2.97 lb^{-1} N (\$2.40–\$6.55 kg^{-1} N) in net losses (Table 6e).

However, our main interest was the cost-effectiveness of the cost-share programs, so we focused 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 6a), we estimated that 171,927 ac (69,576 ha) of cover crops were additional in Iowa (column 4 of Table 6a). The public cost of abating nitrogen through cover-crop cost-share programs in Iowa was estimated at \$1.72–\$4.70 lb^{-1} N (\$3.79–\$10.36 kg^{-1} N), which was less than the reported costs in Maryland, ranging from \$5.80 to \$8.87 lb^{-1} N (\$12.79–\$19.56 kg^{-1} N) (Fleming, 2017; Fleming *et al.*, 2018). Again, the differences in cost-effectiveness were likely driven by the higher payment rate in Maryland. 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 lb^{-1} N (\$11.66–\$51.59 kg^{-1} N), respectively. The major difference between these estimates and our estimate stems from the fact that Marshall *et al.* (2018) measured 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. Finally, our results are in line with the equilibrium price of \$3.13 lb^{-1} N (\$6.90 kg^{-1} N) estimated by Ribaudo *et al.* (2014) in an analysis of a water-quality trading scheme among Chesapeake Bay area farmers.

Conclusion

In this study, we analyzed the effect of cost-share program participation on cover-crop adoption. We first used 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). Secondly, we matched the observations for cost-share recipients with similar non-cost-share recipients based on the propensity scores. Then, we estimated the effect of receiving cost-share on the share of farmland in cover crops across the matched observations. We found that participation in cost-share programs increased the users' share of cover-cropped farmland by an average of 15%, implying an additionality rate of 54%. This suggests that cost-share programs did encourage adoption of cover crops that was additional to that which would have occurred 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–\$4.70 lb^{-1} N (\$3.79–\$10.36 kg^{-1} N). 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 estimated that farmers absorb

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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. Additionally, this study does not venture into farmers' non-economic motives for planting cover crops, which may include environmental stewardship and long-term soil health considerations (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 cost-effective incentive schemes to retain farmers who already plant cover crops, while still encouraging new adoption. Analyses on how cost-share affects those who have never planted cover crops should also be of interest to policymakers. However, current adoption rates suggest ineffectiveness among non-adopters.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1742170521000132.

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