Additionality in cover-crop cost-share programs in Iowa: a matching assessment

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Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7

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

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June 21, 2018

Row-crop farming in the Midwest is a non-point source of nutrient pollution, which contributes to the degradation of waterways, putting pressure on farmers to adopt conservation practices. The use of cover crops has been shown to promote several aspects of soil and water sustainability, including reducing nutrient loss. Despite these on- and off-farm benefits, cover crop adoption remains low, largely due to the costs the farmer incurs; hence, monetary incentives may be effective at increasing the amount of farmland using cover crops in Iowa. This research uses a propensity score matching estimator to analyze the extent to which existing cost-share payments increase farmers' cover-crop use. We find that farmers who received cost-share payments planted cover crops to 192 more acres and covered an additional area equivalent to 18 percent of their land, than similar farmers who did not receive cost share.

JEL CODES: Q12, Q15, Q16, Q18, Q53

Keywords: Conservation agriculture, cover crops, payment for environmental services (PES), agri-environment schemes, additionality, matching estimator

Row-crop farming in the Midwest is a major non-point source of nitrate pollution in waterways, putting pressure on farmers to adopt conservation practices. One promising conservation practices is the use of cover crops, which is known to promote many aspects of soil and water sustainability (Kaspar and Singer 2011; Chatterjee 2013). The Iowa Nutrient Strategy (2014) lists cover crops as one of the practices with the greatest potential for nitrate-N reduction. However, despite the considerable benefits to the cropping system, adoption of cover crops remains very low in the Midwest. Rundquist and Carlson (2017), use satellite imagery to estimate that cover crops were incorporated into corn and soybean rotations in 2.65 percent of Iowa cropland in 2015. One likely explanation for this low adoption rate is that farmers tend to derive negative annual net returns from cover crops, due to high planting and termination costs (Plastina et al. 2018a, 2018b, 2018c). If cost-related factors are a strong deterrent to cover-crop adoption, then cost-share programs could have a significant impact in increasing its use.

The purpose of this paper is to determine whether cost-share programs have had the desired effect of increasing cover-crop acreage in the state of Iowa. 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 defined environmental service is provided by a land manager in exchange for a payment, given the fulfilment of the contract (Ferraro 2008). An important concept in the design of PES programs is *additionality*: the adoption of a practice that would not have occurred in the absence of the PES program. Addressing this is important because if additionality were low, this would suggest that farmers who received the payment largely did not require it to plant cover crops. That is, relatively little of the money would have gone towards achieving policy goals of increasing cover crop acreage, limiting the program’s cost effectiveness. To address the research question, we match responses from a cover crop survey with the 2012 Census of Agriculture and match on observable characteristics to estimate the effect of cost share on farmers' planting of cover crops.

Much of the prior literature examines the effect of payment among many determinants of conservation practice adoption (Prokopy et al. 2008). Many of these studies used stated preference methods to estimate farmers' willingness to adopt conservation practices (Cooper 2003; Cooper and Keim 1996; Ma et al. 2012). However, literature that is more recent makes use of observational micro-data to measure success of PES programs, including the additionality. Pufahl and Weiss

(2009) use a difference-in-difference estimator to analyze the effects of agri-environmental program participation of German farms on farm sales, finding a significant increase. Claassen, Duquette, and Smith (2018) find that additionality rates differ between best-management practices including nutrient management, conservation tillage, and buffer strips. They find higher additionality for practices that take land out of crop production and/or have higher start-up costs. Regarding cover crops specifically, Mezzatesta, Newburn, and Woodward (2013) find that the additionality rate among a sample of farmers in Ohio is 90.6 percent, while Chabé-Ferret and Subervie (2013) estimate that PES programs in France increase cover-crop acreage by 11 hectares per farm. Ongoing work by Ramírez and Arbuckle (2016) finds that receiving cost share increases both cover crop acreage and proportion of acres under cover crops among Iowa farmers.

This paper provides several contributions. First, we provide estimates on the additionality from cover-crop cost-share among Iowa farmers, adding to the limited empirical PES literature. To our knowledge, there are only two prior studies that examine the effects of cost share for cover crops in the United States (Ramírez and Arbuckle 2016; Mezzatesta, Newburn, and Woodward 2013). We improve on these past analyses by providing a better dataset to explore the research question more deeply. First, our sample size of treated adopters is larger than that of the past studies; the estimates of Ramírez and Arbuckle (2016) and Mezzatesta, Newburn, and Woodward (2013) rely on 29 and 24 cost-share recipients, respectively, whereas our data set has 91 treated individuals. Second, we use a unique data set combining responses from a cover-crop survey conducted in 2017 with the 2012 Census of Agriculture. In the survey, we ask detailed questions about farmers' practices with which we calculate partial budgets. This allows us to attempt to provide a measure of farmers' benefits from the cover-crop cost-share programs. While studies such as Chabé-Ferret and Subervie (2013) begin to develop a framework for cost-benefit evaluation of PES programs, the authors note that their analysis is unable to quantify the benefits farmers receive from the program.

We find that cost-share programs do have a positive effect on both acreage and proportion of the farm under cover crops, increasing acreage by 192 acres and proportion by 18 percent of the farm's acres. This suggests that cost-share programs generate additional adoption that would not exist in their absence.

This paper proceeds with background information about cover crops and the existing cost-share programs in Section 1. Section 2 provides a description of the econometric model and empirical analysis. Section 3 describes the survey and dataset used in the analysis. Section 4 presents the empirical results, and Section 5 concludes.

1 Background

Cover crops are planted in the fall after the cash crop to provide winter ground cover. The benefits include the reduction of nitrate and phosphorous leaching. In addition to the public benefits, there are also on-farm benefits of cover crops, including reduced soil loss, increased soil organic matter, and improved soil health (Snapp et al. 2005). However, these agronomic benefits do not necessarily translate to economic benefits, especially in the short term. Among Iowa farmers, Plastina et al. (2018b) find the additional costs from planting and terminating the cover crop amount to around $40 per acre. Moreover, yield gains are modest on average and inadequate to cover the costs, oftentimes leading to short-term profit losses.

Farmers have access to cost-share payments from several sources to help cover at least some of the additional costs due to cover crops. The United States Department of Agriculture's National Resource Conservation Service (2017) estimated that Iowa farmers planted more than 353,000 acres of cover crops in the fall of 2016 with state and federal government support. State-level financial assistance comes from the Iowa Department of Agriculture and Land Stewardship, through the Iowa Water Quality Initiative, state cost-share, and local watershed project. Federal conservation programs that provide cost share for cover crops include the Environmental Quality Incentives Program (EQIP), Conservation Stewardship Program (CSP), and Regional Conservation Partnership Program (RCPP).

Cover crop cost share programs differ in their payments, requirements, and participation length. However, programs typically have annual sign-up periods, as opposed to longer contracts. Farmers can obtain annual payments for up to three years through EQIP and five years through CSP. While EQIP is suitable for farmers just starting their conservation efforts, CSP requires farmers to have existing conservation practices. The payment amount for most programs depends on the cover-crop mixture used, and farmers are also required to follow NRCS seeding guidelines.

2 Research Design

In an ideal setting, we would be able to assign randomly whether a farmer receives a cost-share payment to plant cover crops on a specified amount of land. We would then determine the effect of cost share on cover-crop acreage by comparing the average outcomes of farmers who receive and that of those who do not receive cost share. However, such an experiment is not feasible due to both costs and ethical considerations. Due to random assignment, we would not need to worry about selection bias affecting our results. In reality, each farmer decides whether to apply for cost share and whether to plant cover crops.

Instead, to determine the causal effect of the cost-share program on cover-crop adoption, we use a matching estimator. In the analysis, we use pre-treatment information obtained from the 2012 Census of Agriculture as controls to determine the probability that a farmer would receive cost share. Then, given this estimated propensity score, we match each farmer who planted cover crops with some who did not, but have similar propensity scores as the farmer who did. We are then able to determine the treatment effect of the cost-share payment on cover crop adoption.

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 in 2015. Our two outcome variables of interest, denoted Y_i, are total cover crop acreage and proportion of farm acreage under cover crops in the 2015 planting 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 farmers who currently receive cost-share payments are intrinsically more willing to plant cover crops than farmers who do not receive cost share, even in the absence of cost-share programs: $Y_i(0) \mid T_i = 0 < Y_i(0) \mid T_i = 1$. If we simply compared averages, this would result in an upward bias of our estimate of the effect of cost share on our outcomes of interest.

Instead, we use farmer i's observable characteristics, X_i to obtain the counterfactual outcomes we do not observe. However, conditioning on observable variables poses the difficulty of matching on a large number of covariates (Rosembaum and Rubin 1985). One way to reduce dimensionality 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:

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

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

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

Second, the overlap assumption requires that no observation is certain to be treated or non-treated:

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

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.

$$ATT = E\,[Y_i(1) - Y_i(0) \mid T_i = 1] \tag{4}$$

The identifying assumption is that after conditioning on the propensity score, the covariates no longer affect treatment. However, the covariates still affect the outcome. That is, two farmers with the same probability of being treated need not have the same characteristics. Conditioning on the propensity allows for identification of individual characteristics on the outcome. Additionally, we need the treatment not to affect the outcomes of non-treated individuals. That is, an individual receiving cost share cannot affect whether farmers who did not receive cost share plant cover crops. For example, this would not hold if cost share results in 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.

2.2 Empirical Analysis

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

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

We then match each treated individual to the *m* individuals in the control group with the closest propensity scores. The average of these *m* outcomes serves as the treated individual's potential outcome in the absence of treatment. To ensure sufficient quality of matches, we add a caliper such that we only consider matches within a specified radius, *c*. The researcher chooses the caliper value with consideration of the trade-off of bias and efficiency (Cochran and Rubin, 1973; Rosembaum 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 number of matches lowers the quality, but the increase in information increases efficiency. Thus, the distance between observations is defined as

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

The ATT is calculated as follows:

$$ATT = \frac{1}{N} \sum_{i \in \{i | T_i = 1\}} [Y_i - \omega_{ij}(Y_j | D_{ij})]. \tag{7}$$

In equation , ω_{ij} is the matching weighting matrix to determine the counterfactual. In nearest-neighbor matching, ω_{ij} is the average of the outcomes of the m lowest D_{ij} for each treated observation i.

We use the standard errors proposed by Abadie and Imbens (2006), which account for the fact that the true propensity score is not known. To evaluate the model, we check the balance of the propensity scores between the treated and control groups. Additionally, we check that the covariates are well balanced between the two groups using the standardized mean difference.

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 February 1, 2017, and a second questionnaire was sent to non-respondents in mid-February 2017. Finally, those who still had yet to respond were contacted by telephone. The survey asked detailed questions on the farm operators' practices relating to the planting and termination of cover crops, their experience with cover crops, whether they received a cost-share payment, and if so the amount received. In total, 674 operators responded (a 54 percent response rate). Among the respondents, 440 farmers (65 percent) indicated that they had planted cover crops at some point.[1]

[1] We believe the large quantity of respondents without cover crop experience is primarily due to the rental cropland market and secondarily due to generational change in operators in Iowa.

Table 1: Sample Description

	Planted cover crops			Did not plant cover crops
	Frequency	Acreage	Proportion	Frequency
Cost share	137	306	0.28	-
No cost share	200	263	0.23	317

For the purpose of this paper, we focus on adopters' cover crop behavior during the 2015 planting year. This comprises the majority of farmers in our sample who had planted cover crops and allows for a consistent comparison, as it holds constant cost-share program rules, macro-economic conditions, and time passed since the most recent agricultural census. Our variables of interest are whether the farmer received a cost-share payment to plant cover crops in 2015, the payment received, total acreage planted to the most widely planted cover crop mix, and farm size[2]. We report a summary of the make-up of the respondents in Table 1. There are around the same number of adopters and non-adopters in the sample (334 vs. 340). Among the adopters, about 40 percent received cost share. We also observe that the adopters who received cost share on average planted more cover-crop acres and had a greater proportion of their acres using cover crops. Furthermore, the matching analysis requires a sufficient group of controls for each treated individual; this condition is met as we have 540 controls compared to the 134 treated observations.

The respondents also answered detailed questions related to the planting and terminating of cover crops, and how their subsequent cash-crop costs and revenues differed between fields with and fields without cover crops. We use partial-budget techniques to obtain the annual net return to incorporating cover crops in row crop production.

We then match our survey responses to the 2012 Census of Agriculture, giving us a large set of covariates. These variables are all pre-treatment, which is key to our ability to use propensity-score analysis. The covariates used include farm characteristics, operator characteristics, and operator's attitude toward conservation. We choose most of these variables based on the existing literature (Ramírez and Arbuckle 2016; Chabé-Ferret and Subervie 2013; Mezzatesta, Newburn, and Woodward 2013; Claassen, Duquette, and Smith 2018).

[2] We ask for the farm size using ranges and calculate the estimated farm size using the midpoint of the range the farmer stated.

Table 2: Summary Statistics

Variable	K-Code	Description	Cost Share Mean	Cost Share Median	No Cost Share Mean	No Cost Share Median	Significant Difference (.05 level)
Acres	K46	Total acres operated	924.16	780	711.76	481	Yes
Rented Acres	K44	Acres rented or leased from others	568.96	407	400.27	180	Yes
Farm Sales	TVP	Gross farm sales (in thousands of dollars)	984.53	599.67	715.86	301.04	Yes
Livestock	K1201, K1211, K1247, K1239	Presence of cattle; hogs and pigs; equine; sheep and goats; or other livestock on the operation (1 if present)	0.61	1	0.70	1	Yes
Poultry	K1217	Presence of poultry on the operation (1 if present)	0.10	0	0.07	0	No
Corn Acreage	K67	Corn acreage harvested for grain	419.63	329	327.88	185	No
Soy Acreage	K88	Soybean acreage harvested for grain	308.49	244	224.86	136	Yes
Cover crops	K3456	Acres planted to cover crops	157.94	100	116.27	60	Yes
Tile Drainage	K3450	Acres drained by tile	411.28	300	323.28	146.5	No
Ditch Drainage	K3451	Acres drained by ditch	37.99	0	30.92	0	No
Age	K925	Age of the principal operator (years)	56.34	57	56.62	57	No
Experience	K1834	Number of years since the principal operator began to operate on any farm	31.63	33	31.61	33	No
Off-Farm Labor	K929	Number of days worked off the farm	2.07	1	2.17	1	No
Farm Income	K1578	Percent of the principal operator's total household income from the operation	62.77	100	64.99	100	No

Note: Crop Reporting District variables are not shown

In Table 2, we describe the variables used in calculating the propensity score. All variables come from the described K-code in the 2012 Census of Agriculture. Variables describing 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 = 1*), presence of poultry (*Poultry = 1*), corn acreage (*Corn*), soybean acreage (*Soybeans*), 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. 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*), and percentage of the farmer's household income that comes from farming (*Farm Income*). Lastly, we use the USDA Crop Reporting Districts to capture regional variation. Recipients of cost share on average operated and rented more acres, had livestock less frequently, had higher gross farm sales, harvested more soybeans, and planted more cover crops in 2012. Other variables are not statistically significantly different between the treatment and control groups.

4 Results

4.1 Propensity score estimation

We present the results of the propensity score equation 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 the conservation programs. Farm size also increases the propensity score, suggesting larger farms may have more expertise dealing with government programs. Age increases the probability of receiving cost share at a decreasing rate. This differs from prior literature (Mezzatesta et al. 2013; Ramírez and Arbuckle 2016), where older farmers are less willing to invest in conservation. In addition, having livestock decreases the propensity score. Other variables are not significant at a 95 percent confidence level.

Table 3: Propensity Score Regression Results

Variable	Coefficient		Standard Error
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 Acreage	-0.0014	*	0.0008
Soy Acreage	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

4.2 Treatment effect

Table 4 presents the ATT results of the matching estimation. In our preferred model, we find that the receiving cost share increases the proportion of the farm's cover crops by 18 percentage points. We estimate that farmers who receive cost share would have planted cover crops on 9 percent of their acres in the absence of cost share, whereas they actually planted cover crops on 26 percent of their acres. Also, receiving cost share increases cover crop acres planted on the farm by 192 acres. These results are both significant at a 95 percent confidence level.

Table 4: Average Treatment Effect on the Treated Results

	Coefficient	**95% Confidence Interval**
Proportion of acres using cover crops	0.1767	[0.1498 , 0.2035]
Total cover crop acreage	192.33	[52.30 , 332.36]

4.3 Model evaluation

Table 5: Sample Balance Assessment

Variable	**Standardized Mean Difference**	
	Before Matching	After Matching
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 Acreage	0.1429	0.0777
Soy Acreage	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

We choose the model after varying the number of neighbors matched to each treated observation and the size of the caliper. In our selected model, we match to the seven nearest neighbors and use a caliper of 0.2. We examine the balance of the sample using the standardized mean difference on the matched sample. The standardized mean difference is the difference in means of the treated and control group, divided by the standard deviation of the two groups' average sample variance. Table 5 shows the standardized mean difference for each variable both before and after matching. After matching, all standardized mean differences are less than 11 percent; this is well below the 20 percent threshold that Rosembaum and Rubin (1985) deem to be a large bias. This suggests that matching corrected much of the difference in the characteristics between cost-share participants and non-participants.

5 Conclusion

In this paper, we analyze the effect of cost-share program participation on cover crop adoption. We first use data from the 2012 Census of Agriculture to calculate the propensity score, which is the probability a farmer receives cost share in 2015. Second, we match on the propensity score to estimate the effect of receiving cost share on cover-crop acreage and proportion of farmland under cover crops. We find that cost-share programs increase cover-crop acreage by 192 acres, and increase the proportion of the farm under cover crops by 18 percentage points. This suggests that cost-share programs do encourage cover-crop adoption that would not occur in their absence.

One main 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, this paper does not venture into farmers' non-economic motives for planting cover crops. Using the same survey data used in the present study, (Plastina et al. 2018c) report that on average cover-crop users in Iowa incurred annual losses of about $20 per acre in the 2015-2016 crop year when livestock was not included in the productions system. This suggests that many farmers who currently plant cover crops may have motives other than short-term profit. These could include land-value impacts and environmental stewardship, both of which have been understudied in the literature (Arbuckle and Roesch-McNally 2015). Moreover, since there is evidence that farmers adopt cover crops sans government support, even at a short-term profit loss (Plastina et al 2018a), 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.

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