Cost-Share Effectiveness in the Diffusion of a New Pollution Abatement Technology in Agriculture: The Case of Cover Crops in Iowa

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Abstract

Water quality problems remain severe across much of the United States. Improvements are particularly challenging in agricultural regions where upwards of 90 percent of the pollution load comes from sources that fall outside regulatory control under the Clean Water Act. These nutrient sources are responsible for a large "dead" zone in the Gulf of Mexico, the closure of Toledo's drinking water facility, and ubiquitous damage to recreational amenities. The promotion of a new agricultural pollution abatement technology, cover crops, through cost-share funding opportunities combined with a longitudinal data set including information on adopters both before and after introduction of the subsidy program provides a clear identification strategy to evaluate the effectiveness of funding for this promising new abatement technology. Using propensity score matching and a tobit estimator to correct for non-adoption, we find that cost-share funding significantly increases the proportion of cover crops planted and cover crops acres among both recipients of funds and among adopters.These results have critical implications for finding solutions to address persistent water quality problems with limited conservation budgets.

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1 Introduction

Water quality problems remain severe across much of the United States. According to the Environmental Protection Agency (EPA), nonpoint source (NPS) pollution is the Nation's largest source of water quality problems (EPA 2015). In the U.S., around 40 percent of surveyed rivers, lakes, and estuaries are so polluted that they are not clean enough for basic uses such as fishing or swimming (EPA 1996). Improvements in water quality are particularly challenging in agricultural regions where upwards of 90 percent of the pollution load comes from NPS that fall outside regulatory control under the Clean Water Act. These nutrient sources are responsible for a large "dead" zone in the Gulf of Mexico, the closure of Toledo's drinking water facility, the Des Moines Water Works lawsuit against three drainage counties over water quality, and ubiquitous damage to recreational amenities. In fact, despite the creation of the Hypoxia Task Force in 1997 (EPA Task Force), substantial improvements in water quality are still necessary. For example, the 2014 Gulf Hypoxia zone of oxygen-depleted bottom-water was roughly 13,000 square kilometers, an area much higher than the Hypoxia Task Force goal of 5,000 square kilometers (EPA 2014). Nitrogen and phosphorus applications in agricultural production in the Upper Mississippi River have contributed to the formation of the Gulf Hypoxia (Rabotyagov et al. 2014). Current efforts to reduce agricultural runoff into water streams that are focused on the voluntary adoption of conservation practices have not been able to achieve substantial water quality improvements. It is now clear that to address this growing problem, it will be necessary to substantially change the way agriculture is practiced over much of the Upper Mississippi River Basin. For example, Iowa developed a statewide Nutrient Reduction Strategy in 2013, which is a science and technology-based framework to assess and reduce nutrients to Iowa water and the Gulf of Mexico (Iowa NRS 2013). The strategy calls for a significant voluntary adoption of cover crops, crops that are planted between harvest and the planting of cash crops, which are able to reduce both nitrogen and phosphorus losses by approximately 30 percent (Iowa NRS

2013).

While cover crops have been widely promoted as an effective conservation practice recently, there has been little adoption in Iowa. In 2009, Iowa had fewer than 10,000 cover crops acres. In 2013, the number increased to 300,000 acres planted (Soil and Water Conservation Society 2015). In both years, the number of cover crops acres is very small relative to total corn and soybean crop land, which is around 24 million (USDA NASS 2014). These adoption statistics illustrate that cover crops are fairly new to this region and that substantial efforts must be exerted to increase conservation acres. In fact, several cost-share funding programs have promoted the adoption of cover crops. Based on the Iowa Nutrient Reduction Strategy, cost-share funding became available to implement conservation practices in 2013, including cover crops. At the same time, state and federal programs also provided cost-share funding for new adoption of cover crops. Together, this cost-share funding can be viewed as a pilot adoption program. Given the availability of cost-share and the importance of this practice for water quality, we study the effectiveness of cost-share funding in the planting of cover crops using a unique dataset with yearly farm level data on large farm operators. While the Iowa experience is relatively small, it provides an excellent source of information to draw on for other programs in areas in which cover crops are perceived as a new technology. We use matching methods combined with regression analysis to study the effectiveness of cost-share funding using the Iowa Farm and Rural Life Poll. Focusing on Iowa provides a unique opportunity to collect data on this new conservation practice in this region. Furthermore, Iowa's experience can inform the entire effort to solve the hypoxia zone problem.

Directly comparing cover crop decisions between farmers enrolled in cost-share programs and farmers who are not enrolled could result in estimates that suffer from selection bias and in incorrect policy advice concerning program expansion. To assess the effectiveness of cost-share funding, we need to know what the cover crop planting decision of farmers who received cost-share funding would have been in the absence of the funds. However, we can never observe the counterfactual (Imbens & Wooldridge 2008). Furthermore, since the participation in cost-share programs for cover crops is not random, we also face a selection problem that can come from both observable and unobservable factors. For instance, a farmer who has planted cover crops in the past might be more likely to plant cover crops today if his experience was positive. Similarly, a farmer who participates in a cover crop cost-share program may have invested in conservation practices in the past compared to a farmer who does not participate, since the former might have more experience managing conservation practices or may have lower adoption costs. We use matching methods to pair treated and untreated (control) farmers based on observable characteristics measured before treatment to overcome the selection problem and to have a valid counterfactual. Our unique dataset includes variables that have not been included in previous U.S. cost-share studies such as attitudinal and previous conservation and drainage expenditure information.

After matching and achieving covariate balance and satisfying the overlap assumption, we study two outcomes: the proportion of cover crops acres relative to total farm land and the amount of cover crops acres planted. We estimate two treatment effects: the average treatment effect on the treated and the average marginal treatment effect among adopters of cover crops. Previous studies have focused on the former, but we contribute to the literature by estimating the latter. Given the lack of adoption of cover crops in this region, it is important to take into account that most farmers are not using this practice. By differentiating between adopters and non-adopters, we are able to study the effectiveness of cost-share among farmers who are using cover crops. Our results indicate that, on average, farmers receiving cost-share increase the proportion of cover crop acres by about 20 percentage points relative to farmers who do not get the funds. For acres, we find that receiving cost-share funding induces farmers to plant more cover crops acres on average relative to non-recipients. However, the size of this effect varies between matching specifications.

In order to estimate the average marginal treatment effect among adopters, we follow a two step process. First, we use a Tobit regression on the matched data, since our outcome variables are censored at zero due to the lack of adoption of this conservation practice. The Tobit estimator corrects the bias associated with this censoring (Green 2008). Secondly, we calculate the average marginal effect of receiving cost-share among adopters. We find that, on average, receiving cost-share increases the expected proportion of cover crops by around 18 percentage points among adopters only. For cover crops acres, we find that the average marginal effect of cost-share is about 104 acres among adopters. Taking all the estimation results, we conclude that cost-share funding is effective, as it increases the proportion and acres of cover crops among cost-share recipients and adopters.

2 Literature Review

Matching methods have been employed for program evaluations related to conservation. Liu and Lynch (2011) use matching methods to study the effect of land-use policies focused on the reduction of farmland loss. Ferraro et al. (2007) study the effectiveness of the U.S. Endangered Species Act on species recovery rates using matching methods. Adam et al. (2008) estimate the effectiveness of protected area networks on deforestation rates in Costa Rica. Cooper (2005) analyzes incentive payments for adopting a bundle of best management practices. Conservation Programs have also been studied using difference-in-difference matching. Chabé-Ferret & Subervie (2013) study European Union Agro-environmental schemes implementation in France. These schemes pay farmers to adopt greener practices. They study schemes that are meant to increase crop diversity, the planting of cover crops, the planting of buffer strips, and the conversion to organic farming. Using propensity score matching and difference-in-difference, they estimate the average treatment effect on the treated. They find that the Agro-environmental scheme increases the area planted with cover crops by around 10 ha (around 24 acres) on average (Chabé-Ferret & Subervie 2013). While we would like to use a difference-in-difference approach in this study, the Iowa Farm and Rural Life Poll does not ask the same questions every year. Nonetheless, we use matching techniques on pretreatment variables that are available in our dataset.

A few papers have studied cost-share in the state of Maryland, where cover crops are an established conservation practice. Lichtenberg and Smith-Ramirez (2003) take advantage of the large amount of Maryland farmers receiving cost-share funding for a variety of conservation practices to assess the impact of cost-sharing on overall conservation effort. They study three conservation measures: an aggregate indicator of cost-share funding award, the number of conservation practices adopted, and the acreage served by those conservation practices. They take into account transaction costs, factors influencing government agencies' cost-share funding allocation process, and possible economies of scale and scope. Using full information maximum likelihood, their estimation suggests that political influence and protection of crop productivity influence cost-sharing award decisions, while the proximity to water bodies does not. Furthermore, they find that farmers receiving cost-share use fewer practices and achieve no greater conservation coverage than farmers who do not receive cost-sharing (Lichtenberg & Smith-Ramirez 2003). More recently, Lichtenberg and Smith-Ramirez (2011) study whether cost-share induces farmers to expand cultivation on more vulnerable land for three of the most commonly used conservation practices in Maryland: contour farming, strip cropping, and cover crops. They find that farmers receiving cost-share funding allocate 8 percentage points more cropland to cover crops than in the absence of the funds. Furthermore, farmers who receive cost-share funding are roughly 36 percentage points more likely to use cover crops than farmers without the funds.

Fleming (2015) also studies the direct effect of cost-share funding on cover crops acres in Maryland, but he also studies the indirect effect of cost-share on conservation tillage and contour/strip cropping acres. He employs a two-stage simultaneous equation approach to correct for voluntary self-selection in the funding programs and which accounts for substitution effects among conservation practices. He finds that cost-share funding has a positive and significant effect on cover crops acres in Maryland (Fleming 2015). These studies in Maryland differ from ours as they use data from a state in which there is more adoption of cover crops, and in which indirect effects on other conservation practices are more likely. Our paper focuses on an area in which cover crops are viewed as a new technology. Secondly, we differ in our methodologies based on the nature of the datasets employed in each analysis. While they utilize a cross section, we use the Iowa Farm and Rural Life Poll, which allows us to use information before cost-share funding is received by farmers. On the other hand, we take these Maryland studies as references in the selection of explanatory variables to control for transaction costs and the factors influencing award decision processes.

The previous research that is most relevant for this application is Mezzatesta et al. (2013), who also estimate the average treatment effect of cost-share programs and who address additionality concerns from conservation practices. They use matching techniques to estimate the average treatment effect on the treated of cost-share funding for several conservation practices, including cover crops, in Ohio using cross-sectional data. Their outcome variable is the proportion of acres under a particular conservation practice relative to total farm acres. Furthermore, they address additionality concerns by decomposing the average treatment effect on the treated according to relative contributions of adopters and non-adopters. They find that the average treatment effect on the treated of enrollment in cost-share programs is roughly 23 percentage points for cover crops. Our research utilizes a similar methodology, but we differ in the dataset employed for matching. While they use cross-sectional data, we use a unique dataset with yearly information on farmers that allows us to match treated and control units based on pretreatment characteristics, which is fundamental to obtain a valid counterfactual.

While previous research has studied cost-share funding in the United States, it has been focused on an area in which cover crops are not new and in which there is substantial adoption of the practice. We contribute to the literature by studying the planting of cover crops in an area of the United States in which this conservation practice is relatively new and in which cover crops are widely promoted to attain water quality goals at a local and regional level. Moreover, this area is extremely important as it is heavily farmed and as it contributes to both local water quality problems and the Gulf Hypoxia. Secondly, we contribute to the understanding of adoption decisions by using a unique dataset that allows us to observe characteristics prior to the allocation of cost-share funding, different than these previous U.S. studies that employ cross-sectional data. Hence, we address selection bias through matching techniques using information prior to receiving funding. Third, we also differ from these previous studies as we include attitudinal and past conservation and past drainage expenditure information in our matching process. Fourth, in addition to estimating the average treatment effect on the treated, we contribute to the literature by estimating the average marginal treatment effect among adopters. While some studies concentrate indirect effects (Lichtenberg & Smith-Ramirez 2011; Fleming 2015) of cover crops, we are able to focus on planting of cover crops on its own, given that this is a new conservation practice in this area. In essence, we are concerned about the effectiveness of cost-share funding in the sole planting of cover crops, given the little adoption in the area and the novelty of this practice in the region.

3 Background

Whereas the Iowa Nutrient Reduction Strategy is a relatively new effort that provides guidelines to improve water quality in Iowa and in the Gulf of Mexico, water quality has been promoted by both state and federal conservation programs in the past. These programs often provide cost-share incentives, in which matching funds or incentive payments are given to farmers to cover a proportion of the conservation costs. In Iowa, several cost-share program are available through USDA's Natural Resource Conservation Service (NRSC), including the Conservation Reserve Program (CRP), the Environmental Quality Incentives Programs (EQIP), the Conservation Reserve Enhancement Program (CREP), the Conservation Stewardship Program (CSP), among others. Some of these programs are focused on particular conservation practices such as land retirement in the case of CRP and wetlands in the case of CREP. Other programs promote a variety of conservation practices, including cover crops, such as EQIP or CSP. For instance, EQIP offers cost-share to first cover crop producers. Basic payment rates varied from roughly \$24 to \$35 per cover crop acre depending on the type of cover crop seed employed by the farmer (USDA NRCS 2013).

In August of 2013, \$2.8 million became available statewide to implement conservation practices based on the Iowa Nutrient Reduction Strategy through the Water Quality Initiative (Iowa NRS 2014). The funds were allocated for practices that could be implemented in a short time, with the goal of providing water quality benefits in 2013 and spring of 2014 (Iowa NRS 2014). One of practices that was promoted through this cost-share program was cover crops with a payment rate of \$25 per acre (Swoboda 2013). According to the Iowa NRS 2013-2014 Annual Progress Report, roughly 95,000 acres of cover crops were established through this state cost-share program. This number is very small relative to the total amount of corn and soybean crop land, which is around 24 million acres in Iowa (USDA NASS 2014). Overall, roughly 230,000 acres of cover crops were planted through both Federal and State cost-share program in 2013, capturing around 75 percent of total cover crop acres for that year. Given the availability of cost-share funding in 2013, we use a unique data set to assess the effectiveness of cost-share funding in the planting of cover crops.

4 Methodology

For the estimation of treatment effects, we would like to know the way the treatment participant would behave in the absence of the treatment as first formalized by Rubin (1974). The treatment effect for individual i is the comparison of i's outcome with treatment, denoted by $Y_{1,i}$, and i's outcome without treatment, denoted by $Y_{0,i}$. The fundamental problem when estimating treatment effects is that we only observe one of these potential outcomes for each individual (Holland, 1986). Basically, when estimating causal effects, we face a missing data problem, so we need to predict the unobserved potential outcomes (Rubin, 1976). In order to estimate treatment effects, $E(Y_1 - Y_0|X)$, we compare treated and control individuals that are very similar. Following Rosenbaum and Rubin (1983) and Heckman et al. (1998), two assumptions are made to estimate treatment effects: (1) strong ignorability assumption, in which the treatment assignment, denoted by T, is independent of potential outcomes (Y_0, Y_1) given the covariates X (i.e. $T \perp (Y_0, Y_1)|X$); and (2) overlap assumption, in which there is a positive probability, denoted by $P(T = 1)$ of receiving each treatment for all values of X (i.e. $0 < P(T = 1|X) < 1$ for all X). A weaker version of (1), in which $E(Y_0|X, T) = E(Y_0|X)$ and $E(Y_1|X, T) = E(Y_1|X)$, suffices for estimating the average treatment effect on the treated, defined as $ATT = E(Y_1 - Y_0|X, T = 1)$. For our research question, we focus two outcome variables: Y^1 which is the proportion of cover crops planted relative to total farm acreage and Y^2 which is the amount of acres of cover crops planted. The treatment indicator, T, is defined as follows:

$$T = \begin{cases} 1 & \text{if farmer is enrolled in cost-share program} \\ 0 & \text{if farmer is not enrolled in cost-share program} \end{cases}$$

In order to estimate treatment effects, the literature suggests a two-step process. To start, researchers use pretreatment information to select comparable treated and control units to analyze the treatment effect without using the outcome variable. Secondly, using the matched sample, researchers estimate treatment effects (Stuart & Rubin 2008). For the first step, matching techniques are employed to balance the distribution of covariates in the treated and control groups (Stuart 2010). In essence, by controlling for pretreatment differences between treatment and control, researchers are able to reduce bias by using a valid counterfactual. For the second step, researchers estimate treatment effects. We are interested in estimating two effects: the average treatment effect on the treated and the average marginal treatment effect among adopters. For the first, we estimate the ATT directly using a propensity score estimator:

$$\widehat{ATT} = \frac{1}{N_1}\left[\sum_{i \in I_1 \cap S_p}\left[Y_{1,i} - \hat{Y_{0,i}}\right]\right] \tag{1}$$

with

$$\hat{Y_{0,i}} = \sum_{j \in I_0} \hat{W}(i,j) Y_{0,j}$$

where Y is either Y^1 or Y^2, I_1 denotes the set of treatment observations, I_0 denotes the set of control observations, N_1 is the number of treated observations, S_p denotes the region of common support, and $\hat{W}(i,j)$ are the weights that depend upon the distance between the propensity scores for i and j and the number of matches per treatment observation. To assess the estimation results, researchers use Abadie and Imbens robust standard errors, which take into account that the propensity score is estimated.

To estimate the average marginal treatment effect among adopters, we use the matched data and regress the outcome variable on the treatment status and other relevant covariates. Matching methods and regression adjustment models can complement each other (Rubin & Thomas 2000, Glazerman, Levy & Myers 2003, Abadie & Imbens 2006). Intuitively, by selecting matched samples, the bias due to covariate differences is reduced and regression analysis for remaining small covariate differences increases the efficiency of treatment estimates (Stuart & Rubin 2008) and makes results less sensitive to model specifications (Ho et. al. 2007).

For the first step, propensity score matching is typically employed in non-experimental studies to attain balance and overcome the selection problem (Rosenbaum & Rubin 1983). First, a propensity score is calculated, which is each individual's probability of being included in the treatment, and it is calculated using observed covariates, X (Wooldridge 2010). Smith and Todd (2005) recommend the inclusion of covariates that influence both treatment status and outcome when estimating the propensity score. As emphasized by Ho et. al. (2007), the selection of covariates to be included in regressions can be based on previous research (i.e. Chabé-Ferret & Subervie 2013, Mezzatesta et al 2013, and Lichtenberg & Smith-Ramírez 2003, 2011) and scientific understanding. Furthermore, using covariates measured prior to treatment assignment is fundamental to avoid including variables that may have been affected by the treatment (Stuart & Rubin 2008).

Choosing appropriate covariates, nearest neighbor propensity score matching, and genetic matching are employed to obtain valid counterfactuals. Under nearest neighbor propensity score matching, best controls are found by minimizing a distance measure, the propensity score, for each treated unit one at a time (Ho et al. 2011). Genetic matching is a multivariate matching method that maximizes the balance of covariates across treatment and control (Diamond and Sekhon 2012). In essence, the method minimizes the discrepancy between distribution of potential cofounders in the treated and control groups, which allows for a maximized covariate balance (Sekhon 2011)[1].

We use *teffects psmatch* and *GenMatch* (Sekhon 2012) to estimate the ATT directly using nearest neighbor propensity score matching and genetic matching respectively and to estimate Abadie and Imbens (2012) robust standard errors. The latter take into account

[1] We use *teffects psmatch* in Stata and *GenMatch* (Sekhon 2012) in R to match treatment and controls

the usage of estimated treatment probabilities in the matching process. For nearest neighbor propensity score matching, we utilize several matching specifications, including both probit and logit propensity scores, caliper levels, and number of neighbors to be matched per treated observation. For genetic matching, we also try several specifications including number of neighbors, boots, and population size. To assess covariate balance, we compute standardized mean differences and variance ratios between treatment and control. To verify the overlap assumption, we plot kernel density plots of the propensity scores for both matched and raw datasets.

After data is matched and covariate balance and overlap are attained, we employ a Tobit regression since our outcomes are censored at zero for a significant fraction of the observations. For censored dependent variables, using conventional regression methods such as OLS yield biased results (Greene 2008). Under the standard Tobit model (Tobin 1985), the dependent variable is left censored at zero.

$$Y_i = \beta_0 + \beta_T T_i + X_i^{'} \beta + \varepsilon_i \tag{2}$$

$$Y_i = \begin{cases} 0 & \text{if } Y_i^* \leq 0 \\ Y_i^* & \text{if } Y_i^* > 0 \end{cases} \tag{3}$$

where i indicates the observation, Y_i^* is the latent variable, $X_i^{'}$ is a vector of explanatory variables, T_i is the treatment, β is a vector of unknown parameters, and ε_i is the error term. Both Y^1 and Y^2 are censored at zero, since many farmers report zero cover crops acres. Likewise, no farms report planting cover cover crops on a 100 percent of their acreage, making $Y^1 < 1$ for all farmers. When estimating the treatment effect through these Tobit models, we apply the same set of covariates utilized in the matching process, X, to control for remaining covariate differences. To conclude the analysis, we focus on the average marginal effect of the treatment indicator among uncensored observations:

$$\frac{\partial E[Y|Y>0]}{\partial T} = \beta_T \left[1 - \lambda(\alpha)\left(\frac{X_i\beta}{\sigma} + \lambda(\alpha)\right)\right] \tag{4}$$

where $\lambda(\alpha) = \frac{\phi\frac{X_i\beta}{\sigma}}{\Phi\frac{X_i\beta}{\sigma}}$ is the Inverse Mills Ratio, σ is the Tobit scale, $\Phi()$ is the standard normal cdf and $\phi()$ is the standard normal pdf. This marginal effect indicates the treatment effect on uncensored observations (i.e. on observations where $Y > 0$). However, since we are interested in the marginal effect of the treatment indicator, we compute the average discrete first-difference between treatment and control for the expected uncensored outcome using Stata's *margins*, which takes into account the matching weights and uses the Delta-method to calculate standard errors.

5 Data

We use data from the Iowa Farm and Rural Life Poll (IFRLP) to estimate the effect of cost-share programs in the planting of cover crops in Iowa, which provides us with a unique opportunity to learn about this emerging conservation practice. The IFRLP is an annual longitudinal survey of Iowa farmers that started in 1982, which has a sample of roughly 2000 large operators that are repeatedly sampled. This survey is the longest-running survey of its kind in the United States (Arbuckle, Jr. et al. 2013). Iowa State University Extension in partnership with Iowa Agricultural Statistics and the Iowa Department of Agriculture and Land Stewardship are in charge of the survey. They mail the survey to the same group of farmers every spring. Nonetheless, as a response to attrition due to retirement and other factors, new samples are randomly drawn from the Census of Agriculture master list to refill the panel sample. As these new samples are drawn, smaller-scale farmers often decide not to participate. Arbuckle (2013) compares IFRLP (2008) and the Census of Agricultural statistics (2007) for Iowa and finds that the IFRLP sample has large-scale farmers. As in Arbuckle's (2013) study, this concentration of large farm operators is beneficial for our research purposes as large-scale farms operate a substantial amount of acreage relative to small-scale farms. Furthermore, we want to make sure our study captures large farmers, who ultimately have a larger impact on the environment.

The IFRLP focuses primarily on conservation-related policy, decision making, behavior, and attitudes among farmers. Questions from the annual survey are often developed in consultation with public agency stakeholders such as the Iowa Department of Natural Resources, the Iowa Department of Agriculture and Land Stewardship, and the USDA NRCS and are focused on a few particular subjects each year. The surveys are meant to facilitate the development and improvement of research and extension programs and to help local, state, and national leaders in their decision-making process (Arbuckle et al. 2011). For our analysis, we use data from the 2010 and 2011 polls, which provide pretreatment covariates.[2] In addition, the 2014 poll is used since it contains information for our outcome variables and identifies which farmers received cost-share funding to plant cover crops, which determines our treatment variable. We construct the proportion of cover crops using information on cover crops acres and the aggregate of responses on the amount of farmland acres devoted to several farming categories. Lastly, the 2014 poll also contains some pretreatment variables that do not change after harvest, when cover crop decisions are made and when cost-share is received. Using this data, we study the effect of cost-share funding on our two outcome variables.

Based on the 2014 poll alone with over one thousand observations, roughly 14 percent of surveyed farmers stated that they planted cover crops in 2013. The mean among cover crops adopters was 98 acres (IFRLP 2014). The majority use cover crops on less than 100 acres of their land. After merging the polls from 2010, 2011 and 2014, we have 588 observations.

[2] Each poll contains questions about the previous year

While we lose observations by merging the responses from the three years, we proceed with the merging because we want to match based on pretreatment variables from the older surveys. Once we exclude observations with missing variables or inconsistent responses, our final sample is 530 observations. Table 1 summarizes adoption among these observations. With this subset of the polls, we observe that roughly 17 percent of respondents adopted cover crops in 2013. There are almost twice as many adopters without cost-share as with this funding.

Focusing on our outcome variables, Table 2 contains summary statistics among those who adopted cover crops from the merged surveys. For the proportion outcome, the mean is around 20 percent, and the median is roughly 12 percent for the whole dataset, showing that most farmers fall below the average proportion. Among cost-share recipients, the mean proportion is around 24 percent, which is about 5 percentage points higher than the mean among non-recipients. The range of the proportion is between 0.2 percent and 80 percent among all farmers, which is larger than the range among cost-share recipients. For acres, Table 2 shows that adopters planted around 109 acres in 2013. Among cost-share recipients only, an average of 119 acres were planted in 2013, which is about 15 acres higher than the mean among non-recipients. The range goes from 1 to 1700 acres among all farmers and among non-recipients. It is worth noting the large difference between maximum acres among recipients and non-recipients. First, we observe that the maximum of the whole dataset comes from a non-recipient of cost-share. Secondly, we observe that the maximum was 1700 and 500 among non-recipients and recipients respectively, illustrating a large difference between both groups. While non-recipients have a larger maximum, the average is higher among recipients. It is plausible that some of these summary statistics for non-recipients are substantially influenced by this maximum. In fact, half of the farmers without cost-share planted fewer than 35 acres. In contrast, the median among cost-share recipients was 75 acres. Despite having a much larger maximum acres among non-recipients, the remaining summary statistics are higher among cost-share recipients. From these tables, we observe that while there are more non-recipient adopters, their amount of acres planted are substantially lower relative to the acres planted among cost-share recipients.

To match treatment observations to valid counterfactuals, we use a list of covariates that affects both treatment and outcome variables. Following the literature, we use similar covariates as previous studies (Chabé-Ferret & Subservie 2013; Mezzatesta et al. 2013; and Lichtenberg & Smith-Ramírez 2003 & 2011) as well as additional variables available in the IFRLP. For instance, we include whether a farmer believes that Iowa farmers should do more to reduce nutrient and/or sediment runoff into waterways. We also include variables capturing whether the farmer had incurred in any costs associated with conservation practices and whether the farmer had any expenditure associated with agricultural drainage over the last 10 years in 2010. Our covariates occurred prior to receiving cost-share funding and prior to planting cover crops in 2013.

Table 3 describes each covariate used in the matching process and subsequent Tobit models, displaying a combination of demographic and farm characteristics as well as some conservation information that might affect the enrollment into the cost-share program and the subsequent cover crops planting decision. Pretreatment outcome variables are ideal explanatory variables to include in both matching and regression models. However, we do not have information about previous cover crops acres planted. As a proxy, we use an indicator variable that captures the farmers who adopted cover crops in the last five years prior to 2010. Farm and farming characteristics such as soil erosion problems, the presence of water running through or along the farm, farm size, proportion of farm acreage rented, the management of livestock, gross farm sales, and the proportion of farm acreage devoted to grain crops are included to help predict program enrollment as well as outcome variables. We emphasize the importance of soil erosion problems, as this indicator variable is influenced by soil erodibility, slope gradient and length, vegetation, conservation measures, and rainfall intensity and runoff. In particular, the higher the slope, the greater the amount of soil erosion by water. Moreover, cover crops help decrease soil erosion. We also include location information to capture some of the differences among geographic locations based on weather, soil characteristics, and other factors that are different among agricultural districts. Demographic and labor information such as age, experience, farm income, education level, and the number of days worked off farm are also included. Lastly, we include farmers' attitudes towards reducing nutrient or sediment runoff into waterways and previous conservation costs and drainage expenditures. The latter is included since land with little slope is more likely to require drainage systems.

Table 4 summarizes the explanatory variables prior to any matching process, showing some statistical significant difference in means between treated and control groups prior to matching. For instance, the sample mean of the dummy variable indicating water running on or along the farm is 0.90 for farmers receiving cost-share funding and 0.72 for farmers not receiving cost-share funding, a difference that is significantly different at a 1 percent level. The difference on the natural log of farm land is significantly different among treatment and control groups at the 5 percent level. Lastly, differences in age, age squared, and the indicator variable for prior use of cover crops are significantly different at a 10 percent level. This table illustrates the importance of matching before any treatment analysis, since the treatment and control groups exhibit explanatory variables that are significantly different.

6 Matching Results

For the first step of our analysis, we try different specifications of two matching algorithms: nearest neighbor propensity score matching and genetic matching. We use different caliper levels, discarding options, distance measures (i.e. Logit, Probit, and Mahalanobis), and different number of control units to match to treated observations. As emphasized by Stuart (2010), we choose the best matched data set without using the outcome variable. For this section, we report results from the best matching method for our data. Robustness checks based on other matching methods are reported under the Robustness Checks Section.[3] We choose the best method based on the lowest standardized mean differences among all covariates and the verification of the overlap assumption. We obtain the best matching result using nearest neighbor propensity score matching with a probit propensity score, five nearest neighbors, no caliper, and allowing for replacement of controls.

We first report the probit propensity score results in Table 5. The probit estimation shows that having planted cover crops in the five years prior to 2010 has a positive effect in receiving treatment and its coefficient is statistically significant at a 1 percent level. Farm size and having water going through or along the farm also have a positive effect and their coefficients are statistically significance at a 5 percent level. The sign and significance of these coefficients are intuitive. In particular, farm size is a piece of information that is included in cost-share application processes and that is used by administrative bodies making cost-share award decisions. As explained by Lichtenberg and Smith-Ramírez (2003), we expect farm size to increase the likelihood of receiving cost-share, since larger farm operators are probably more knowledgeable about farm programs, more experienced dealing with government officials and application processes, and more influential politically. As far as the presence of water bodies, they explain that proximity to water bodies should be a decision criteria for awarding cost-share funds. They hypothesize that the coefficient on this water indicator should be positive and statistically significant, which is observed in our regression results. Looking at other explanatory variables, age affects treatment selection negatively, meaning that younger farmers are more likely to enroll in a cost-share program for cover crops. This negative relation has been observed in previous studies (Lichtenberg & Smith-Ramírez 2003 and Mezzatesta et al 2013), and it is explained by shorter time horizons and possibly resis-

[3]Results from other matching methods are available upon request.

tance to change among older farmers. In contrast, farm experience increases the likelihood to enroll in the cost-share program. This positive relation is also observed by Lichtenberg and Smith-Ramírez (2003). More experienced farmers are likely to be more knowledgeable about conservation funding opportunities and application processes, decreasing their application transaction costs and increasing their likelihood of applying and subsequently receiving funding.

After matching using the specified method, we have 29 treated units matched to 117 control units for a total of 146 observations. Table 6 summarizes the standardized mean differences and variance ratios between treatment and control for all covariates. The former is the difference in sample means between treatment and control groups divided by the standard deviation of the average sample variance of both groups. The highest absolute standardized mean difference is 0.12. Only three covariates have absolute standardized mean differences above 0.10. Following Rosenbaum and Rubin (1985), absolute standardized mean differences below 0.20 are desirable. Moreover, according to Rubin (2001), each variance ratio should be between 0.5 and 2, since a ratio for a perfectly balance covariate is 1. Table 6 also summarizes the variance ratios of the matched sample showing that every ratio falls within the desired range. Figure 3 provides a graphical illustration of the improved balance of the variance ratios. After matching, we observe that variance ratios lie within the desired range of 0.5 and 2. Based on both standardized mean differences and variance ratios of covariates, we conclude that we attain a good balance.

To assess the common support of the matched sample, we use Figure 1, which depicts the overlap of the propensity scores between treatment and control groups before and after matching. Figure 1 displays the estimated propensity scores of treated, depicted in red, and control units, depicted in blue, for both raw and matched datasets, which illustrates the overall distribution of propensity scores in treated and control groups. From this figure, we observe that matched treated and control units have overlapping propensity scores, which is illustrated on the right panel. We also illustrate that the overlapping assumption is satisfied through two box plots of the estimated propensity scores before and after matching. Figure 2 shows the box plot of the estimated propensity scores from the raw treated and control groups on the left and the matched sample on the right. We can see that matched treated and control groups look very similar after matching.

7 Results

7.1 Estimation Results for the Proportion of Cover Crops Planted Relative to Total Farm Acreage

After finding the matching method that attains the best balance among treatment and control groups, we estimate two treatment effects. First, we directly estimate the average treatment effect on the treated. Secondly, we use a Tobit regression to estimate the average marginal treatment effect among adopters of cover crops. For the first method, we estimate the average treatment effect on the treated directly using equation (1), as explained in the methodology section. We take into account matching weights and compute Abadie and Imbens robust standard errors, which take into account that the propensity score is estimated. Estimation results are summarized in Table 7. We find that for cost-share funding recipients, getting the funding increases the proportion of cover crops planted by 20 percentage points on average relative to farmers who do not obtain any funds. This estimation result is statistically significant at the 1 percent level.

Since the proportion of cover crops planted is censored at zero due to common non-adoption of cover crops, we utilize a Tobit model to secondly estimate the average marginal treatment effect of cost-share funding on the proportion of cover crops acres relative to total farm acreage (Y^1) among adopters, as explained in the methodology section. For the Tobit regression, we use the weights from the matching procedure and employ the same set of covariates used in the matching process (X) in addition to the treatment indicator (T). Table 9 summarizes the results from the Tobit regression on the proportion of cover crops acres. We observe that the treatment indicator (i.e. T = cost.share.I) affects the proportion positively, and its coefficient is statistically significant at a 1 percent level, confirming the effectiveness of cost-share funding in the planting of cover crops. Other covariates are statistically significant, correcting for residual covariate imbalance between the groups (Ho et. al. 2007).

In order to assess the magnitude of the effectiveness of cost-share funding among adopters, we compute the average marginal treatment effect on the expected proportion of cover crops acres planted. While estimating the marginal effect, we focus on uncensored observations (i.e. adopters) and we take into account the weights from the matching procedure and the discrete nature of the treatment indicator. Table 10 summarizes the average marginal treatment effect and its standard error, which is calculated using the Delta-Method. The average marginal effect of receiving cost-share funding on the expected proportion of cover crops acres planted is around 18 percentage points among adopters, which is statistically significant at the 1 percent level. In other words, on average, we expect that farmers receiving cost-share increase the proportion of cover crops planted by 18 percentage points of their acreage relative to cover crop adopters who do not receive cost-share funding. Comparing both treatment estimations, we find that both are positive, statistically significant and similarly sized. We conclude that having cost-share funding increases the proportion of farm land devoted to cover crops among cost-share funding recipients and among adopters.

7.2 Estimation Results for Cover Crop Acres Planted

As with the proportion of cover crops, we follow the same estimation methods for assessing the effectiveness of cost-share funding in the amount of cover crops acres (Y^2), our second outcome variable. We first estimate the average treatment effect on the treated directly and find that receiving cost-share funding increases cover crops acres by roughly 81 acres. In other words, cost-share funding induces farmers to plant an additional 81 cover crop acres compared to non-recipient farmers on average. Using Abadie and Imbens robust standard errors, we find that this coefficient is statistically significant at the 5 percent level. Results from this estimation are summarized in Table 12.

Secondly, we use a Tobit regression to estimate the average marginal treatment effect on expected cover crops acres among adopters. Again, we use the weights from the matching procedure and regress the outcome variable on the same set of covariates using the matching process (X) as well as the treatment indicator (T). Table 14 summarizes the results from the Tobit regression and shows that the coefficient on the treatment indicator is positive and statistically significant at the 1 percent level, confirming cost-share effectiveness in the planting of cover crops. Lastly, to assess the magnitude of the effectiveness of cost-share funding among adopters, we find that the estimated average marginal treatment effect is around 104 acres, which is summarized in Table 15. On average, we expect that farmers receiving cost-share increase the planting of cover crops by 104 acres relative to cover crop adopters who do not receive cost-share funding. We use the Delta-Method to calculate standard error and take into account the discrete nature of the treatment indicator. We find that the average marginal effect is statistically significant at the 1 percent level. Comparing the estimated ATT and the estimated average marginal treatment effect among adopters, we find that both are positive and statistically significant, but that they differ in size. We also find that the confidence interval for the estimated ATT is larger than the one for the estimated average marginal treatment effect. We conclude that having cost-share funding increases cover crops acres among adopters and cost-share funding recipients, but the magnitude of each effect is different among both subsets, with the effect among adopters having a smaller confidence interval.

8 Robustness Checks

As robustness checks, we repeat each estimation using different matched datasets from other matching specifications that attain a good balance during the first step of our research analysis. Nearest neighbor propensity score matching with a probit propensity score, four nearest neighbors, a 0.20 caliper, and allowing for replacement of controls also provides a decent balance. The lowest absolute standardized mean difference is 0.13.[4] Furthermore, nearest neighbor propensity score matching with a logit propensity score, five nearest neighbors, a 0.20 caliper, and allowing for replacements offers a decent match. The lowest standardized mean difference under this matching model is 0.19, which is higher than the other two matching models [5]. Lastly, we also include results from a genetic matching (Sekhon 2011) model with five neighbors and allowing for replacement.[6]. This matching method did not attain the best balance, with the highest absolute standardized mean difference being .33. However, we decide to include the best matching outcome under the genetic algorithm method. Tobit regressions are run for each outcome variable using each matched data set. For the six regressions, the coefficient on the treatment indicator is positive, and it is statistically significant at the 1 percent level. Hence, we conclude that the sign and statistically significance of the treatment indicator does not vary across matching specifications.

[4]Complete matching results are available upon request
[5]Complete matching results are available upon request
[6]Complete matching results are available upon request

For the proportion outcome variable, Table 8 summarizes estimated ATT coefficients under the three methods. We find that the second best matching method, displayed on the first row of the table, has the same estimated ATT coefficient, 0.20, as our main results in Table 7. With the other two matching methods, the estimated ATT is 2 percentage points higher than the estimated coefficient from the best matching model. Overall, all the coefficients are statistically significant at the 1 percent level and they are similar in size. We therefore conclude that receiving cost-share funding increases the proportion of cover crops acres by around 20 percentage points among funding recipients relative to non-recipients. Switching from recipients to adopters only, Table 11 shows the estimated average marginal treatment effect on the expected outcome under each matching specification. We observe that the three estimated effects are very similar in size and are slightly higher than the marginal treatment effect estimated under the chosen matching model displayed in Table 10. It is worth noting that these marginal effects are similar to the estimated ATT under each method. We conclude that cost-share funding increases the proportion of cover crops planted by roughly 20 and 18 percentage points among funding recipients and adopters respectively.

For acres of cover crops planted, Table 13 summarizes estimated ATT coefficients under each matching specification. We observe that using the second best matched dataset, the estimated ATT is around 74 acres, which is statistically significant at the 1 percent level, and it is around 7 acres lower than the estimated ATT using the best matched dataset (See Table 12). For the other two matching specifications, the ATT coefficients are similar in size, but they are around 20 acres higher than the estimated ATT from Table 12. We conclude that having cost-share funding increases the amount of acres planted among recipients, but the magnitude of its effect differs between matching specifications. These differences might be explained by the large 95 percent confidence interval for the estimated ATT from Table 12. Switching from recipients to adopters only, Table 16 summarizes the estimated average marginal treatment effect results from the three matching specifications. We observe that the estimated effects are similar in size and statistically significant at the 1 percent level. They are also very similar to the main results from Table 15, showing less variation compared to estimated ATTs. We also note that the 95 percent confidence interval is smaller in Table 15 compared to Table 12. We conclude that receiving cost-share funding increases the expected amount of acres planted by around 104 acres among adopters of cover crops relative to those who do not obtain cost-share funding.

9 Conclusions

Cover crops have been promoted to address agricultural water pollution at local and regional levels through Federal and State conservation programs. Based on the Iowa Nutrient Reduction Strategy, in August of 2013, additional cost-share funding became available to establish cover crops, among other conservation practices, with the goal of providing water quality benefits in 2013 and spring 2014 (Iowa NRS 2014). The availability of cost-share funding provides a unique opportunity to study micro-level adoption decisions of this emerging technology in this region. Specifically, we use matching methods combined with regression analysis to study the effectiveness of cost-share funding on the proportion of cover crops acres planted relative to total farm acreage and the amount of cover crops acres planted using a unique dataset that contains yearly information on large farm operators.

Following a two-step process, we first match treated and control units based on pretreatment information using a variety of matching specifications and two matching algorithms: nearest neighbor propensity score matching and genetic matching (Sekhon 2012). We choose the best matched data set based on standardized mean difference, variance ratios, and the overlap of propensity scores between treatment and control groups. For the second step, we estimate two treatment effects for both outcomes (i.e. proportion and acres): the average treatment effect on the treated and the average marginal treatment effect among adopters. For the former, we estimate the ATT directly and use Abadie and Imbens robust standard errors. For the latter and given that our outcomes are censored at zero, we use a Tobit model in which we regress each outcome variable on the treatment indicator and other relevant covariates. We then estimate the average marginal treatment effect among uncensored observations.

We find that receiving cost-share funding has a positive effect on both cover crops acres and on the proportion of cover crops. In particular, receiving cost-share funding increases the proportion of cover crops acres by around 20 percentage points among recipients of the funds on average. The program also increases acres among recipients of the funds, but the estimated size effect varies by matching method. Focusing on adopters only, we use Tobit regressions and find that the treatment coefficients are statistically significant at the 1 percent level for each expected outcome variable, implying that receiving cost-share acres has a positive effect on cover crop acres and on the proportion of cover crops even when controlling for high non-adoption of cover crops. For the average marginal treatment effects, we find that, on average, we expect that farmers receiving cost-share increase the proportion of cover crops by around 18 percentage points relative to cover crop adopters who do not receive funds. For acres, the results show that, on average, we expect farmers receiving cost-share to plant an additional 104 cover crops acres relative to cover crop adopters without funding. In the end, cost-share funding is effective in increasing cover crops acres and the proportion of cover crops planted among both recipients of the funds and adopters of cover crops. Since cost-share is effective in increasing the planting of cover crops, policy makers concerned about water pollution from agriculture in this region, where cover crops are relatively new, could allocate more cost-share funds to this practice. These results could assist policy makers in finding effective solutions to address persistent water quality problems with limited conservation budgets.

10 Tables and Figures

10.1 Summary Statistics Iowa Farm and Rural Life Poll

Table 1: Cover Crops Adoption

Number of Non-adopters	Number of Adopters with Cost-Share	Number of Adopters without Cost-Share	Number of Observations
442	29	59	530

Table 2: Summary Statistics for Cover Crops Outcome Variables among Adopters

Outcome Variable	Subset	Min	Median	Mean	Max
Y^1: Proportion	All	0.002	0.1237	0.196	0.80
Y^1: Proportion	Cost-Share=1	0.017	0.186	0.244	0.80
Y^1: Proportion	Cost-Share=0	0.002	0.068	0.172	0.80
Y^2: Acres	All	1	45	109.20	1700
Y^2: Acres	Cost-Share=1	8	75	119.17	500
Y^2: Acres	Cost-Share=0	1	35	104.27	1700

This table focuses on the behavior of adopters only (i.e $Y^1 > 0$ and $Y^2 > 0$).

Table 3: Explanatory Variables Description

Covariate	Definition
cover.crops.2010.I	=1 if farmer planted cover crops in the last five years prior to 2010
water.on.or.along.farm	=1 if farmer indicated that creeks, streams, or rivers run through or along the farm
soil.erosion	=1 if farmer indicated to have had significant soil erosion on any of his or her land in the last five years in 2011
attitude.reduction	=1 if farmer believes that Iowa farmers should do more to reduce nutrient or sediment runoff into waterways
conservation.costs.I	=1 if farmer had incurred in any costs associated with conservation practices (excluding tile or similar drainage systems) over the past 10 years in 2010
drainage.expenditure.I	=1 if farmer had any expenditure associated with agricultural drainage systems over the past 10 years in 2010
log.ag.land	natural log of total farm acreage operated in 2013
rented	proportion of farm acreage rented in 2013
labor.off.farm	number of days worked off the farm in 2009
gross.farm.sales.I	=1 if farmer had gross farm sales above $250,000 in 2009
farm.income.I	=1 if percent of total net household income from the farm was above 51% in 2009
age	age of farmer
age.sq	age squared
college	=1 if the highest level of education completed was at least a Bachelor's degree in 2011
Central	=1 if farm is located in Central Agricultural District
East.Central	=1 if farm is located in East Central Agricultural District
West.Central	=1 if farm is located in West Central Agricultural District
North.Central	=1 if farm is located in North Central Agricultural District
North.East	=1 if farm is located in North East Agricultural District
North.West	=1 if farm is located in North West Agricultural District
South.Central	=1 if farm is located in South Central Agricultural District
South.West	=1 if farm is located in South West Agricultural District
livestock.I	=1 if farmer managed livestock in 2013
exp	number of years farming in the USA
exp.sq	experience squared
grains	proportion of farm acreage devoted to grain crops in 2013

Table 4: Summary Statistics of Explanatory Variables

	Treatment	Control	Difference in Means
cover.crops.2010.I	0.24	0.09	0.15 *
water.on.or.along.farm	0.90	0.72	0.18 ***
soil.erosion	0.31	0.28	0.03
attitude.reduction	0.83	0.83	0.00
conservation.costs.I	0.59	0.51	0.08
drainage.expenditure.I	0.59	0.54	0.05
log.ag.land	6.14	5.63	0.51 **
rented	0.37	0.32	0.05
labor.off.farm	90.48	78.94	11.54
gross.farm.sales.I	0.38	0.28	0.10
farm.income.I	0.52	0.51	0.01
age	62.66	66.18	-3.52 *
age.sq	4025.28	4463.62	-438.34 *
college	0.38	0.34	0.04
Central	0.17	0.14	0.03
East.Central	0.07	0.14	-0.07
West.Central	0.10	0.12	-0.02
North.Central	0.10	0.13	-0.03
North.East	0.17	0.12	0.05
North.West	0.14	0.14	0.00
South.Central	0.14	0.06	0.08
South.West	0.07	0.07	0.00
livestock.I	0.28	0.24	0.04
exp	39.79	41.40	-1.61
exp.sq	1671.17	1852.33	-181.16
grains	0.83	0.78	0.05

*** Significant at 1% level
** Significant at 5% level
* Significant at the 10% level
Statistical significance is based on Welch Two Sample t-tests.

Figure 1: Balance Plot of Propensity Score

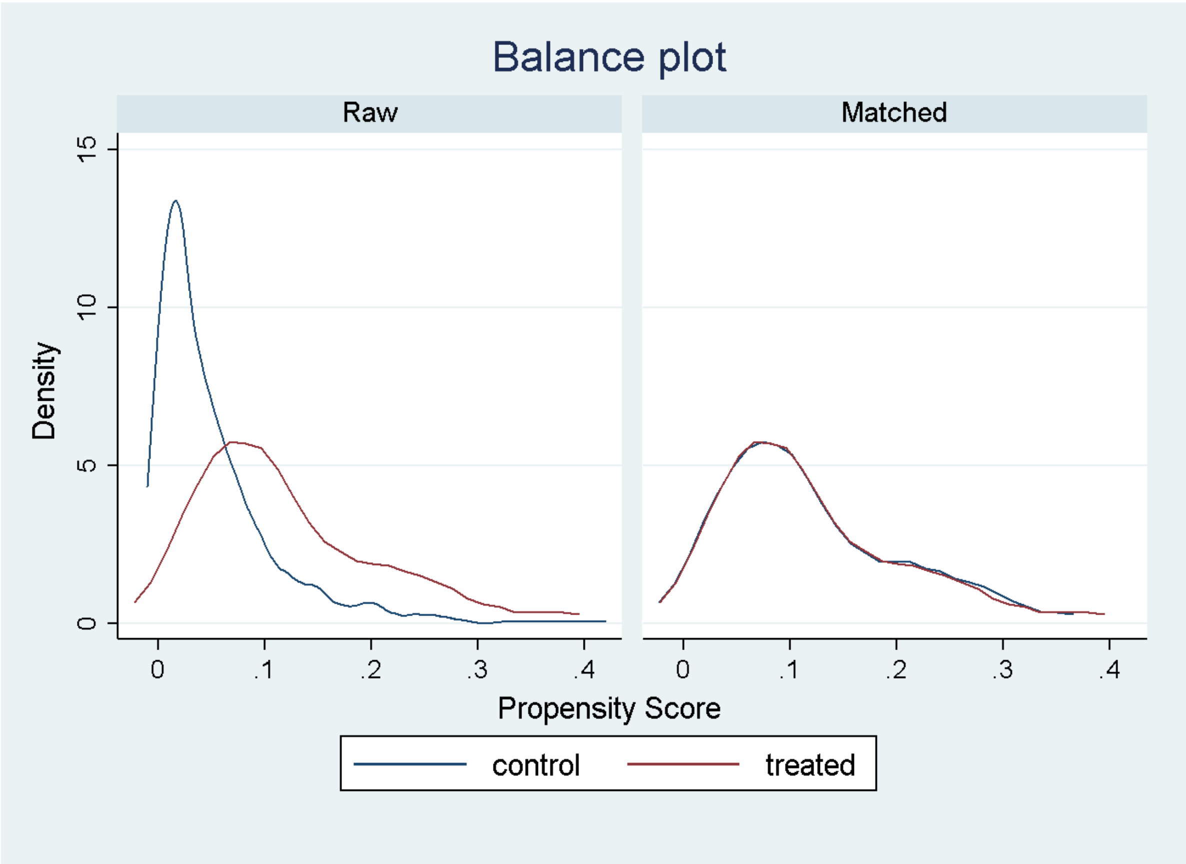

Figure 2: Box Plot of Propensity Score

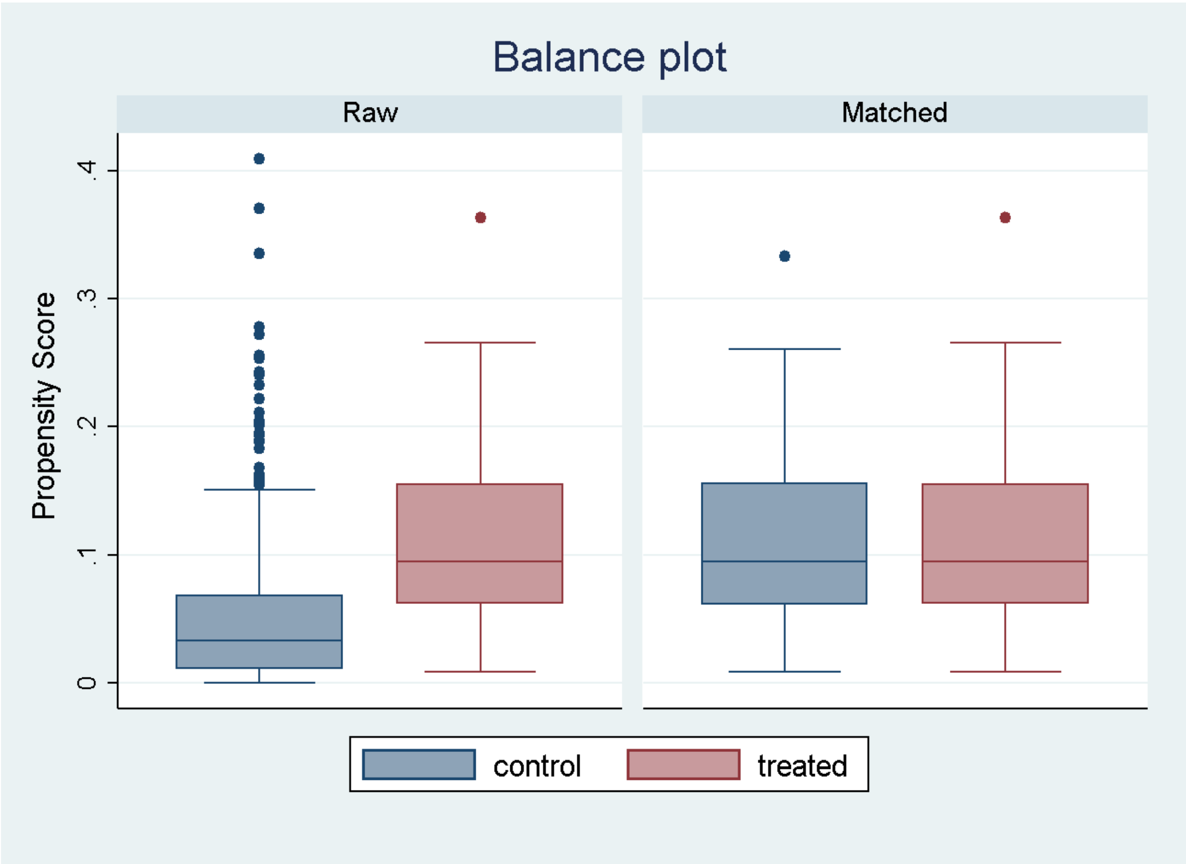

Figure 3: Variance Ratio of Residuals

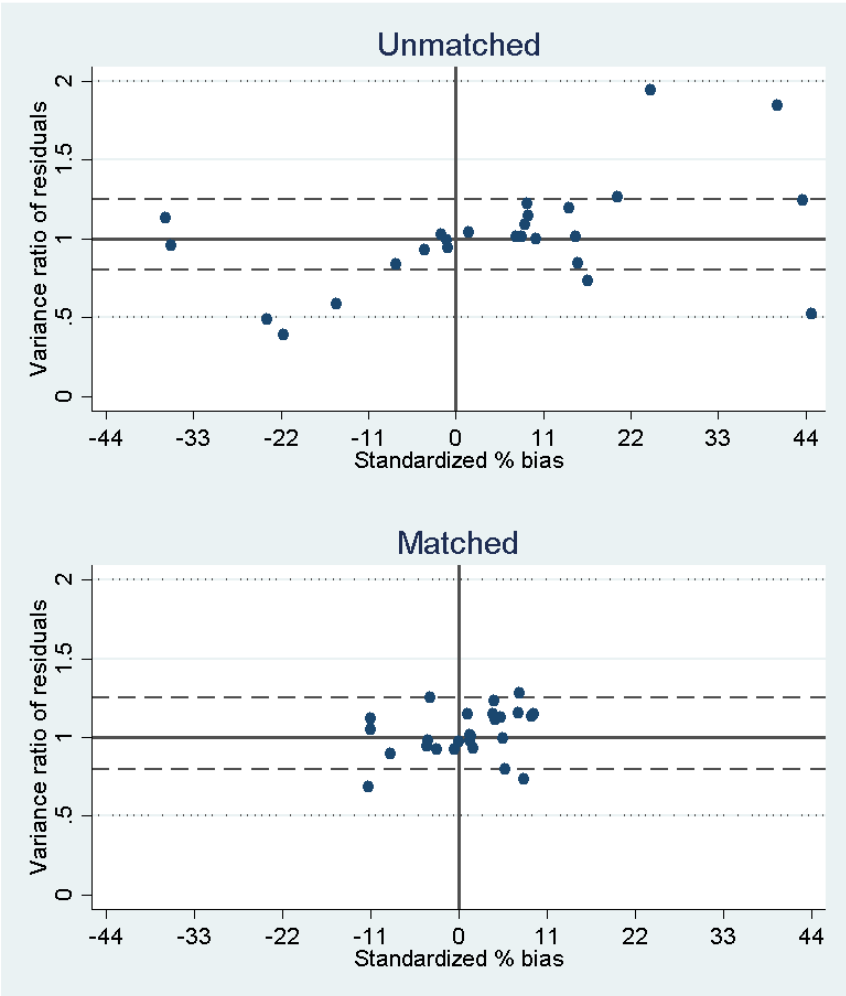

Table 5: Probit Propensity Score Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.5179	3.5331	0.15	0.8835
cover.crops.2010.I	0.7391	0.2732	2.71	0.0068 ***
water.on.or.along.farm	0.5947	0.3012	1.97	0.0483 **
soil.erosion	-0.0268	0.2306	-0.12	0.9073
attitude.reduction	-0.1646	0.2676	-0.62	0.5385
conservation.costs.I	-0.1535	0.2381	-0.64	0.5190
drainage.expenditure.I	-0.1136	0.2343	-0.48	0.6278
log.ag.land	0.3062	0.1530	2.00	0.0453 **
rented	-0.1975	0.3536	-0.56	0.5765
labor.off.farm	0.0006	0.0011	0.53	0.5946
gross.farm.sales.I	-0.1487	0.2857	-0.52	0.6028
farm.income.I	-0.1656	0.2605	-0.64	0.5249
age	-0.2086	0.1217	-1.71	0.0864 *
age.sq	0.0014	0.0010	1.51	0.1323
college	-0.0072	0.2252	-0.03	0.9745
Central	0.6780	0.5641	1.20	0.2294
East.Central	0.3855	0.6004	0.64	0.5209
West.Central	0.4840	0.5941	0.81	0.4153
North.Central	0.3949	0.5900	0.67	0.5033
North.East	0.7596	0.5711	1.33	0.1835
North.West	0.6671	0.5871	1.14	0.2559
South.Central	1.1256	0.6072	1.85	0.0638 *
South.West	0.5587	0.6335	0.88	0.3778
livestock.I	-0.0161	0.2489	-0.06	0.9484
exp	0.1300	0.0719	1.81	0.0706 *
exp.sq	-0.0015	0.0009	-1.71	0.0869 *
grains	0.1054	0.4948	0.21	0.8313

*** Significant at 1% level
** Significant at 5% level
* Significant at the 10% level

Table 6: Matching Results

	Stand. Mean Difference	Variance Ratio
cover.crops.2010.I	0.06	1.09
water.on.or.along.farm	0.02	0.94
soil.erosion	0.01	1.01
attitude.reduction	-0.11	1.25
conservation.costs.I	-0.11	1.05
drainage.expenditure.I	0.01	1.00
log.ag.land	0.01	1.16
rented	0.08	0.84
labor.off.farm	0.09	1.19
gross.farm.sales.I	0.01	1.01
farm.income.I	0.05	1.00
age	0.04	1.14
age.sq	0.05	1.03
college	-0.08	0.97
Central	0.07	1.15
East.Central	-0.12	0.69
West.Central	0.00	1.00
North.Central	0.05	1.14
North.East	-0.04	0.94
North.West	-0.04	0.92
South.Central	0.04	1.09
South.West	-0.03	0.92
livestock.I	0.09	1.11
exp	-0.04	1.43
exp.sq	-0.01	0.97
grains	0.06	0.94

Table 7: Average Treatment Effect on the Treated for the Proportion of Crops Acres Relative to Total Farm Acreage (Y^1)

	Coefficient	AI Robust Std. Error	z	P> $\|z\|$	[95% Conf.	Interval]
ATT	0.20	0.04	4.73	0.000 ***	0.12	0.29

*** Significant at 1% level

Table 8: Average Treatment Effect on the Treated for the Proportion of Cover Crops (Y^1) using Other Matching Specifications

Method	ATT Coefficient	AI Robust Std. Error	P value
Nearest[2]	0.20	0.04	0.000 ***
Nearest[3]	0.22	0.04	0.000 ***
Genetic[4]	0.22	0.04	0.000 ***

*** Significant at 1% level
[2] : probit propensity score matching with 4 neighbors and 0.20 caliper
[3] : logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement, 500 boots and 100 population size

Table 9: Tobit Model for Proportion of Cover Crops Planted Relative to Total Farm Acreage (Y^1)

	Estimate	Robust Std. Error	t value	Pr(>|t|)
(Intercept)	1.47	0.82	1.79	0.077
cost.share.I	0.40	0.05	8.65	0.000 ***
cover.crops.2010.I	0.13	0.06	2.09	0.039 **
water.on.or.along.farm	-0.03	0.06	-0.44	0.662
attitude.reduction	-0.01	0.09	-0.09	0.927
soil.erosion	-0.09	0.06	-1.49	0.140
conservation.costs.I	0.04	0.05	0.83	0.408
drainage.expenditure.I	0.03	0.06	0.59	0.558
log.ag.land	-0.10	0.04	-2.74	0.007 ***
rented	0.05	0.08	0.60	0.552
labor.off.farm	-0.00	0.00	-0.30	0.763
gross.farm.sales.I	0.11	0.06	1.88	0.062 *
farm.income.I	0.04	0.06	0.60	0.552
age	-0.03	0.03	-1.06	0.292
age.sq	0.00	0.00	0.99	0.324
college	-0.00	0.06	-0.07	0.948
Central	0.18	0.15	1.19	0.238
East.Central	0.12	0.15	0.76	0.446
West.Central	-0.00	0.13	-0.02	0.985
North.Central	-0.07	0.13	-0.55	0.586
North.East	0.08	0.15	0.51	0.611
North.West	0.10	0.16	0.61	0.541
South.Central	0.18	0.16	1.15	0.251
South.West	0.12	0.17	0.69	0.493
livestock.I	-0.04	0.06	-0.73	0.464
exp	-0.02	0.02	-0.73	0.466
exp.sq	0.00	0.00	1.02	0.310
grains	-0.02	0.12	-0.18	0.858

*** Significant at 1% level
** Significant at 5% level
* Significant at the 10% level
Number of observations = 146
Censored observations = 97, uncensored observations = 49

Table 10: Average Marginal Treatment Effect on the Expected Proportion of Cover Crops Acres Relative to Total Farm Acreage (Y^1) among Adopters

	Marginal Effect	Delta-Method Std. Error	z	P> $\|z\|$	[95% Conf.	Interval]
cost.share.I	0.18	0.02	8.65	0.000 ***	0.14	0.22

*** Significant at 1% level

Table 11: Average Marginal Treatment Effect on the Expected Proportion of Cover Crops Acres Relative to Total Farm Acreage (Y^1) among Adopters using Other Matching Specifications

Method	Marg. Effect	Delta-Method Std. Error	z	P> $\|x\|$	[95% Conf.	Interval]
Nearest[2]	0.20	0.04	4.51	0.000 ***	0.11	0.28
Nearest[3]	0.22	0.04	5.37	0.000 ***	0.14	0.30
Genetic[4]	0.21	0.02	8.82	0.000 ***	0.16	0.25

*** Significant at 1% level
[2]: probit propensity score matching with 4 neighbors and 0.20 caliper
[3]: logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement 500 boots and 100 population size

Table 12: Average Treatment Effect on the Treated for Cover Crops Acres (Y^2)

	Coefficient	AI Robust Std. Error	z	P> |z|	[95% Conf.	Interval]
ATT	81.37	32.37	2.51	0.012 **	17.92	144.82

** Significant at 5% level

Table 13: Average Treatment Effect on the Treated for Cover Crops Acres (Y^2) using Other Matching Specifications

Method	ATT Coefficient	AI Robust Std. Error	P value
Nearest[2]	73.90	27.82	0.008 ***
Nearest[3]	102.70	9.39	0.000 ***
Genetic[4]	104	24.2	0.000 ***

*** Significant at 1% level
[2]: probit propensity score matching with 4 neighbors and 0.20 caliper
[3]: logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement, 500 boots and 100 population size

Table 14: Tobit Model for Proportion of Cover Crops Acres Planted (Y^2)

	Estimate	Robust Std. Error	t value	Pr(>|t|)
(Intercept)	614.10	544.93	1.13	0.262
cost.share.I	280.85	59.75	4.70	0.000 ***
cover.crops.2010.I	136.81	85.35	1.60	0.112
water.on.or.along.farm	30.82	49.84	0.62	0.538
attitude.reduction	102.57	75.42	1.36	0.176
soil.erosion	-22.25	44.04	-0.51	0.614
conservation.costs.I	14.99	41.23	0.36	0.717
drainage.expenditure.I	124.18	66.13	1.88	0.063
log.ag.land	-6.24	32.73	-0.19	0.849
rented	51.50	79.29	0.65	0.517
labor.off.farm	-0.22	0.22	-1.00	0.321
gross.farm.sales.I	147.00	69.79	2.11	0.037 *
farm.income.I	2.40	45.20	0.05	0.958
age	-14.47	22.17	-0.65	0.515
age.sq	0.13	0.18	0.75	0.454
college	-35.51	44.58	-0.80	0.427
Central	328.88	177.49	1.85	0.066 .
East.Central	230.67	180.71	1.28	0.204
West.Central	201.40	159.85	1.26	0.210
North.Central	132.29	143.43	0.92	0.358
North.East	260.87	196.72	1.33	0.187
North.West	240.47	179.41	1.34	0.183
South.Central	221.84	172.12	1.29	0.200
South.West	186.70	167.15	1.12	0.266
livestock.I	-26.34	49.76	-0.53	0.598
exp	-49.44	27.01	-1.83	0.070 .
exp.sq	0.74	0.37	2.00	0.048 *
grains	-148.65	95.84	-1.55	0.124

*** Significant at 1% level
** Significant at 5% level
* Significant at the 10% level
Number of observations = 146
Censored observations = 97, uncensored observations = 49

Table 15: Average Marginal Treatment Effect on the Expected Cover Crops Acres Planted (Y^2) among Adopters

	Marginal Effect	Delta-Method Std. Error	z	P> |z|	[95% Conf.	Interval]
cost.share.I	103.78	17.66	5.88	0.000 ***	69.16	138.34

*** Significant at 1% level

Table 16: Average Marginal Treatment Effect on the Expected Cover Crops Acres Planted (Y^2) among Adopters using Other Matching Specifications

Method	Marg. Effect	Delta-Method Std. Error	z	P> |z|	[95% Conf.	Interval]
Nearest[2]	104.92	19.40	5.41	0.000 ***	66.90	142.93
Nearest[3]	103.65	14.12	7.34	0.000 ***	75.98	131.32
Genetic[4]	106.17	20.35	5.22	0.000 ***	66.29	146.05

*** Significant at 1% level
[2]: probit propensity score matching with 4 neighbors and 0.20 caliper
[3]: logit propensity score matching with 5 neighbors and 0.25 caliper
[4]: genetic matching with 5 neighbors, replacement 500 boots and 100 population size

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