ADDITIONALITY AND THE ADOPTION OF FARM CONSERVATION PRACTICES

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1.0 Introduction

Federal agricultural conservation programs, such as the Conservation Reserve Program (CRP) and the Environmental Quality Improvement Program (EQIP), have invested billions of dollars to incentivize farmers to enhance environmental benefits. Funding for major USDA conservation programs was approximately 24 billion dollars during the period 2002-2007, and the portion allocated to working-lands programs have increased considerably starting in 2002 relative to land retirement programs (ERS 2009). The effectiveness of federal cost-share programs depends in part on whether payments induce a positive change in farmer behavior. In this paper, we use propensity score matching methods to estimate the level of additionality from enrollment in federal cost-share programs for six conservation practices.

Propensity score matching estimators were developed by Rosenbaum and Rubin (1983) and have been applied in various economic studies. These estimators are used to estimate the average treatment effect on the treated (ATT), serve to reduce the dimension of the matching problem, and attempt to eliminate or reduce the bias induced by nonrandom program enrollment, which is a classic selection problem in nonexperimental studies. Assuming certain identifying assumptions are met, matching estimators are appealing because they generate counterfactuals in an intuitive manner, remove outliers, and impose few specification assumptions.

Matching methods have been used for program evaluation in several contexts pertaining to conservation. Andam et al. (2008), for example, analyzed the effect of protected areas in reducing deforestation rates in Costa Rica and found that deforestation rates in protected areas are 11% lower than in similar unprotected areas. Matching methods have been used to analyze policies aimed at reducing future urban development with adequate public facility ordinances (Bento et al. 2007) and reducing farmland loss with purchase of development rights programs (Liu and Lynch 2011). Ferraro et al. (2007) analyzed the impact of the US Endangered Species Act on species recovery rates and found significant improvements in recovery rates but only when the listing was combined with significant government funding.

The previous studies focused primarily on programs or polices that protect against future environmental degradation. Conversely, federal cost-share programs are conservation programs that emphasize environmental enhancement through land restoration and the adoption of conservation practices. Studies examining such programs exist, but are limited in number. Using Natural Resource Inventory data, Lubowski et al. (2008) estimate a land-use change model where CRP is included as an alternative, in order to analyze the effect of CRP on land retirement. They find that approximately 90% of land enrolled under CRP constitutes additional land retirement, implying that CRP significantly increases the likelihood of land retirement. Lichtenberg and Smith-Ramirez (2011) estimate the impact on land allocation of a cost-share program in Maryland using a switching regression model. They find that cost-share funding induce farmers to adopt conservation practices they would not have used without funding; however, it also has the unintended consequence of inducing slippage (i.e., pasture and vegetative cover converted to cropland).

In this paper, we estimate the level of additionality from enrollment in federal cost-share programs for six conservation practices. We apply matching estimators to quantify additionality, estimated as the ATT, which equals the average increase in conservation effort of enrolled farmers relative to their counterfactual effort without funding. Our study analyzes conservation adoption and enrollment decisions using data from a farmer survey in Ohio. The survey includes farmer enrollment in major federal conservation programs, such as CRP, EQIP, and others. The conservation practice types include conservation tillage, cover crops, hayfield establishment, grid sampling, grass waterways, and filter strips.

We develop a new methodological approach to decompose the ATT according to the relative contributions of adopters and non-adopters. We define “adopters” as enrolled farmers who would adopt the practice even in the absence of cost-share funding, while “non-adopters” are enrolled farmers who would not adopt the practice without funding. Matching estimators are used to generate counterfactuals from the non-enrolled farmers to estimate the likelihood that enrolled farmers are adopters or non-adopters for each practice type, in addition to the relative contribution for each group to the overall ATT.

Our empirical analysis provides three main results. First, the overall ATT for enrollment in cost-share programs is positive and significant for each of the six practice types. That is, cost-share programs induce farmers to increase the average proportion of conservation acreage adopted for all practices. Second, the percent additionality, defined as the percent increase in conservation acreage relative to the total conservation acreage adopted for enrolled farmers, varies dramatically between practice types. Specifically, the percent additionality is highest for filter strips (92.0%), hayfields (91.0%), and cover crops (86.7%), while it is lowest for conservation tillage (18.0%). Finally, the new methodological approach that we formulate to decompose ATT into the relative contributions of adopters and non-adopters also provides valuable policy insights. For instance, the ATT for adopters is not significant for all practice types, except filter strips, suggesting that adopters are not significantly expanding the proportion of conservation acreage. Furthermore, decomposition estimates suggest that the differences in % ATT between practice types are mainly determined by the fraction of enrolled farmers that are adopters and non-adopters. Practice types that have a large fraction of non-adopters, such as filters trips and hayfields, exhibit larger values for % ATT.

The paper is structured as follows. First, we discuss the propensity score matching method and assumptions. Then, we formulate the decomposition of the ATT and derive the respective estimators for each component in the decomposition. Next, we describe and summarize the data from our farmer survey in Ohio. Thereafter, we provide the estimation results for the ATT, % ATT, and components of the decomposed ATT. We conclude with policy implications for conservation programs.

2.0 Decomposition of the Propensity Score Estimator

In this section, we formalize the ATT and discuss the identification assumptions needed for its estimation. Then, we develop the propensity score matching estimator and derive the decomposition of the ATT.

2.1 Propensity Score Matching Estimator

Define an indicator variable *D* equal to one if farmer *i* enrolled in a federal conservation program to fund the adoption of conservation practice *p*, and *D* equals zero if a farmer did not enroll in a program. Further, define the potential outcome variables Y_1 and Y_0 for each farmer *i* and practice *p*. Let Y_1 be the proportion of farm acreage that farmer *i* adopts of practice *p* if they enrolled in a program (*D=1*), and let Y_0 be the proportion of farm acreage they adopted of practice *p* if they do not enroll (*D=0*), where $0 \leq Y_0 \leq 1$ and $0 \leq Y_1 \leq 1$. We can only observe one of these two outcome variables for any given farmer.

The treatment effect of enrolling in a conservation program on practice *p* is defined as the additional conservation effort adopted by a farmer as a result of program enrollment relative to not being enrolled. For farmer *i* and practice *p*, this is expressed as the difference between Y_1 and Y_0 as $\tau = Y_1 - Y_0$. Because we are interested in the average effect of the program across all enrolled farmers, we define the additionality for practice *p* as the expected treatment effect for the enrolled group of farmers *D=1*. The ATT is defined as:

$$ATT = E\left[Y_1 - Y_0 \mid D = 1\right] = E\left[Y_1 \mid D = 1\right] - E\left[Y_0 \mid D = 1\right]. \qquad (1)$$

The application of matching estimators requires two identification assumptions to be satisfied. The first assumption that justifies the use of matching estimators states that the potential outcome Y_0 must be independent of program enrollment conditional on the set of observable covariates *X*, i.e., $Y_0 \perp D | X$. The vector of observed covariates *X* should affect both the decision to enroll and the potential outcomes. Rosenbaum and Robin (1983) demonstrated that if such a condition is satisfied, then it holds as well conditional on the propensity score, where the propensity score is defined as the probability that a farmer enrolls given *X*, $P = P(D=1 | X)$. The conditional independence assumption becomes $Y_0 \perp D | P$. The propensity scores can be estimated using discrete choice models, typically a probit or logit model.

The second assumption states that for all farmer characteristics *X*, there is a positive probability of either enrolling or not enrolling, $0 < P(D=1 | X) < 1$. This assumption is known as the common support condition and implies that for each enrollee there exists a match within the group of non-enrolled farmers with a similar set of covariates *X*.

Let H_1 denote the set of enrollees and H_0 the set of non-enrollees. Each enrollee and non-enrollee has a set of defining characteristics, X_i and X_j, and propensity scores, P_i and P_j, respectively, where $i=1,...,I$ and $j=1,\ldots,J$. The sets H_1 and H_0 only include those farmers on the common support. Propensity scores are obtained from a probit model, such that $P_i = P(D_i = 1 | X_i)$ and $P_j = P(D_j = 1 | X_j)$.[1] For propensity score kernel matching, all non-enrollees *J* in H_0 are used as matches, where the weights

[1] To assess the estimates of the propensity scores derived from a probit model using the covariates *X*, we use the propensity score covariate balancing test proposed by Dehejia and Wahba (1999).

$W(i,j)$ are determined based on a kernel function, a bandwidth parameter, and the differences between P_i and P_j. For propensity score nearest-neighbor matching, only the *m* nearest non-enrollees are used as matches for each enrolled farmer *i*, where $m \geq 1$, and distance is determined by the difference between P_i and P_j. Each of the *m* nearest-neighbor matches for enrollee *i* receive an equal weight of $W(i,j) = \frac{1}{m}$, while all other non-enrollees in the set H_0 receive a weight of zero. For both matching procedures, it holds that $\sum_{j \in H_0} W(i,j) = 1$ for each farmer *i*.

The propensity score matching estimator generates a counterfactual for each enrollee *i*, $\hat{Y}_0^i$, given by the weighted average

$$\hat{Y}_0^i = \hat{E}\left[Y_0^i \mid P_i, D_i = 1\right] = \sum_{j \in H_0} W(i,j) Y_0^j \ . \tag{2}$$

where Y_0^j is observed outcome for the non-enrollee *j*.[2] The matching estimator for the ATT is the average of the counterfactuals for the set of *I* enrollees in H_1:

$$A\hat{T}T = \frac{1}{I} \sum_{i \in H_1} \left(Y_1^i - \hat{Y}_0^i\right) = \frac{1}{I} \sum_{i \in H_1} Y_1^i - \frac{1}{I} \sum_{i \in H_1} \hat{Y}_0^i \ . \tag{3}$$

Using (3), the matching estimators for $E\left[Y_1 \mid D = 1\right]$ and $E\left[Y_0 \mid D = 1\right]$ are

[2] The expression $\hat{E}\left[Y_0^i \mid P_i, D_i = 1\right]$ denotes the empirical estimate of $E\left[Y_0^i \mid P_i, D_i = 1\right]$. Refer to Smith and Todd (2005) for further clarification on this expression.

$$\hat{E}\left[Y_1 \mid D=1\right]=\frac{1}{I}\sum_{i\in H_1} Y_1^i \tag{4}$$

and

$$\hat{E}\left[Y_0 \mid D=1\right]=\frac{1}{I}\sum_{i\in H_1}\sum_{j\in H_0} W\left(i,j\right)Y_0^j \ . \tag{5}$$

2.2 Decomposing the ATT for Adopters and Non-Adopters

Define two types of farmers based on their potential outcome in the absence of funding Y_0: non-adopters are characterized by $Y_0 = 0$, and adopters are characterized by $Y_0 > 0$. The ATT in equation (1) is decomposed into two parts to determine the relative amount of the ATT that is attributable to adopters and non-adopters. Using conditional probabilities and expectations based on Y_0, the ATT can be decomposed into:

$$\begin{aligned} ATT = {} & P\left(Y_0=0 \mid D=1\right)\cdot\left\{E\left[Y_1 \mid Y_0=0, D=1\right]-E\left[Y_0 \mid Y_0=0, D=1\right]\right\} \\ & +P\left(Y_0>0 \mid D=1\right)\cdot\left\{E\left[Y_1 \mid Y_0>0, D=1\right]-E\left[Y_0 \mid Y_0>0, D=1\right]\right\}. \end{aligned} \tag{6}$$

The first line of this equation represents the portion of the ATT that corresponds to non-adopters. The term $E\left[Y_1 \mid Y_0=0, D=1\right]$ is the proportion of acreage that non-adopters dedicate to the conservation practice with funding, while $E\left[Y_0 \mid Y_0=0, D=1\right]$ is the expected proportion they adopt without funding. The difference is the additional amount adopted by enrolled non-adopters as a result of receiving funding. Note that $E\left[Y_0 \mid Y_0=0, D=1\right]$ equals zero by definition.

The second line in (6) is the portion of the ATT associated with adopters. Once again, the difference $E\left[Y_1 \mid Y_0 > 0, D=1\right] - E\left[Y_0 \mid Y_0 > 0, D=1\right]$ equals the additional amount adopted by adopters as a result of receiving funding. The ATT is the weighted average of these two differences according to the probabilities $P\left(Y_0 = 0 \mid D=1\right)$ and $P\left(Y_0 > 0 \mid D=1\right)$. Given that $Y_0 \geq 0$, it holds that:

$$P\left(Y_0 = 0 \mid D=1\right) + P\left(Y_0 > 0 \mid D=1\right) = 1. \tag{7}$$

We define the respective ATT for enrolled non-adopters and adopters as

$$ATT_n = E\left[Y_1 \mid Y_0 = 0, D=1\right] - E\left[Y_0 \mid Y_0 = 0, D=1\right] \tag{8}$$

and

$$ATT_a = E\left[Y_1 \mid Y_0 > 0, D=1\right] - E\left[Y_0 \mid Y_0 > 0, D=1\right]. \tag{9}$$

and the probability that an enrolled farmer is either a non-adopter or an adopter as

$$P_n = P\left(Y_0 = 0 \mid D=1\right) \tag{10}$$

and

$$P_a = P\left(Y_0 > 0 \mid D=1\right). \tag{11}$$

The decomposed ATT in (6) can be expressed as:

$$ATT = P_n \cdot ATT_n + P_a \cdot ATT_a\ . \tag{12}$$

This clarifies that additionality for a conservation practice depends not only on the gains of each type of farmer, but also on the likelihood that an enrolled farmer is either a non-adopter or an adopter.[3]

3.0 Proposed Estimators for the Components of the Decomposition

Below we derive the estimators for each of the decomposed terms. We first discuss the estimators for the probabilities P_n and P_a, followed by the discussion of the estimators for ATT_n and ATT_a.

3.1 Estimators for the Probabilities of Non-Adopters and Adopters

We first derive the estimators for P_n and P_a (refer to (10) and (11)). We define a binary variable B_0 to explain how we use matching estimators to derive the estimators for the probabilities. Specifically, B_0 equals one if a farmer would adopt a practice without funding, and zero otherwise, i.e., $B_0 = 1$ if $Y_0 > 0$, and $B_0 = 0$ if $Y_0 = 0$. The expectation of B_0 can be expressed in terms of probability that Y_0 is greater than zero:

$$E\left[B_0 \mid D=1\right] = P\left(B_0 = 1 \mid D=1\right) = P\left(Y_0 > 0 \mid D=1\right). \tag{13}$$

[3] Note, $P_n = P\left(Y_0 = 0 \mid D=1\right)$ is the probability that an enrolled farmer is a non-adopter, which is different from the probability that a non-adopter enrolls, which is given by $P\left(D=1 \mid Y_0 = 0\right)$. The same is true for P_a.

An estimate for $E\left[B_0 \mid D=1\right]$ is obtainable using a matching estimator; as such, the estimate for $P\left(Y_0>0 \mid D=1\right)$ is obtainable as well via a matching estimator. The two probabilities needed for the decomposition of the ATT are $P\left(Y_0>0 \mid D=1\right)$ and $P\left(Y_0=0 \mid D=1\right)$. Given an estimate for $P\left(Y_0>0 \mid D=1\right)$, we obtain an estimate for $P\left(Y_0=0 \mid D=1\right)$ using (7).

We derive the estimators for the probabilities based on propensity score matching. The propensity score matching estimator generates a counterfactual for each enrollee *i*, $\hat{B}_0^i$, given by the weighted average

$$\hat{B}_0^i=\sum_{j \in H_0} W(i, j) B_0^j , \tag{14}$$

where B_0^j is the B_0 for non-enrollee *j*, and $\hat{B}_0^i \in[0,1]$. Note that $\hat{B}_0^i$ is the estimate of the probability that an enrolled farmer with propensity score P_i is an adopter, such that

$$\hat{B}_0^i=\hat{E}\left[B_0^i \mid P_i, D_i=1\right]=\hat{P}\left(Y_0^i>0 \mid P_i, D_i=1\right). \tag{15}$$

The matching estimator for $E\left[B_0 \mid D=1\right]$ is then the average of the counterfactuals for the set of *I* enrollees in H_1:

$$\hat{E}\left[B_0 \mid D=1\right]=\frac{1}{I} \sum_{i \in H_1} \hat{B}_0^i . \tag{16}$$

Consequently, given equation (13), the estimator for $P\left(Y_0>0 \mid D=1\right)$ is:

$$\hat{P}\left(Y_0 > 0 \mid D = 1\right) = \frac{1}{I}\sum_{i \in H_1} \hat{B}_0^i \,. \tag{17}$$

The estimator for $P\left(Y_0 = 0 \mid D = 1\right)$ is obtained by substituting (17) into (7):

$$\hat{P}\left(Y_0 = 0 \mid D = 1\right) = 1 - \frac{1}{I}\sum_{i \in H_1} \hat{B}_0^i = \frac{1}{I}\sum_{i \in H_1}\left(1 - \hat{B}_0^i\right). \tag{18}$$

3.2 Estimators for the ATT of Non-Adopters and Adopters

In this section, we derive the estimators on ATT_a for adopters and ATT_n for non-adopter that are defined in equations (8) and (9), respectively. Each ATT consists of the difference of two conditional expectations. The expectations are of Y_1 and Y_0, where each expectation is conditioned on a value of Y_0 and D=1. We estimate each of the conditional expectations separately, and then take their difference to obtain the estimators for ATT_n and ATT_a. We first derive the estimators for the conditional expectations of Y_1, then for the conditional expectations of Y_0, and finally for each ATT. Notice that the estimators we derive are applicable to kernel or nearest-neighbor matching

The estimators for $E\left[Y_1 \mid Y_0 = 0, D = 1\right]$ and $E\left[Y_1 \mid Y_0 > 0, D = 1\right]$ are given by:

$$Non-adopter: \ \hat{E}\left[Y_1 \mid Y_0 = 0, D = 1\right] = \frac{\sum_{i \in H_1}\left(1 - \hat{B}_0^i\right)Y_1^i}{\sum_{i \in H_1}\left(1 - \hat{B}_0^i\right)} \tag{19}$$

and

$$Adopter:\ \hat{E}\left[Y_1 \mid Y_0 > 0, D = 1\right] = \frac{\sum_{i \in H_1} \hat{B}_0^i Y_1^i}{\sum_{i \in H_1} \hat{B}_0^i}. \tag{20}$$

These estimators are the weighted average value of Y_1 across all *I* enrollees weighted by the estimated probability that an enrollee is either a non-adopter, $1-\hat{B}_0^i$, or an adopter, $\hat{B}_0^i$. Thus, the expectation of Y_1 for non-adopters weighs enrollees that are more likely to be non-adopters more heavily than those that are not. The opposite holds true for the conditional expectation of Y_1 for adopters.

We now derive the estimators for $E\left[Y_0 \mid Y_0 = 0, D = 1\right]$ and $E\left[Y_0 \mid Y_0 > 0, D = 1\right]$, which are the last two terms in equations (8) and (9). The set of non-enrollees H_0 can be subdivided into two groups based on the observed outcomes for each non-enrollee B_0^j: those that are non-adopters, $B_0^j = 0$, and those that are adopters $B_0^j = 1$. The estimator for the conditional expectation of Y_0 for non-adopters, $E\left[Y_0 \mid Y_0 = 0, D = 1\right]$, equals zero by definition, so no estimator is required. The estimator for the conditional expectation of Y_0 for adopters, $E\left[Y_0 \mid Y_0 > 0, D = 1\right]$, equals the weighted average of Y_0^j values for the set of non-enrollees that are adopters,

$$Adopter: \ \hat{E}\left[Y_0 \mid Y_0 > 0, D = 1\right] = \frac{\sum_{i \in H_1} \sum_{j \in H_0} W(i, j) B_0^j Y_0^j}{\sum_{i \in H_1} \sum_{j \in H_0} W(i, j) B_0^j}. \tag{21}$$

Now that we have estimators for each of the conditional expectations found in (8) and (9), the estimators for the ATTs are easily obtained. The estimator for the ATT of non-adopters is obtained by substituting (19) into (8), where recall that $E\left[Y_0 \mid Y_0 = 0, D = 1\right] = 0$, and the estimator for the ATT of adopters is obtained by substituting (20) and (21) into (9):

$$Non-Adopter: \ A\hat{T}T_n = \frac{\sum_{i \in H_1} \left(1 - \hat{B}_0^i\right) Y_1^i}{\sum_{i \in H_1} \left(1 - \hat{B}_0^i\right)} \tag{22}$$

and

$$Adopter: \ A\hat{T}T_a = \left[\frac{\sum_{i \in H_1} \hat{B}_0^i Y_1^i}{\sum_{i \in H_1} \hat{B}_0^i}\right] - \left[\frac{\sum_{i \in H_1} \sum_{j \in H_0} W(i, j) B_0^j Y_0^j}{\sum_{i \in H_1} \sum_{j \in H_0} W(i, j) B_0^j}\right]. \tag{23}$$

4.0 Survey Background and Data Summary

For this study, we conducted a farmer survey in southwestern Ohio within 25 counties in and around the Great Miami River Watershed. The study area is dominated by agricultural uses (83% of land area) particularly for row-crop production in corn, soybeans, and wheat. Typical livestock operations include swine, beef cattle, and dairy. Our survey questionnaire was conducted in 2009 through the Ohio Division of the National Agricultural Statistical Service (NASS). The sample of farmers was drawn from the NASS master list of farmers and a random stratified sampling was used to ensure a sufficient number of responses from large commercial farms. The survey was mailed to 2000 farmers with follow-up phone calls. There were a total of 768 survey respondents. However, useable responses varied by practice type depending on whether the farmer completed the survey information for each practice type. The survey contains questions on farmer socioeconomic characteristics, farm management and operation, and land quality characteristics.

The survey also includes information on the acreage adopted for the following six conservation practices in 2009: conservation tillage, cover crops, hayfields (or grassland establishment), grid sampling, grass waterways, and filter strips. Conservation tillage leaves crop residue on fields to reduce soil erosion and runoff. Cover crops provide soil cover on cropland when the soil would otherwise be bare. Hayfields and grassland establishment retire cropland to a less intensive state to provide habitat and other conservation benefits. Grid sampling improves the efficiency of nutrient application rates to maximize crop yields, while reducing excess fertilizer that potentially would runoff or leach into surrounding water bodies. Grass waterways are located in the natural drainage areas within cropland to reduce soil erosion and gully formation. Filter strips are typically planted grass along stream banks to capture sediment, nutrients, and pesticides from runoff before they enter surrounding water bodies. We categorize these six practices into two groups. First, practices for environmentally sensitive areas, filter strips and grass waterways, are almost exclusively used along stream banks or in natural drainage areas, respectively. Second, field practices include conservation tillage, cover crops, hayfields, and grid sampling, and they are often adopted as a practice for a significant portion of the cropland.

For each practice type, the survey asks whether the farmer received cost-share funding from enrollment in any of the federal conservation programs. The federal programs included explicitly in the survey are EQIP, CRP, Conservation Reserve Enhancement Program (CREP), and Conservation Security Program (CSP), The Great Miami River Watershed has a regional water quality trading program (WQTP) (Newburn and Woodward, forthcoming). The WQTP was included in the survey because it similarly provides cost-share funding for conservation practices. An “other” option was included in the survey to capture any other federal or state conservation programs not already listed above, such as wetland and grasslands programs.

In Table 1, we report farmer decisions on conservation practice adoption and program enrollment for the six practices. Farmer decisions are categorized into three groups: no adoption, adoption without funding, and adoption with funding. For example, conservation tillage has 104 (18%) farmers who did not adopt this practice, 385 (67%) farmers who adopted without funding, and 88 (15%) farmers who received cost-share support for this practice. The total number of useable observations for conservation tillage is 577.

TABLE 1

Farmer Adoption and Enrollment by Conservation Practice Type

Practice Type	No Adoption	Adoption without Funding	Adoption with Funding	Total
Conservation Tillage	104 (18)	385 (67)	88 (15)	577 (100)
Cover Crops	522 (85)	68 (11)	24 (4)	614 (100)
Hayfields	529 (88)	54 (9)	20 (3)	603 (100)
Grid Sampling	331 (61)	159 (29)	55 (10)	545 (100)
Grass Waterways	251 (47)	138 (26)	146 (27)	535 (100)
Filter Strips	404 (73)	56 (10)	93 (17)	553 (100)

All numbers are also represented as percentages within the parentheses. There were a total of 768 survey respondents; however, the number of useable observations varies by practice type due to missing information, such as farmer characteristics and acreage adopted.

From Table 1, we observe that there exists large variability across practices in the percentage of farmers not adopting a practice. However, the percentage adopting with funding does not exhibit as much variation. Conservation tillage is the most adopted practice and has the largest number of farmers adopting without funding. Conversely, filter strips, cover crops, and hayfields are the least adopted overall and the least adopted without funding. However, unlike cover crops and hayfields, filter strips has the second largest number of farmers adopting with funding. Grid sampling and grass waterways have roughly the same number of farmers adopting without funding, however, grass waterways has the largest number of farmers adopting with funding.

For our empirical analysis, the treatment group for a given practice type is comprised of farmers who enrolled in any cost-share program for this practice. The control group is comprised of farmers who did not enroll in any program. Table 2 summarizes farmer enrollment in the conservation cost-share programs. CRP was the dominant funding source for enrolled farmers who adopted grass waterways and hayfields. However, there was not a single dominant funding source for enrolled farmers who adopted conservation tillage, filter strips, cover crops, or grid sampling.[4] Enrollment in the Great Miami WQTP represents only a small fraction of overall enrollment in Table 2. The CSP program rules are known to allow cost-share funding for both new and existing conservation practices. As such, CSP funds may be directed towards subsidizing conservation effort that is not additional. As a robustness check, in the results section we estimate additionality for all programs, all programs excluding CSP, and only CSP to test whether there are significant differences between CSP and other programs on the additionality estimates.

TABLE 2

Farmers Enrolled in Cost-Share Programs by Conservation Practice

Practice Type	EQIP	CSP	CRP	CREP	WQTP	OTHER
Conservation Tillage	16	36	25	1	5	11
Cover Crops	6	3	2	0	6	4
Hayfields	1	1	14	2	0	1
Grid Sampling	13	21	3	1	2	6
Grass Waterways	10	15	89	6	3	15
Filter Strips	8	15	48	18	1	8

[4] Some farmers reported receiving funding from more than one program for the same practice. For example, a farmer could receive EQIP funding for a filter strip on one field, and CRP funding for a filter strip on another field.

Table 3 summarizes the average proportion of acreage, relative to the total acreage of the property, a farmer adopts in a conservation practice.[5] Summarized values are provided for enrolled and non-enrolled farmers, as well as across all of these farmers. The set of non-enrolled farmers includes both farmers who adopted a practice without funding and farmers who did not adopt the practice (Table 1). Thus, for practices where the number of farmers who did not adopt is large, the average proportion for non-enrolled farmers is weighed heavily by zero values. For example, the average proportion of hayfield acreage for non-enrolled farmers is small (0.014) due to the large number of farmers that did not adopt the practice. The average proportions for environmentally sensitive practices are small as well. The reason is that filter strips and grass waterways, by design, are solely focused along stream banks and in natural drainage areas rather than across the entire field, and thus, represent a smaller proportion of total farm acreage. Overall, the average proportions for enrolled farmers were largest for conservation tillage and grid sampling, followed by hayfields and cover crops. For environmentally sensitive practices, the average proportions for enrolled farmers were roughly the same.

[5] Farmers that reported a proportion of adopted conservation acreage greater than 1 for field practices and greater than 0.15 for environmentally sensitive practices were dropped because they were considered inaccurate survey responses.

TABLE 3

Average Proportion of Conservation Adoption on Farm Acreage by Practice Type

Practice Type	Non-Enrolled Farmers	Enrolled Farmers	All Farmers
Conservation Tillage	0.520	0.747	0.554
Cover Crops	0.020	0.239	0.029
Hayfields	0.014	0.265	0.022
Grid Sampling	0.194	0.718	0.247
Grass Waterways	0.006	0.016	0.009
Filter Strips	0.001	0.011	0.002

Prior to estimating the ATT, the covariates X that are included in the first-stage estimation of the propensity scores must be determined. The covariates X should consist of those variables that are believed to affect both the outcomes and enrollment decisions (Smith and Todd, 2005). Propensity scores are estimated using a probit model, where the dependent variable is the enrollment variable *D*. The propensity scores were assessed for all practices.[6] Table 4 provides the definition of each of the covariates used in the estimation, as well as the summary statistics. Because each practice has a different number of total observations, we only provide the results for grid sampling. The average values on the covariates do not vary significantly between practice types.

[6] Refer to section 2.1 for information on the test used to assess the propensity scores.

TABLE 4

Summary Statistics on Explanatory Variables for Grid Sampling

Variable	Definition	Mean	Std. Dev
Farm Revenue	=1 if farm revenue exceeded $250,000 in 2009	0.275	0.447
Farm Horizon	=1 if farm will be operated by family within the next 5 years	0.877	0.329
Age	age	56.736	11.583
Experience	years of farming experience	31.914	12.913
Education	=1 if education exceeds high school	0.437	0.496
Soil type	=1 if dominant soil texture is clay	0.754	0.431
	=1 if dominant soil texture is loam or sandy	0.246	0.431
Household Income	=1 if 0% - 10% of household income comes from farming	0.209	0.407
	=1 if 10% - 50% of household income comes from farming	0.328	0.470
	=1 if more than 50% of household income comes from farming	0.462	0.499
Acres Rented	proportion of farm acreage rented in 2009	0.425	0.365
Acres in Grain	proportion of farm acreage devoted to grain crops in 2009	0.805	0.281
Slope	proportion of farm acreage with slope 0%-2%	0.559	0.384
	proportion of farm acreage with slope 2%-6%	0.384	0.362
	proportion of farm acreage greater than 6% slope	0.058	0.138
Farm Size	natural log of total farm acreage operated in 2009	5.769	1.073
Streams	=1 if a river or stream borders or runs through the property	0.583	0.493
Livestock	=1 if managed livestock in 2009	0.486	0.500

The estimated probit coefficients for grid sampling are provided in Table 5. The variables that are significant at the 99% level are education, acres in grain, and high slope.

TABLE 5

Estimated Coefficients from Probit Model to Compute Propensity Scores for Cost-Share Enrollment in Grid Sampling

Variable	**Estimated Coeff.**	**Std. Error**
Farm Revenue	0.182	0.230
Farm Horizon	0.714*	0.385
Age	0.009	0.011
Experience	-0.009	0.010
Education	0.580***	0.170
Soil Type: Not Clay	0.121	0.189
Medium Income	0.255	0.259
High Income	0.113	0.278
Acres Rented	-0.124	0.274
Acres in Grain	1.844***	0.712
Medium Slope	0.370	0.235
High Slope	1.526***	0.560
Farm Size	0.200	0.142
Streams	-0.160	0.169
Livestock	0.053	0.179
Constant	-5.660***	1.184
Log Likelihood	-151.404	

Note: Statistical significance: 99% (***), 95% (**), 90%(*). Estimates of the propensity scores were assessed using the test proposed by Deheija and Wahaba (1999). All practices passed the test. For grid sampling, both age and experience were needed in the probit specification to past the test. For all other practices, only age was needed and experience was not included.

5.0 Estimation Results of Additionality and the Decomposed Effects

In this section we provide the estimation results on additionality and the decomposed components of the ATT for the six conservation practices.[7] Table 6 provides the

[7] We tested for significant differences in % ATT given all programs except CSP and only CSP for conservation tillage, grid sampling, grass waterways, and filter strips. We did not test this difference for

estimates for the overall ATT, % ATT, and each component of the decomposed ATT for all practices. The estimation is performed using propensity score matching with the Epanechnikov kernel algorithm, where the common support requirement is enforced and the kernel bandwidth is 0.02.[8, 9] The standard errors and 95% confidence intervals (CI) were generated using a bootstrap procedure based on 1,000 simulations. [10]

TABLE 6

Average Treatment Effect on the Treated and Decomposed Effects for Non-Adopters and Adopters using Propensity Score Kernel Matching

Conservation Tillage	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.1348	0.0321	0.0756	0.2006
% ATT	18.0	3.8	10.7	25.4
P_n	0.1242	0.0206	0.0883	0.1684
P_a	0.8758	0.0206	0.8316	0.9117
ATT_n	0.6976	0.0364	0.6374	0.7783
ATT_a	0.0549	0.0320	-0.0041	0.1170
Matched enrolled farmers = 87, Matched non-enrolled farmers = 489				

cover crops and hayfields because enrollment numbers in CSP are too small (refer to Table 2). We found that % ATT for these four practices is higher when considering only CSP enrollees than for all programs except CSP. However, the differences were not statistically different from zero. As such, additionality estimates in this section are for all programs, including CSP.

[8] We impose the common support trimming option in Stata using 2% trimming. Refer to Leuven and Sianesi (2003).

[9] Matching quality was assessed using a two-sample t-test to check for significant differences in covariate means across matched groups. All covariates were balanced successfully for all practices. Refer to Caliendo and Kopeinig (2008) for information on the covariate balancing test.

[10] The bootstrapping procedure used 1,000 random draws from the data set of farmers, with replacement and using the same number of farmers in each draw equal to the number in the original data set. The 95% bootstrapped CI consists of the 26th and 975th largest parameter estimates.

Cover Crops	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.2072	0.0423	0.1343	0.2971
% ATT	86.7	7.7	66.6	95.4
P_n	0.8639	0.0370	0.7745	0.9250
P_a	0.1361	0.0370	0.0750	0.2255
ATT_n	0.2392	0.0408	0.1691	0.3260
ATT_a	0.0038	0.0939	-0.2048	0.1637
Matched enrolled farmers = 24, Matched non-enrolled farmers = 590				

Hayfields	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.2033	0.0626	0.0613	0.3163
% ATT	91.0	8.4	67.7	96.3
P_n	0.8914	0.0344	0.7997	0.9347
P_a	0.1086	0.0344	0.0653	0.2003
ATT_n	0.2182	0.0617	0.0847	0.3336
ATT_a	0.0814	0.1083	-0.1902	0.2482
Matched enrolled farmers = 18, Matched non-enrolled farmers = 583				

Grid Sampling	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.4788	0.0557	0.3352	0.5535
% ATT	65.8	5.7	50.7	72.1
P_n	0.5775	0.0478	0.4564	0.6492
P_a	0.4225	0.0478	0.3508	0.5436
ATT_n	0.7229	0.0441	0.6263	0.8019
ATT_a	0.1451	0.0706	-0.0263	0.2472
Matched enrolled farmers = 54, Matched non-enrolled farmers = 490				

Grass Waterways	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.0097	0.0018	0.0059	0.0131
% ATT	61.6	7.4	44.8	73.3
$\mathbf{P_n}$	0.5652	0.0412	0.4939	0.6493
$\mathbf{P_a}$	0.4348	0.0412	0.3507	0.5061
$\mathbf{ATT_n}$	0.0158	0.0016	0.0130	0.0192
$\mathbf{ATT_a}$	0.0018	0.0027	-0.0041	0.0071
Matched enrolled farmers = 144, Matched non-enrolled farmers = 389				

Filter Strips	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.0098	0.0019	0.0065	0.0139
% ATT	92.0	3.5	83.7	96.9
$\mathbf{P_n}$	0.8373	0.0346	0.7579	0.8900
$\mathbf{P_a}$	0.1627	0.0346	0.1100	0.2421
$\mathbf{ATT_n}$	0.0107	0.0019	0.0073	0.0149
$\mathbf{ATT_a}$	0.0050	0.0030	0.00009	0.0117
Matched enrolled farmers = 92, Matched non-enrolled farmers = 460				

The overall ATT in Table 6 is estimated based on equation (3). The % ATT in Table 6 is the ratio of the overall ATT in equation (3) and $E\left[Y_1 \mid D=1\right]$ in equation (4)

$$\%\,ATT = \frac{ATT}{E\left[Y_1 \mid D=1\right]} \cdot 100 \tag{24}$$

Note that the overall ATT is equal to $E\left[Y_1 \mid D=1\right] - E\left[Y_0 \mid D=1\right]$, which therefore has an upper bound of $E\left[Y_1 \mid D=1\right]$. The % ATT can be interpreted as the percentage increase in the proportion of conservation acreage normalized by the total proportion of conservation acreage adopted, conditional on enrollment. The % ATT is thus equal to the percent additionality. The formulation of the ATT decomposition is given by equation (12). The estimated average probabilities P_a and P_n that for the set of enrolled farmers that are adopters or non-adopters are calculated based on equations (17) and (18) , respectively. Meanwhile, the values ATT_n and ATT_a for non-adopters and adopters are calculated using equations (22) and (23), respectively.

The overall ATT is positive and statistically significant for all six practices (Table 6). Specifically, the bootstrapped 95% confidence intervals do not contain zero for any of the six practice types. This suggests that enrollment in cost-share programs achieves a significantly positive level of additionality for each practice type. The ATT values are higher for the field practice types than those of environmentally sensitive practices. The reason is that filter strips and grass waterways, by design, are solely focused along stream banks and in natural drainage areas rather than across the entire field, and thus, represent a smaller proportion of total farm acreage. Remember that the proportion of conservation acreage adopted by enrolled farmers is less than 0.02 for both filter strips and grass waterways (Table 3).

To compare the level of additionality between practice types, we use the % ATT in equation (24) that normalizes the overall ATT by the upper bound on the proportion of conservation acreage adopted by enrolled farmers, $E\left[Y_1 \mid D=1\right]$. The largest % ATT is found for filter strips, hayfields, and cover crops with 92.0%, 91.0%, and 86.7%, respectively (Table 5). Moderate percent additionality was found for grid sampling and grass waterways with % ATT at 65.8% and 61.6%. Conservation tillage had the lowest percent additionality at only 18.0%. In sum, this suggests that while cost-share funding from enrollment in conservation programs achieve a positive ATT for all practice types, certain practice types achieve higher percent additionality than others.

To test whether the % ATT values are statistically different across practice types, we construct bootstrapped confidence intervals of the difference in % ATT for all pair-wise combinations of practice types (Table 7). For example, the difference in % ATT between cover crops relative to conservation tillage has a 95% bootstrapped confidence interval spanning lower and upper bounds of 48.7 % to 81.3%, respectively. This indicates that cover crops have a significantly higher % ATT than conservation tillage. Meanwhile, the difference in % ATT between cover crops and hayfields is not statistically significant from zero because the bootstrapped confidence interval spans from -23.1% to 24.4%. When comparing the two environmentally sensitive practices, filter strips has a statistically larger % ATT than grass waterways.

We performed robustness checks on the estimates of the ATT, % ATT, and the decomposed effects using propensity score matching with the nearest-neighbor algorithm based on four neighbors (m=4), with replacement. The results are provided in Table A.1 in the Appendix A.1. The nearest-neighbor algorithm results in larger standard errors, i.e., wider bootstrapped confidence intervals, than the kernel algorithm. This causes the ATT_a for filter strips to not be statistically different from zero. The algorithm also leads to a negative ATT_a for hayfields, however, it is not statistically different from zero. Nonetheless, this reduces the value of the % ATT for hayfields considerably, from

91% to 83%. Other than these differences, parameter estimates for all practices are quite similar across the two algorithms. We generated as well the bootstrapped confidence intervals of the difference in % ATT for all pair-wise combinations, as in Table 7, using the nearest-neighbor algorithm. The statistical significance of the differences in % ATT remained the same based on the alternative matching algorithm. Consequently, the similarity in the parameter estimates and the differences in % ATT demonstrate the robustness of the results to different matching algorithms.

TABLE 7

Bootstrapped 95% Confidence Intervals for Pair-wise Differences in % ATT using Propensity Score Kernel Matching (Row minus Column)

	Conservation Tillage	**Cover Crops**	**Hayfields**	**Grid Sampling**	**Grass Waterways**	**Filter Strips**
Conservation Tillage						
Cover Crops	[48.7, 81.3]					
Hayfields	[48.5, 82.0]	[-23.1, 24.4]				
Grid Sampling	[30.4, 56.8]	[-40.4, -3.8]	[-41.2, -1.6]			
Grass Waterways	[25.4, 57.7]	[-46.0 -1.8]	[-46.7, -1.7]	[-16.3, 20.7]		
Filter Strips	[62.6, 82.5]	[-25.4, 8.1]	[-26.1, 8.2]	[17.4 42.7]	[15.6, 48.7]	

The components of the decomposed ATT help to explain the relative contributions of non-adopters and adopters to the overall ATT, which, in turn, explains the differences in % ATT between practice types. Table 6 highlights that ATT_a is less than ATT_n for all practice types as expected. Interestingly, ATT_a is positive but not statistically different from zero for all practices, except for filter strips. This implies that adopters are not significantly expanding the proportion of conservation acreage. Hence, practices for which a large fraction of enrolled farmers are adopters (i.e., P_a is large) typically have a lower % ATT. Consider conservation tillage where ATT_n is 0.70, while ATT_a is only 0.07. The fraction of enrolled farmers for conservation tillage that are adopters, $P_a = 0.87$, is much larger than that of non-adopters, $P_n = 0.13$. Consequently, because a large fraction of enrolled farmers are adopters, the overall ATT is small relative to the total amount of conservation coverage, and thus, the % ATT is relatively low for conservation tillage.

Practices where P_n is considerably larger than P_a have higher % ATT values. When comparing the environmentally sensitive practice types, the fraction of enrolled farmers that are non-adopters for filter strips is $P_n = 0.84$, while for grass waterways $P_n = 0.57$ (Table 6). As such, the % ATT is larger for filters strips (92.0%) than for grass waterways (61.6%). Similar results are found when comparing field practices. Cover crops and hayfields have larger P_n values than grid sampling and conservation tillage. As such, the % ATT values for cover crops and hayfields, 86.7%, and 91.0%, respectively, exceed that of grid sampling and conservation tillage, 65.8% and 18.0%, respectively. The % ATT for conservation tillage is considerably smaller than for the other five practices because it has the smallest value for P_n. Notice that the % ATT depends as well on the relative magnitude of ATT_a to ATT_n. The closer to one is the ratio of ATT_a to ATT_n, the smaller is the effect of P_n and P_a on the % ATT. Nonetheless, since the ratio of ATT_a to ATT_n ranges from 0.08 for conservation tillage to 0.47 for filter strips, the probabilities P_n and P_a affect considerably the % ATT.

The heterogeneity in P_a and P_n, and consequently in % ATT, across practices may presumably be related to differences in the private net benefits provided by each conservation practice. This follows from the assumption that higher onsite benefits of a practice should increase the likelihood that a farmer is an adopter even without cost-share payment. Conservation tillage, for example, provides a modest or negligible reduction in yields to most farmers without requiring significantly greater expenditures. This provides positive private net benefits and results in a large P_a for conservation tillage. Filter strips, cover crops, and hayfields, on the other hand, reduce the amount of land in production without providing onsite benefits, such as an increase in yield or nutrient retention. As a consequence, private net benefits are expected to be negative, and the majority of enrolled farmers would not adopt such practices without financial support (i.e., large P_n). Grass waterways and grid sampling also impose opportunity costs on the farmer, but they provide greater onsite benefits than filter strips, cover crops, and hayfields. Grass waterways reduce the amount of working land, but retain nutrients that would otherwise be depleted, while grid sampling requires significant investments in management and technological resources, but is expected to considerably increase farmer yields. These practices are thus expected to have a larger proportion of enrolled adopters than filter strips, cover crops, and hayfields.

If we compare the two environmentally sensitive practices, filter strips and grass waterways, which provide the same offsite benefits (i.e., a reduction in nutrient runoff into streams), we see that filter strips has a statistically greater % ATT than grass waterways. Presumably, this is due to the fact that grass waterways provide larger private net benefits than filter strips due to their larger onsite benefits. This leads to a larger fraction of enrolled adopters for grass waterways than for filters strips, and a reduction in the % ATT of grass waterways. Our results on % ATT thus coincide with what we would expect to observe based on private net benefits: larger additionality (i.e., % ATT) for practices with lower private net benefits, and lower additionality for practices with larger private net benefits.

It should be acknowledged that if there exist unobserved covariates that influence both enrollment and the potential outcomes, then the estimated ATT may be biased (Guo and Fraser 2010). Rosenbaum (2002) developed a method that determines the extent to which a matching estimator is sensitive to unobserved selection bias by altering the estimated odds (i.e., propensity scores) of program enrollment and quantifying how much these alterations affect the estimated ATT. A study that is not sensitive to unobserved bias would find that the ATT is robust to changes in the propensity scores (Guo and Fraser 2010). Results from the sensitivity analysis are provided in Appendix

A.5. Overall, results suggest that ATT estimates for all practices, except for conservation tillage, show moderate to high levels of robustness to unobserved bias.

6.0 Conclusions

Federal cost-share funding for the adoption of conservation practices on working lands have increased considerably starting in 2002. The efficiency of cost-share programs depends in part on the degree to which they provide additional conservation effort. In this paper, we use propensity score matching to estimate the level of additionality from enrollment in federal cost-share programs for six conservation practices. Our results indicate that the enrollment achieves positive and significant levels of additionality for each of the six practice types. That being said, the percent additionality varies dramatically between practice types. Specifically, the percent additionality is highest for filter strips (92.0%), hayfields (91.0%), and cover crops (86.7%), while it is lowest for conservation tillage (18.0%).

Valuable policy insights are provided by the new methodological approach that decomposes ATT into the relative contributions of adopters and non-adopters. Both types of farmers can provide additionality as long as each adopts more conservation acreage than they would have in the absence of payment. We found, however, that the ATT for adopters is not statistically significant for all practice types, except filter strips, suggesting that adopters are not contributing to the expansion of conservation acreage. Furthermore, decomposition estimates suggest that the differences in % ATT between practice types are mainly determined by the fraction of enrolled farmers that are adopters and non-adopters. Practice types that have a large fraction of non-adopters, such as filters trips and hayfields, exhibit larger values for % ATT. This methodological approach to decompose ATT is broadly applicable for program evaluation in other contexts where program participants can be categorized into two distinct groups.

The practice of offering payment incentives to farmers or landowners to improve environmental stewardship is growing in popularity. For example, emerging markets for ecosystem services are being developed that offer payments to landowners to improve carbon sequestration and water quality via land restoration and the adoption of agricultural BMPs. In such programs, additionality is a major concern because it is a principal measurement of program effectiveness. As we move towards a greater implementation of incentive-based programs to address environmental concerns, analysis of existing programs is crucial to determining whether such programs lead to increased conservation effort. In this paper, we apply matching estimators to measure additionality for federal incentive-based programs, as well as develop a methodology that decomposes additionality into the relative contributions of adopters and non-adopters. This provides greater insight into the effect of incentive-based programs on different types of program participants and quantifies the gains achieved by each.

Appendix

In this appendix, we present the results for propensity score matching with the nearest-neighbor algorithm and provide validation of the estimators we propose for each component of the decomposition. First, we provide the results for propensity score matching with the nearest-neighbor algorithm. Then, we validate the estimators for the conditional expectation of Y_1, equations (19) and (20), and follow with the validation for the estimators of the conditional expectation of Y_0, equation (21). Finally, we provide validations for the estimators of the respective ATT for non-adopters and adopters, equations (22) and (23), respectively. The estimators for the probabilities, given by (17) and (18), are used in the validation process. The last section discusses the sensitivity analysis.

A.1 Propensity Score Nearest-Neighbor Matching Results

In this section, we provide the results for the ATT, % ATT, and the decomposed effects based on propensity score nearest-neighbor matching. Results were discussed in section 5. Table A.1 below provides the results.

TABLE A.1

Average Treatment Effect on the Treated and Decomposed Effects for Non-Adopters and Adopters using Propensity Score Nearest-Neighbor Matching (m=4) with Replacement

Conservation Tillage	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.1489	0.0459	0.0491	0.2261
% ATT	19.9	5.8	6.4	28.9
$\mathbf{P_n}$	0.1293	0.0383	0.0540	0.2033
$\mathbf{P_a}$	0.8707	0.0383	0.7967	0.9460
$\mathbf{ATT_n}$	0.7035	0.0756	0.5496	0.8492
$\mathbf{ATT_a}$	0.0666	0.0422	-0.0243	0.1358
Matched enrolled farmers = 87, Matched non-enrolled farmers = 226				

Cover Crops	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.1972	0.0458	0.1162	0.3003
% ATT	82.5	11.1	57.8	98.9
$\mathbf{P_n}$	0.8438	0.0741	0.6905	0.9762
$\mathbf{P_a}$	0.1563	0.0741	0.0238	0.3095
$\mathbf{ATT_n}$	0.2293	0.0441	0.1684	0.3391
$\mathbf{ATT_a}$	0.0239	0.1679	-0.3748	0.3279
Matched enrolled farmers = 24, Matched non-enrolled farmers = 76				

Hayfields	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.1861	0.0686	0.0434	0.3127
% ATT	83.4	18.6	31.9	100.0
$\mathbf{P_n}$	0.8750	0.0821	0.6786	1.0000
$\mathbf{P_a}$	0.1250	0.0821	0.0000	0.3214
$\mathbf{ATT_n}$	0.2209	0.0656	0.0797	0.3446
$\mathbf{ATT_a}$	-0.0575	0.2410	-0.5976	0.4619
Matched enrolled farmers = 18, Matched non-enrolled farmers = 64				

Grid Sampling	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.4846	0.0747	0.2732	0.5633
% ATT	66.6	9.1	40.7	74.8
P_n	0.5926	0.0752	0.3750	0.6568
P_a	0.4074	0.0752	0.3432	0.6250
ATT_n	0.7207	0.0678	0.5267	0.7883
ATT_a	0.1412	0.1525	-0.2893	0.3132
Matched enrolled farmers = 54, Matched non-enrolled farmers = 144				

Grass Waterways	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.0100	0.0021	0.0051	0.0136
% ATT	63.6	10.2	37.8	77.1
P_n	0.5677	0.0558	0.4650	0.6757
P_a	0.4323	0.0558	0.3243	0.5350
ATT_n	0.0159	0.0019	0.0125	0.0200
ATT_a	0.0023	0.0037	-0.0068	0.0082
Matched enrolled farmers = 144, Matched non-enrolled farmers = 246				

Filter Strips	Estimate	Std. Error	95% Bootsrapped CI	
ATT	0.0099	0.0019	0.0062	0.0140
% ATT	93.4	5.6	76.7	98.2
P_n	0.8478	0.0472	0.7321	0.9128
P_a	0.1522	0.0472	0.0872	0.2679
ATT_n	0.0110	0.0020	0.0072	0.0150
ATT_a	0.0040	0.0050	-0.0040	0.0165
Matched enrolled farmers = 92, Matched non-enrolled farmers = 202				

A.2 Validation of the Estimators for the Conditional Expectation of Y_1 for Non-Adopters and Adopters

To demonstrate the validity of the proposed estimators for the conditional expectations of Y_1, we rely on the following decomposition of $E[Y_1 \mid D=1]$:

$$\begin{aligned} & E[Y_1 \mid D=1] = P(Y_0 = 0 \mid D=1) \cdot E[Y_1 \mid Y_0 = 0, D=1] \\ & + P(Y_0 > 0 \mid D=1) \cdot E[Y_1 \mid Y_0 > 0, D=1] \end{aligned} \tag{25}$$

When we substitute the estimators (17), (18), (19), and (20) into (25), we should obtain the matching estimator for $E[Y_1 \mid D=1]$ given by (4). Substituting these estimators into (25), we obtain:

$$\hat{E}[Y_1 \mid D=1] = \left[\frac{1}{I}\sum_{i\in H_1}\left(1-\hat{B}_0^i\right)\right] \cdot \left[\frac{\sum_{i\in H_1}\left(1-\hat{B}_0^i\right)Y_1^i}{\sum_{i\in H_1}\left(1-\hat{B}_0^i\right)}\right] + \left[\frac{1}{I}\sum_{i\in H_1}\hat{B}_0^i\right] \cdot \left[\frac{\sum_{i\in H_1}\hat{B}_0^i Y_1^i}{\sum_{i\in H_1}^{n}\hat{B}_0^i}\right] \tag{26}$$

which, after canceling terms and noting that $\sum_{i\in H_1}\left(1-\hat{B}_0^i\right) + \sum_{i\in H_1}\hat{B}_0^i = 1$, yields:

$$\hat{E}[Y_1 \mid D=1] = \frac{1}{I}\sum_{i\in H_1} Y_1^i \tag{27}$$

Thus, our proposed estimators for each of the decomposed terms yield the standard matching estimator for $E[Y_1 \mid D=1]$ given by (4).

A.3 Validation of the Estimators for the Conditional Expectation of Y_0 for Non-Adopters and Adopters

The matching estimator for $E\left[Y_0 \mid D=1\right]$ is given by equation (5). Substituting equation (2) into (5), we obtain

$$\hat{E}\left[Y_0 \mid D=1\right]=\frac{1}{I}\sum_{i\in H_1}\sum_{j\in H_0}W\left(i,j\right)Y_0^j \ . \tag{28}$$

Noting that $\sum_{j\in H_0}W\left(i,j\right)Y_0^j=\sum_{j\in H_0}W\left(i,j\right)\left(1-B_0^j\right)Y_0^j+\sum_{j\in H_0}W\left(i,j\right)B_0^jY_0^j$ and

$\sum_{j\in H_0}W\left(i,j\right)\left(1-B_0^j\right)Y_0^j=0$, we have that

$$\sum_{j\in H_0}W\left(i,j\right)Y_0^j=\sum_{j\in H_0}W\left(i,j\right)B_0^jY_0^j \ . \tag{29}$$

Substituting equation (29) into (28), the standard matching estimator can now be expressed as

$$\hat{E}\left[Y_0 \mid D=1\right]=\frac{1}{I}\sum_{i\in H_1}\sum_{j\in H_0}W\left(i,j\right)B_0^jY_0^j \ . \tag{30}$$

To demonstrate the validity of the proposed estimators for the conditional expectations of Y_0, we rely on the decomposition of $E\left[Y_0 \mid D=1\right]$ given by

$$E\left[Y_0 \mid D=1\right]=P\left(Y_0>0 \mid D=1\right)E\left[Y_0 \mid Y_0>0, D=1\right], \tag{31}$$

where $E\left[Y_0 \mid Y_0 = 0, D = 1\right] = 0$ and drops out of the formulation. When we substitute the estimators (17) and (21) into (31), we should obtain the matching estimator for $E\left[Y_0 \mid D = 1\right]$ given by (30). Substituting these estimators into (31), we obtain

$$\hat{E}\left[Y_0 \mid D = 1\right] = \left[\frac{1}{I}\sum_{i\in H_1}\hat{B}_0^i\right]\cdot\left[\frac{\sum_{i\in H_1}\sum_{j\in H_0} W\left(i,j\right)B_0^j Y_0^j}{\sum_{i\in H_1}\sum_{j\in H_0} W\left(i,j\right)B_0^j}\right] = \frac{1}{I}\sum_{i\in H_1}\sum_{j\in H_0} W\left(i,j\right)B_0^j Y_0^j\ , \tag{32}$$

where $\hat{B}_0^i$ is given by equation (14). Thus, our proposed estimators for each of the decomposed terms yield the standard matching estimator for $E\left[Y_0 \mid D = 1\right]$ given by (30).

<u>A.4 Validation of the Estimators for the ATTs of Non-Adopters and Adopters</u>

To demonstrate the validity of the proposed estimators for the ATT, we begin with the decomposition of the ATT given by (12). When we substitute in the estimators, (17), (18), (22), and (23) into (12), we should obtain the matching estimator for the ATT given by (3). Substituting the estimators into (12), we obtain:

$$\begin{aligned} A\hat{T}T = &\left[\frac{1}{I}\sum_{i\in H_1}\left(1-\hat{B}_0^i\right)\right]\cdot\left[\frac{\sum_{i\in H_1}\left(1-\hat{B}_0^i\right)Y_1^i}{\sum_{i\in H_1}\left(1-\hat{B}_0^i\right)}\right] \\ &+\left[\frac{1}{I}\sum_{i\in H_1}\hat{B}_0^i\right]\cdot\left\{\left[\frac{\sum_{i\in H_1}\hat{B}_0^i Y_1^i}{\sum_{i\in H_1}^{n}\hat{B}_0^i}\right]-\left[\frac{\sum_{i\in H_1}\sum_{j\in H_0} W\left(i,j\right)B_0^j Y_0^j}{\sum_{i\in H_1}\sum_{j\in H_0} W\left(i,j\right)B_0^j}\right]\right\}, \end{aligned} \tag{33}$$

which can be rewritten as:

$$\hat{ATT} = \left\{ \left[\frac{1}{I} \sum_{i \in H_1} \left(1 - \hat{B}_0^i\right) \right] \cdot \left[\frac{\sum_{i \in H_1} \left(1 - \hat{B}_0^i\right) Y_1^i}{\sum_{i \in H_1} \left(1 - \hat{B}_0^i\right)} \right] + \left[\frac{1}{I} \sum_{i \in H_1} \hat{B}_0^i \right] \cdot \left[\frac{\sum_{i \in H_1} \hat{B}_0^i Y_1^i}{\sum_{i \in H_1} \hat{B}_0^i} \right] \right\}$$
$$- \left\{ \left[\frac{1}{I} \sum_{i \in H_1} \hat{B}_0^i \right] \cdot \left[\frac{\sum_{i \in H_1} \sum_{j \in H_0} W(i,j) B_0^j Y_0^j}{\sum_{i \in H_1} \sum_{j \in H_0} W(i,j) B_0^j} \right] \right\}. \tag{34}$$

The first term in equation (34) equals the matching estimator for $E\left[Y_1 \mid D=1\right]$ given by (26), and the second term equals the matching estimator for $E\left[Y_0 \mid D=1\right]$ given by (32). Thus, equation (34) yields:

$$\hat{ATT} = \hat{E}\left[Y_1 \mid D=1\right] - \hat{E}\left[Y_0 \mid D=1\right] = \frac{1}{I} \sum_{i \in H_1} Y_1^i - \frac{1}{I} \sum_{i \in H_1} \hat{Y}_0^i \,, \tag{35}$$

which equals the standard matching estimator for the ATT given by equation (3).

A.5 Sensitivity Analysis

Rosenbaum (2002) developed several methods for testing sensitivity to hidden bias. We use the Wilxocon singed rank statistic based on nearest-neighbor propensity score matching using only matched pairs (m=1). Using this approach, we determine the upper bounds on the significance level (critical p-values) for the ATT given different values of Γ. If ATT remains significant for values of Γ greater than 1.75, we can then conclude that estimates are at least moderately robust to potential hidden bias.[11] In other words, the higher the value of Γ under which ATT remains significantly different from zero, the more conclusive is the evidence that there exists a positive effect of program enrollment on farmer adoption decisions. Note that the test does not determine whether or not hidden bias exists, but rather, how sensitive the estimate would be to hidden bias *if* such an unobserved confounder existed (Rosenbaum 2002).

In Table 10 we provide the results of the sensitivity analysis for all practices. The first column provides the Γ values and the second column (sig+) provides the corresponding upper bound on the p-value for the ATT. The results suggest that robustness to hidden bias varies considerably across the different practices. For conservation tillage, the results suggest that if an unobserved covariate caused the odds ratio to differ by a factor of around 1.3, then the ATT would no longer be significant at the 95% confidence level. For filter strips, however, the ATT remains significant up to a factor of 12, implying that the additionality estimate for filter strips is quite robust to unobserved bias. Γ values for the remaining practices range from around 2.2 to 4.2, which suggests that all practices, except for conservation tillage, show moderate to high levels of robustness to unobserved bias. This implies that we can conclude with greater confidence that for most practices, program enrollment has a statistically significant effect on conservation effort. This suggests that hidden bias alone cannot explain the association between enrollment and conservation effort.

[11] Studies by DiPrete and Gangl (2004), Andam et al. (2008), Ferraro et al. (2007), and Liu and Lynch (2011) consider Γ values greater than around 1.75 (for a 95% confidence level) imply the ATT estimates are at least moderately robust to hidden bias.

TABLE A.2

Results for Rosenbaum Sensitivity Analysis

Conservation Tillage		Cover Crops		Hayfields		Grid Sampling	
Γ	**sig+**	**Γ**	**sig+**	**Γ**	**sig+**	**Γ**	**sig+**
1	0.003	1	0.001	1.8	0.004	2.2	0.004
1.05	0.006	1.2	0.002	2.2	0.008	2.4	0.007
1.1	0.009	1.4	0.006	2.6	0.013	2.6	0.011
1.15	0.015	1.6	0.012	3	0.020	2.8	0.018
1.2	0.022	1.8	0.020	3.4	0.028	3	0.026
1.25	0.032	2	0.030	3.8	0.036	3.2	0.036
1.3	0.045	2.2	0.043	4.2	0.044	3.4	0.048
1.35	0.060	2.4	0.058	4.6	0.052	3.6	0.062

Grass Waterways		Filter Strips	
Γ	**sig+**	**Γ**	**sig+**
2	0.000	6	0.002
2.2	0.001	7	0.005
2.4	0.002	8	0.010
2.6	0.005	9	0.017
2.8	0.012	10	0.025
3	0.024	11	0.036
3.2	0.044	12	0.048
3.4	0.071	13	0.061

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